Mysore 2034: An Integrated Geoinformatics Approach for Real Estate Valuation and Urban Growth

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Abstract

Urban growth plays a significant role in shaping real estate market values of developing cities like Mysore. This paper delves into futuristic relationship between urban growth and property values, using data spanning from 2014 to 2024 and predicting trends up to 2034 through geographically weighted regression model Random Forest Regression model. The study includes analysis of 110 key locations, including factors like proximity to the central business area, railway station, bus stand, and local amenities like school and hospitals. Our use of the Random Forest regression model enables accurate predictions of future property values by understanding complex relationships between these variables. The strong correlation between guideline values and market values provides a reliable basis for predicting future real estate trends. This correlation is essential for stakeholders, including developers, investors, and policymakers, as it supports strategic decision-making based on market projections. The expected significant rise in property values indicates that Mysore is poised for considerable growth, driven by strategic developments and improved infrastructure. Furthermore, the proximity to key urban nodes such as the central business area, railway stations, and bus stands shows significant determinant of property values, reflecting the influence of accessibility and convenience on market demand. A significant surge in property values is projected, estimating a significant increase of 118% by 2034. This indicates Mysore's robust economic potential and its ability to sustain growth over time. Notably, this growth trajectory is further catalyzed by the construction of new expressway between Mysore and Bengaluru to enhance connectivity and accessibility between the two cities. The research also highlights the interplay between urban growth and property values in the context of Mysore, a developing city. It addresses various crucial factors like the impact of urban infrastructure, regulatory frameworks.

Keywords: Guideline Value, Market Values, Proximity, Random Forest Regression Model, Urban Growth

1. Introduction

Although the developed world and developing countries differ in the percentage of people living in cities, as well as in the way in which urbanization is occurring, there is a global trend of urban population growth. India is witnessing unprecedented urbanization that has led to the growth of real estate sector, particularly housing. However, since independence providing affordable housing has been a challenge [1]. The property valuation in India is through evaluating the market value and the guideline value and is normally delivered as a report. The property valuation is generally conducted on the basis of wants from an individual, or contributing to the institution that is looking to provide finance for the purchase of the property. Valuation considers property details that include unit rate, the extent of the land and construction, physical details of the premises, the state of dwelling and information on any quick issues that is required to direct, as well as resources on comparative selling in the area. Valuation of property is estimated by three techniques, namely, cost technique, comparative technique and income technique [2]. Fixation of market value plays an important factor for the property valuation [3]. Market value is defined as the highest price between a willing buyer, who would pay, and a willing seller, who would bear, both being fully knowledgeable. Market value is fixed by the demand of the property by the government. In today's real estate market, obtaining accurate property valuation is critical for informed decision-making.

The traditional methods, such as comparable sales and income capitalization, depends heavily on property characteristics and financial data [2] and [4]. However, these methods fails to fully capture the significant impact of a property's location on its value. Geoinformatics, is a field that integrates geographic information systems (GIS) with other analytical tools, that offers a powerful approach to spatial analysis. By leveraging GIS capabilities, various locational factors, like proximity to amenities, crime rates, and environmental quality, affect property values is explored. The report aims, the potential of geoinformatics in real estate valuation estimation, aiming to provide a more comprehensive and data driven approach to property valuation are being. Geoinformatics is a dynamic field which combines geography, information technology, and spatial analysis. It allows to capture, manage, analyze, and visualize geographical data. The data encloses physical landscapes and natural resources to demographic information and infrastructure networks [5].

Geoinformatics provides the spatial context, while the regression models quantify the relationship hid within the data. A regression model is a statistical technique used for estimating the relationship between a dependent variable (often denoted by Y) and one or more independent variables (often denoted by X) [6]. It's essentially a tool to uncover how changes in the independent variables can predict changes in the dependent variable. Regression models is used to analyze historical sales data and create a model that predicts housing prices based on various property characteristics. Also, the Regression Model approach often fails to capture the spatial variability in housing markets, where Random Forest offers a powerful alternative that addresses this limitation. This means the model can capture local trends of house prices, accounting for the fact that factors influencing value might differ across locations within a study area [7]. Random Forest allows to identify how factors like proximity to amenities, crime rates, or specific neighborhood characteristics are influencing house prices in specific locations [8] and [9].

1.1 Literature Review

The Geoinformatics helps to identify patterns and trends in geographically distributed data. This reveals hidden connections between seemingly disparate phenomena [10]. With the help of Geoinformatics researchers are predicting the site rates which is crucial for the stake holders. In this work, accurately identifies the restrictions of traditional land valuation methods, emphasizes the need for objective and spatially explicit data. By analyzing the relationship between guideline value and market rate, the potential variation between official valuations and actual market prices. High-resolution satellite imagery was acquired for the study area. The imagery was processed and analyzed to extract various land use and land cover information, such as vegetation cover, water bodies, and built-up areas. The collected data was integrated with the remote sensing data and analyzed using GIS software. Spatial interpolation techniques were employed to create continuous maps of land value distribution across the study area. The relation between land value and various factors, including distance to transportation networks, proximity to schools and hospitals, and land use type, were investigated using statistical methods. The study dispenses a valuable contribution to the field of land valuation, particularly in the context of remote sensing and GIS applications. The findings have practical implications for real estate professionals, urban planners, and policymakers involved in land valuation and urban development initiatives [2] and [11].

By using BP Neural Networks, an artificial neural network employed to model the complex relationships between the spatial data obtained from GIS and the benchmark land prices [12] and [13]. The data driven automate the valuation process by leveraging GIS data and neural network learning. This reduces subjectivity and potentially improves efficiency. BP neural networks are then used to capture non-linear relationships between variables, making them well-suited for modeling the complex factors affecting land price. GIS allows for incorporating a 6 wide range of spatially-dependent factors that traditional valuation methods might miss. The data sets applicability to other cities with distinct urban structures and market dynamics needs investigation. By using Random Forest model, Data mining provides information from the data sets that is utilized by drawing comparisons, associate patterns, classifying the objects, to predict future trends based on the current and past standards of any given situation provide a clear set of data. Data-driven models are less susceptible to bias and human error compared to traditional valuation methods. Data collections involves data on property sale like location, property characteristics, market method and sale price. Data cleaning and preprocessing where the collected data is analyzed, identifying the missing data and correcting inconsistent data. Linear regression model relations the features and the sale price as a linear equation. Random forest ensemble learning algorithm that combine multiple decision trees to make predictions.

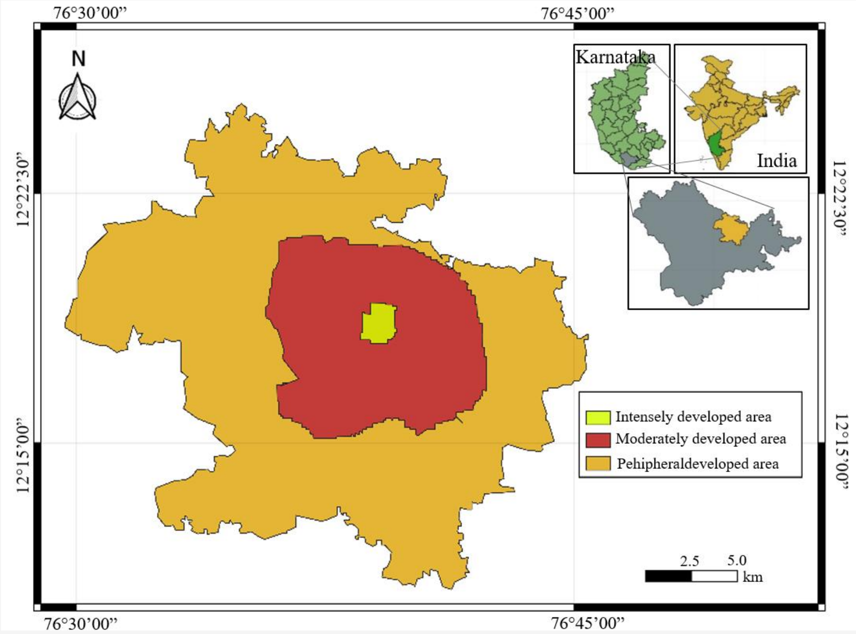

Figure 1: Location of Mysore, India

Each decision tree is trained on a random subset of the features and data points, making the overall model robust to overfitting and able to capture complex relationship. The performance of the trained model needs to be evaluated on a separate portion of the data by model evaluation.

2. Study Area

The study area selected for study is Mysuru district. The present study area located in southern part of India in Karnataka state shown in Figure 1. It is bounded to the East by Mandya district, on the south by Chamarajanagar district, on the west by Kodagu district, and on the north by Hassan district. The geographical extents of the study area are latitude of 11°73′N to 13°04′N and Longitude 75°90′E to 77°00′E, which consist an area of 11,815 km².Mysuru, is a city in the southwest Indian state of Karnataka. It is the second-largest city in the state and the 14th-largest city in India. Mysore is the cultural heart of Karnataka, that has transformed into a vibrant city where tradition thrives alongside modern industry. Mysore is known for its royal palaces, temples, and gardens. This introduction will delve into the diverse range of industries that shape Mysore's economy, with a particular focus on the booming IT sector. The city has also emerged as the second-largest IT hub in Karnataka. Mysore's industrial prowess has extended beyond IT. The city is also a major center for education, commerce, and industry. Mysore's infrastructure development plays an important role in supporting its growing population and economic activity. The city has an airport with domestic connectivity, and expansion plans are underway. Recently Bangalore-Mysore expressway has led to economic development of Mysore and increased property prices in some areas near 11 Mysore.

3. Data and Method

3.1 Methodology

The methodology of this study is illustrated in Figure 2. Digitizing the map is initial step for the zoning the map and generating the input data for result analysis. In this study, Mysore city maps of 2031 from MUDA (Mysore urban development authority). The maps are Mysore CDP (Comprehensive Development Plan), Land Use Map, Road Classification Map, Zoning Map and City Conurbation map of 2031. Initially, zoning map of Mysore 2031 from MUDA department is classified as Intensely developed area, moderately developed area and peripheral area of Mysore city to evaluate the site rates based on the development. Further zoning map is georeferenced and digitalized for further data generation shown in Figure 3. Subsequently, by using digitalized zoning map data is collected. The data is fed to the Random Forest Regression model where correlation of variables and creating the least square fit. The model obtained is fit into 2034 model and Analysed in GIS.

3.2 Data Collection

3.2.1 Data sets of points of interest (POI)

All the collected data is georeferenced and processed in QGIS shown in Figure 3. The collected 110 points were considered for the prediction of site rates. The location of some points considered are in the areas Mandi Mohalla, K R Mohalla, Devaraja Mohalla, Lashkar Mohalla, N R Mohalla, Tilak Nagar, Chamrajpura, Agrahara, R S Naidu Nagar, Bannimantap, Udayagiri, Raghavendra Nagar, Rajiv Nagar, Yadavagiri, B M Shree Nagar, Bogadi 2nd Stage, Muniswamy Nagar, Sarswathipuram, Mahadeshwara Badavane, Kanakadasa Nagar, Hebbal 2nd stage, BEML Nagar, Jayalakshmipura, Vijayanagar 2nd Stage, Indira Nagar, Gayathripuram, Krishnamurthy Puram, Ramachandra Agrahara, kuvempunagar, Arvinda Nagar, Bilwa, Siddhartha Layout, Visveshwara Nagar, K C Layout, Vidyaranypuram, Rajendra Nagar, Hebbal Industrial Area, Eklavya Nagar, Hootgali Industrial Layout, Hulikere, Magarahalli, Mundiranagar, Hanchya, Sahukara Hundi, Basavanahalli, Rajajinagar, Kamaravalli, Gayathri layout, Nagawala, Rayankere Post, Moogiahana Hundi, kenchalagodu, Daripura, Salundi, Avverhalli, Nandini layout, Chikkagowdana Hundi, Udbur, KBL Layout, Belwadi, Illavala Hobli, Charanahalli, Madapura, Yandahalli, Chikkalli, Salundi, Anand Nagar and Kadakola.

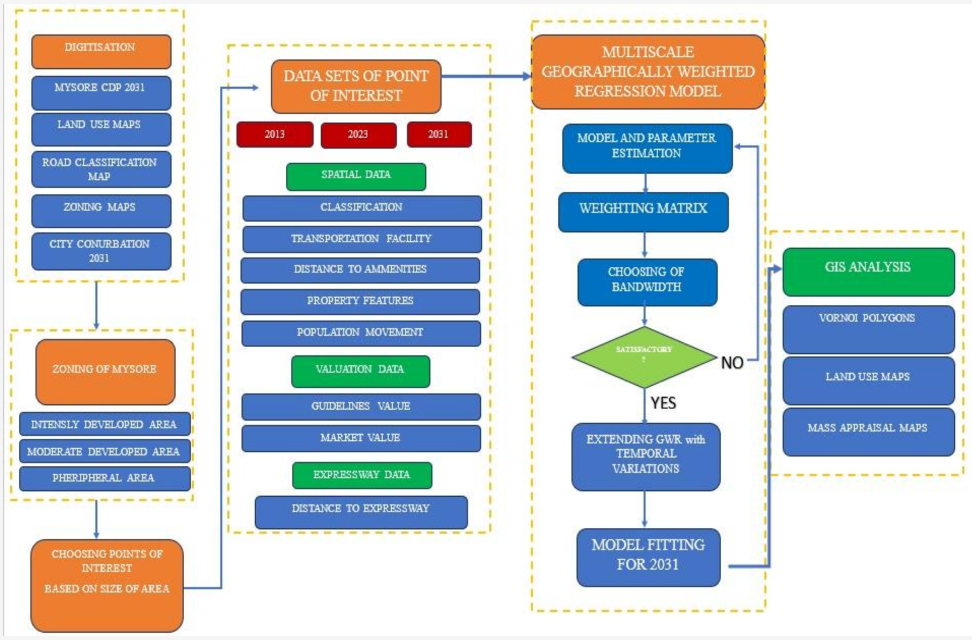

Figure 2: Methodology adopted for study area

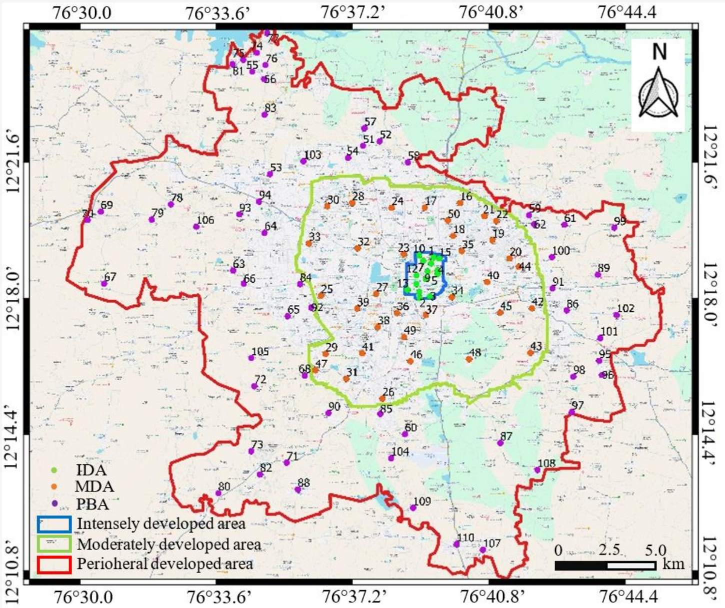

Figure 3: Zoning map of Mysore and points of interest

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3.2.2 Distance to amenities

The availability of bus stand, parks, hospitals and super market in buffer zone close to point of interest is determined in distance to amenities. This data is collected from QGIS. Figure 4 shows the availability in the buffer zone.

3.2.3 Transportation facility

The transportation facility identified as the distance from airport, Main bus stand and railway station to the point of interest. Figure 5, Figure 6 and Figure 7 shows the distance between the point. The point of interest considered in intensely developed area and around can reach the railway station in the time range of 5 minutes. The point of interest in the moderately developed area can reach within 10 minutes. Figure 6 shows the similar time range as considered to travel the railway station. While, the Intensely developed area and some parts of Moderately developed area which are at north part takes more time.

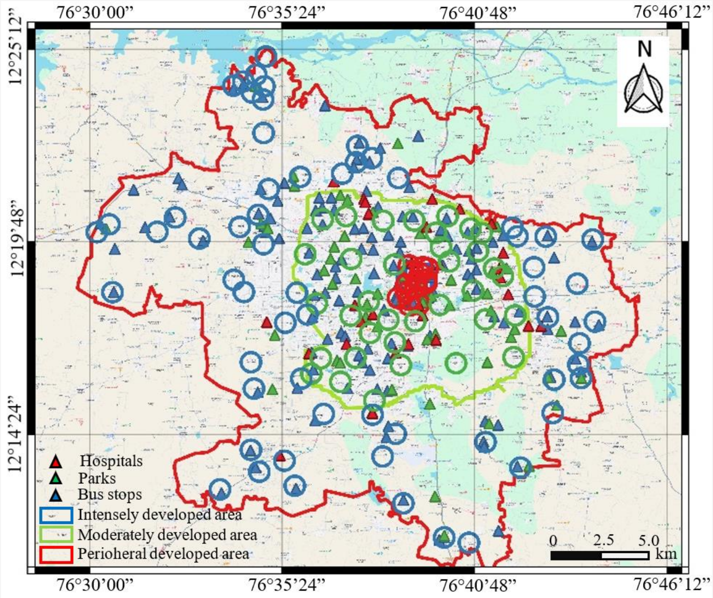

Figure 4: Nearest amenities to POI

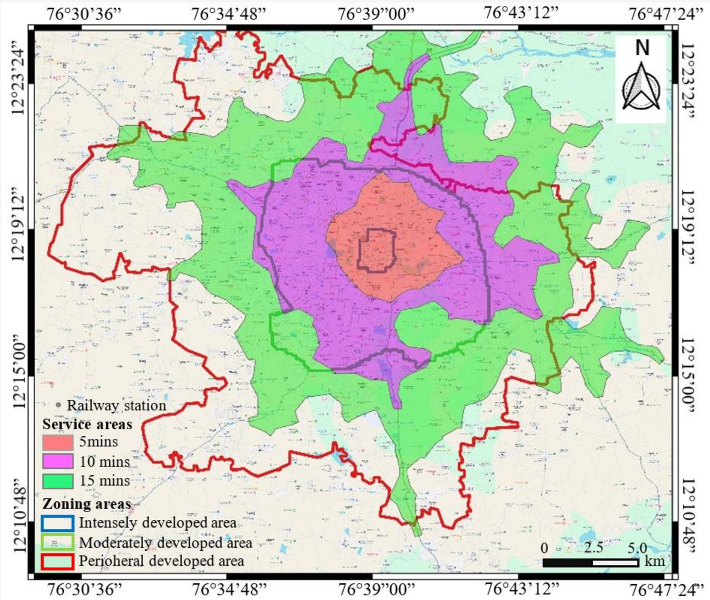

Figure 5: Transportation facility to Railway Station

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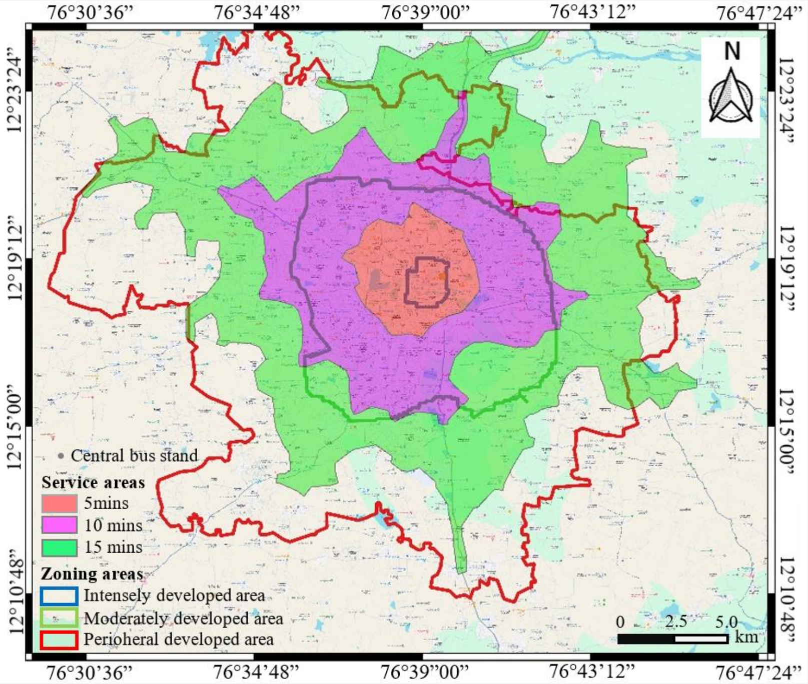

Figure 6: Transportation facility to Central Bus stand

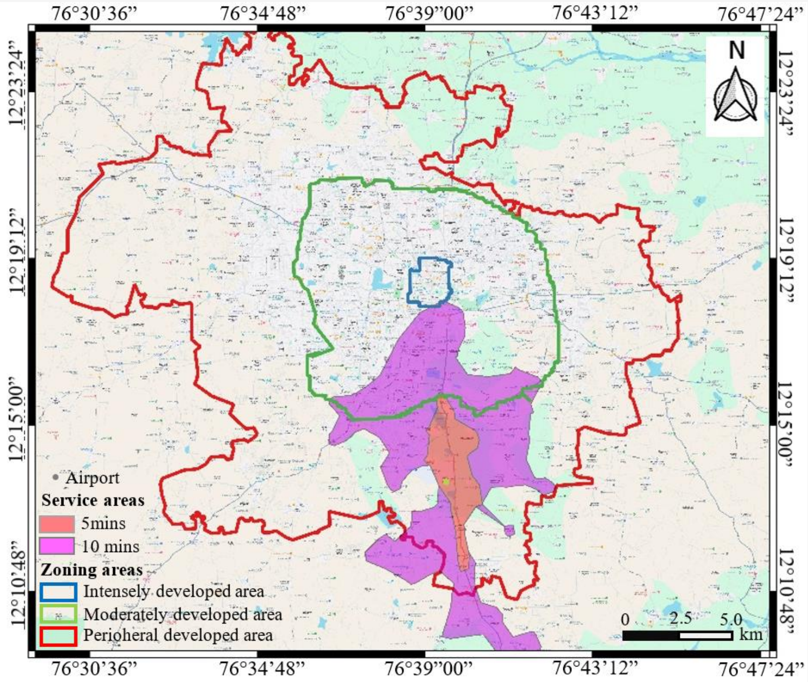

Figure 7: Transportation facility to Airport

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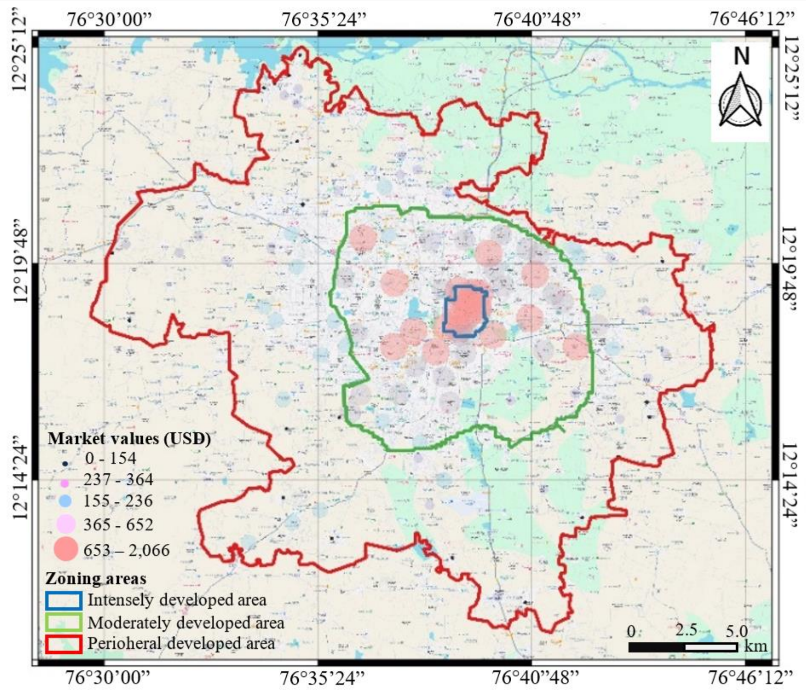

Figure 8: Market value

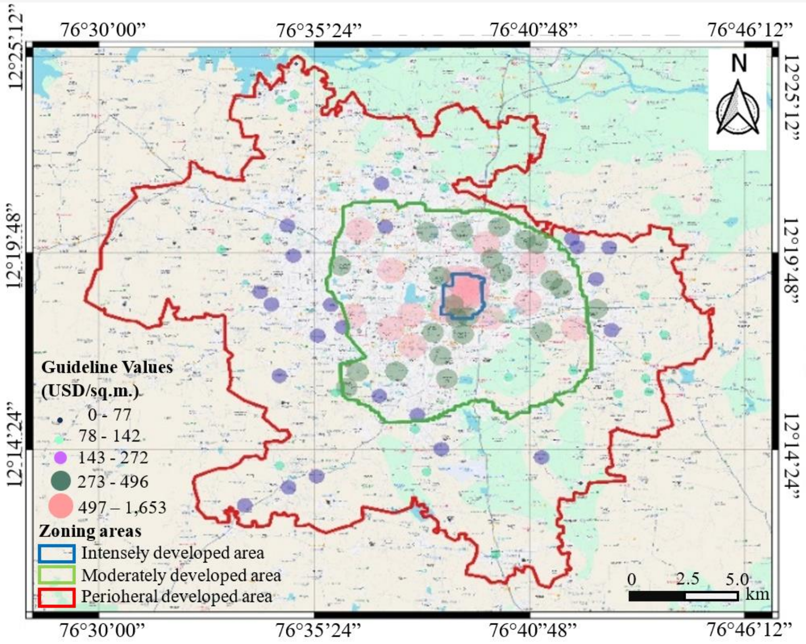

Figure 9: Guideline value

3.2.4 Market value

Market price, on the other hand, is the actual price at which a specific property is bought or sold. Market values are government determined value and may vary depending on location, property type, and other factors.

They use a comparative market analysis (CMA) to compare similar properties that have recently sold in the area. Figure 8 represents Market value at different locations. Market Value is determined by conducting survey from various real estate people.

3.2.5 Guideline value

Guideline values are set and defined by the government. Guideline values can vary significantly depending on the location and type of property. The guideline value is usually lower than the market value, reflecting a minimum threshold. A property might sell for more than the guideline value based on market conditions. Figure 9 represents the guideline value at different locations. Guideline values are obtained from the Mysore Urban Development Authority

3.3 Random Forest Regression Model

Random Forest Regression is a machine learning algorithm used for regression tasks, which means predicting a continuous output. It is an ensemble learning method that builds multiple decision trees and merges their results to improve the predictive performance and control overfitting [12]. Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest (Figure 10). The algorithm is part of the Scikit-learn library in Python, a widely-used library for machine learning. In Random Forest Regression, the dataset is divided into subsets, and each subset is used to build a separate decision tree. These trees are trained on different parts of the data and with different features. The final prediction is made by averaging the predictions of all individual trees, which helps in reducing the variance of the prediction and increases accuracy. Scikit-learn's 18 implementation of Random Forest Regression is user-friendly and highly efficient [13]. It allows users to set various parameters to tune the performance of the model. One of the main advantages of using Random Forest Regression is its ability to handle a large number of input variables without overfitting, making it suitable for datasets with many features. Additionally, it provides an estimate of the importance of each variable in the prediction, which can be useful for feature selection. The mathematical formulation for Random Forest Regression is given in equation 1 [14].

$$y = \frac{1}{B}\sum_{b}^{B} T_b(x)$$

Equation 1

Where:

y is the average of predictions from all individual trees

B is the total number of decision trees for the bootstrap samples (x_i and y_i)

x_i is the featured variable 1and

y_i is the target value

$T_{b(x)}$ is the prediction made by the b^{th} decision tree for input x_i

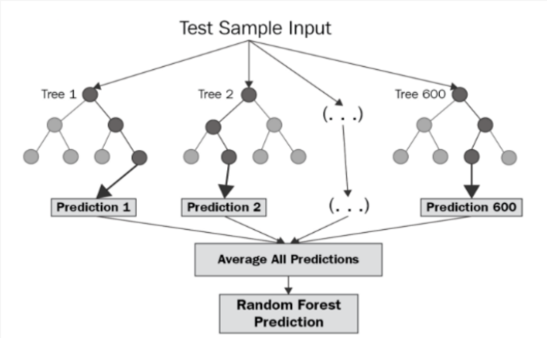

Figure 10: Random forest regression model

3.4 Voronoi Polygon

Voronoi diagrams are fundamental data structures extensively used for computational geometry. At their core, Voronoi diagrams partition a plane into regions based on the distance to a set of points called seeds or generators. Each region consists of points that are closer to a particular seed than to any other seed. These regions are Voronoi polygon [15]. Depending on the class of objects, distance functions, and embedding space, various variants of Voronoi diagrams are defined. This Voronoi polygon Voronoi diagram allows quick identification of the nearest site to any given point. This property is useful for location-based services such as finding the closet store or facility. Further, Voronoi diagrams partition space into regions based on proximity to sites. They can be used for spatial clustering and segmentation tasks. Mathematical definition of Voronoi Polygons is as shown below. Given a set of n distinct points $P=\{p_1,p_2,\ldots,p_n\}$ in a plane, the Voronoi polygon (or cell) $V(p_i)$ for a point p_i is defined in equation 2.

$$V(p_i)= \{x \in R^2 \mid d(x,p_i) \leq d(x,p_j) \text{ for all } j \neq i\}$$

Equation 2

Where:

$d(x,p_i)$ is the Euclidean distance between point x and p_i

$V(p_i)$ is the Voronoi cell containing all points x that are closer to p_i than to any other point p_j.

4. Results

4.1 Data Collection and Preprocessing

From the methodology used the data is collected and processed. The study focused on predicting real estate values (guideline value and market value) for Mysore in 2034. Data was collected for 110 locations, including the following variables:

i. Guideline value for 2014 and 2024
ii. Market value for 2024
iii. Number of hospitals, bus stands, educational centres, parks and supermarkets

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iv. Road width in front of corresponding location.
v. Distances from the sub urban bus stand, railway station, airport, and expressway

4.2 Correlation Analysis

A correlation matrix was generated to understand the relationships between the collected variables, guideline values, and market values. The analysis reveals a high correlation of 0.96 between the 2024 guideline value and the 2014 guideline value. The analysis also reveals a high correlation of 0.996 between the 2024 guideline value and the 2024 market value. This strong correlation indicates a very close relationship between these two variables, making them suitable for predictive modelling. Figure 11 and Figure 12 Cross Correlation matrix is obtained from Random Regression Model.

4.3 Predictive Modelling

4.3.1 Random Forest regression

Random Forest Regression was employed to train the model and develop predictive equations for:

i. The guideline value between 2014 and 2024.
ii. The relationship between the 2024 guideline value and the 2024 market value.

Model 1: Predicting 2024 Guideline Value from 2014 Guideline Value

Data: 2014 guideline value and additional location-based variables.

Model: Random Forest Regression.

Performance: The model achieved a score of 91% and Normal Root Mean Square Error (NRMSE) of 0.053, indicating high accuracy in predicting the 2024 guideline value from the 2014 data.

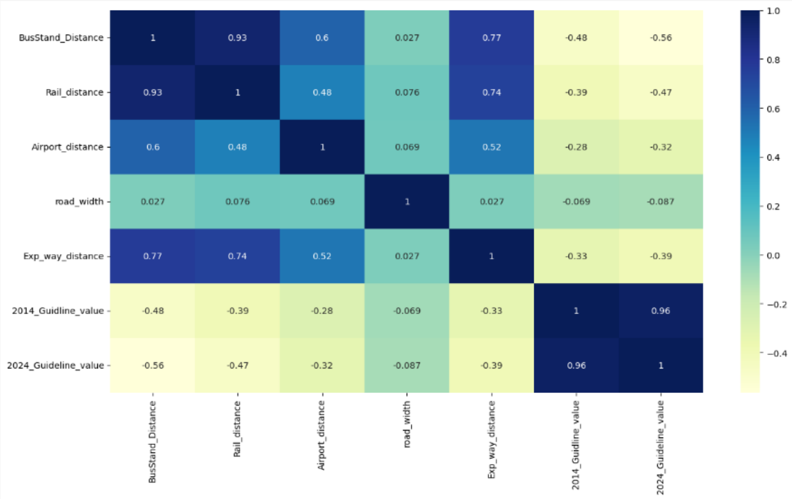

Figure 11: Cross Correlation Matrix for Guideline Value 2014 and 2024

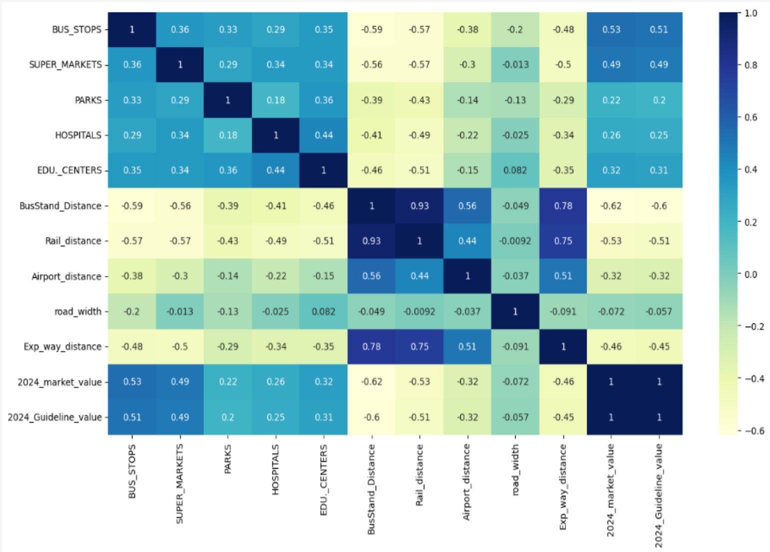

Figure 12: Cross correlation matrix for guideline value 2024 and market value 2024

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The resulting linear equation for predicting the 2024 guideline value GV_{2024} from the 2014 guideline value GV_{2014} shown in equation 3.

$$GV_{2024} = 1.63\ GV_{2014} + 5901 \quad \text{Equation 3}$$

Model 2: Predicting 2024 Market Value from 2024 Guideline Value

Data: 2024 guideline value and additional location-based variables.

Model: Random Forest Regression.

Performance: The model achieved a score of 96% and Normal Root Mean Square Error (NRMSE) of 0.068 indicating high accuracy in predicting the 2024 market value from the 2024 guideline value.

The resulting linear equation for predicting the 2024 market value MV_{2024} from the 2024 guideline value GV_{2024} shown in equtaion 4.

$$MV_{2024} = 1.2 GV_{2024} + 5113 \quad \text{Equation 4}$$

4.4 Predicting 2034 Values

Using the above models, the guideline value and market value for 2034 were predicted as follows:

4.4.1 Predicting 2034 guideline value

The guideline value for 2034 GV_{2034} was predicted using the equation 5 derived from Model 1:

$$GV_{2034} = 1.63 GV_{2024} + 5901 \quad \text{Equation 5}$$

4.4.2. Predicting 2034 market value

The market value for 2034 MV_{2034} was predicted using the equation 6 derived from Model 2:

$$MV_{2034} = 1.2 GV_{2034} + 5113 \quad \text{Equation 6}$$

Through the use of Voronoi polygons, Voronoi diagrams provide a clear and intuitive way to display the spatial distribution of real estate values, highlighting regional variations and trends. This visualization technique is particularly useful for urban planners and developers to identify hotspots of growth and areas requiring intervention. The average growth in real estate rates was found to be 118%. This significant increase underscores the dynamic nature of the Mysore real estate market and highlights the city's potential for future development. Such growth rates are indicative of underlying economic and infrastructural developments that are likely driving demand and pushing up property values.

5. Conclusion

This study navigates into the relationship between urban expansion and property valuation in Mysore, addressing the critical need for insights into the evolving real estate landscape. With rapid urban growth and infrastructural development reshaping the city, understanding the factors influencing property values is essential for stakeholders. Leveraging data from 2014 to 2024 and employing geoinformatics and random forest regression modelling, the study aims to forecast property valuations for 2034 across 110 locations. Such insights are vital for urban planners, developers, and policymakers, enabling informed decisions on urban development, investment strategies, and infrastructure planning. Additionally, the initiation of new expressways linking Mysore and Bengaluru is anticipated to further boost the property appreciation, particularly in areas adjacent to the corridor. The study aimed to gain insights into the real estate dynamics of Mysore by predicting guideline values and market values for the year 2034. The analysis focused on a comprehensive dataset comprising guideline values from 2014 and 2024, market values from 2024, and various location-based variables such as the number of hospitals, bus stands, educational centres, and supermarkets, as well as distances from key infrastructural hubs.

By understanding the real estate dynamics, the correlation analysis played a crucial role in understanding the relationship between guideline values and market values. The exceptionally high correlation coefficient of 0.996 between the 2024 guideline value and market value and 0.96 correlation between the 2024 guideline value and 2014 guideline value underscored the strong association between these variables. This reflects the responsiveness of the real estate market to regulatory frameworks and economic factors.

5.3 Robust Predictive Modelling with Random Forest Regression

After correlation analysis, Random Forest Regression technique is used for predicting real estate values. The models developed achieved an impressive accuracy score of 96%, indicating their effectiveness in capturing the underlying patterns in the data. By leveraging both the 2014 guideline value and additional location-based variables, the model successfully predicted the guideline value for 2024. Similarly, using the 2024 guideline value as the predictor, the model accurately forecasted the guideline value and market value for the year 2034.

By Predicting the model, Voronoi polygons was used, where we can visualize the site rates across different regions of the city and the predicted rates for 2034. This visualization technique is particularly useful for urban planners and developers to identify hotspots of growth and areas requiring intervention. The average growth in real estate rates was found to be 118%. This significant increase underscores the dynamic nature of the Mysore real estate market and highlights the city's potential for future development.

5.4 Future Scope

Incorporation of additional variables, such as demographic trends, economic indicators, and policy developments, to enhance the predictive accuracy of the models. Ongoing monitoring and validation of the models against real-time data will be critical for ensuring their continued relevance and effectiveness in guiding decision-making processes.

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