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Cobb-Douglas Hybrid Modelling Approach with Fuzzy-AHP Indexing for Residential Land Value Determining: A Case Study of Konya/Turkey

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Abstract

In this study, for mass real estate appraisal forecasting, the hybrid mathematical model has been developed by combining Cobb-Douglas one of the nonlinear regression models, and linear modeling. The real estate attributes that create the model were grouped under four main-title: local, spatial, physical and legal features. While Cobb-Douglas was used for the value forecast based on the real estate attributes in each part of the model, an integrated model was created with a linear approach. As a different approach, local and spatial features, which are among the real estate attributes, were used as indexes for reasons such as preventing data confusion in the model and using according to the spatial analysis results of distances. Local and spatial index were prepared with the Fuzzy Analytic Hierarchy Process (FAHP) method to use within the model. For indexes, in the central districts of Konya, 10 local-specific attributes were used, while 12 spatial-specific attributes. The data set has been prepared using legal and physical attributes with market values collected from 457 parcels in the study area. Local and spatial attributes were added as indexes to the data set used in the hybrid model. In addition, modeling was done with the data set used in the Cobb-Douglas Hybrid Model (C-DHM) according to the Linear Multiple Regression Analysis (Linear MRA) method. The developed C-DHM's results was integrated with Geographical Information Systems (GIS). The performance values between the hybrid model and market values were examined. Results showed that R2 value for C-DHM and Linear MRA used as indexes was found to be 0,85 and 0,80. When the values obtained from C-DHM and market value are compared, it is seen that model gives successful results.

Keywords:
Fuzzy Analytic Hierarchy Process (FAHP), Cobb-Douglas Hybrid Model (C-DHM), local and spatial indexing, mass real estate appraisal, geographic information systems (GIS)

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INTRODUCTION

Real estate appraisal is important for local managers who are responsible for providing various public services to their citizens. The local government uses real estate taxes that it receives at certain rates according to the type and value of the real estate within the management boundary as the biggest source of meeting these services. Thus, the local government must ensure the fairness of the real estate taxes by accurately deciding the real estate value for both the country and the citizens. The most critical issue to meet the justifications is the methods applied in determining the real estate value. Nowadays, mass real estate appraisal is newly emerging and new methods are being developed.

Mass appraisal refers to the process of determining the value of all real estate in the relevant area. Generally, the common method for mass appraisal is Multiple Linear Regression Analysis (MRA). After years of applications, especially the linear MRA models has been accepted as the most common usage model because of its expression with a clear mathematical formula, the wide use of tax departments and the long-term stable application advantages (Lin and Mohan, 2011; Del Giudice et al., 2017). The traditional MRA model is a type of global model that generates using observed data, in which a single parameter is estimated for each variable in the model (Wang, H. et al., 2020). It is a frequently encountered situation in literature that real estate value estimation and attributes effects of multivariate linear regression method are also used (Yalpir and Bayrak, 2017; Ghosalkar and Dhage, 2018; Georgiadis, 2018; Bartram, 2019; Pérez-Rave et al., 2019; Baird et al., 2020).

Out of Linear MRA, many methods have been developed and contribute to the literature for mass real estate appraisal systems (Peterson and Flanagan, 2009; Wang et al., 2015; Zhou et al., 2018; Dimopoulos and Bakas, 2019; Peter et al., 2020). These methods, which have various expressions such as mass valuation, automatic valuation or advanced valuation method; are used algorithms as fuzzy systems, hedonic modelling, artificial intelligence, random forest. Sometimes we can come across as a hybrid method integrated into these methods (González, 2008; Hill, 2013; Unel and Yalpir, 2019(a); Guan et al., 2008; Zurada et al., 2011; McCluskey et al., 2012; Shi et al., 2020). However, since many of these methods are difficult to implement and understand, they cannot be used in practice. The common property of the mentioned methods is that they use attributes to reach the result. All methods interpret the investigation results according to different mathematical algorithms using subject-related attributes.

All the attributes affecting the value with the Linear MRA method have a direct effect weight on the dependent variable. In other words, this technique calculates by establishing a correlation between independent variables and dependent variable. Whereas, there is a need for a model that needs to be distinguished according to the characteristics of the factor affecting the real estate value. Since the

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value is formed according to the supply and demand in the market conditions, it cannot be expected to be in a linear direction. The hybrid model, created by using Cobb-Douglas (non-linear) model and the linear regression model, enables the opportunity to category the attributes. Cobb-Douglas hybrid model (C-DHM) can be used to produce value maps through Geographic Information Systems (GIS).

Too many attributes that affect the value problems in modelling and database creation. It is possible to categorize the attributes in the appraisal model and then implement a mass appraisal using the coefficients obtained as a result of the modelling. The plenty of local and spatial attributes creates problems in its use in modelling and in creating a dataset. Indexing to reduce these distance-based attributes will reduce the workload time and cost, especially in other applications that must mass appraisal.

There are studies with indexing in the literature. Studies are used in areas such as health and economy (Guler and Bilici, 2017; Dewi et al., 2017). There are different expressions of indexing, sometimes in the form of suitability, sometimes sensitivity and sometimes risk maps, depending on the purpose of the applications (Ozkazanc et al., 2020; Taghizadeh-Mehrjardi et al., 2020; Abedi Gheshlaghi et al., 2020). The main logic here is to add multiple factors to get a single result. In study by Jensen et al. (2012), created Habitat 'Suitability Index Map for practitioners for industrial symbiosis. In the related study, the maps of nine spatial variables formed as a result of GIS analysis were collected with a single index map. Finally, they made them ready for decision support through index maps. The combination of attributes that are effective for such applications also requires a method. In general, it is observed that Multi-Criteria Decision Analysis (MCDA) systems are highly preferred in uses that need spatial combining (Cordão et al., 2020; Bakirman and Gumusay, 2020; Uyan, 2013). Today, hybrid methods that develop with the use of artificial intelligence techniques take place in the literature.

GIS is an indispensable tool in analysing many attributes based on spatial. The real estate appraisal is linked to the real estate location. This location sometimes stands out as a coordinate and sometimes an address. Yet, whatever the case, the locational expression shows that there are also neighbourhood relations that affect real estate. In other words, whether the attributes of real estate are located in the form of spatial or non-spatial, they are affected by the neighbourhood relations. The element that we can see this effect best is the value of the real estate. GIS is also required in the production of value maps (Locurcio et al., 2020; Mete and Yomralioglu, 2019). For an important application such as the property tax system, GIS should be utilized in the most effective use.

This study aims to make mapping that will reduce the number of variables by using Fuzzy Analytic Hierarchy Process (FAHP) for local and spatial attributes in mass real estate appraisal and to create a method for the real estate value with C-DHM approach. Grouping the attributes make eases the use of the value-determining model, especially by creating local and spatial indexes. How the modelling with the developed C-DHM, is effective in the value determined will be able to display. The application can gain an important place in the literature with a view to producing local and spatial indexes. The difference from similar studies is that the model is established with combining linear and nonlinear approaches (i.e. C-DHM). Thus, when a new/different real estate attribute is included in the model, the model cannot need to be installed from the beginning due to its linear form, and real estate attribute(s) can be added to the existing model. This statement means: If the mass appraisal model is to be applied for a different study area, the model will not be affected by the new attributes of the real estate in the region. So new attributes will be evaluated without affecting the model. Another difference is that: Since the excess of attributes affecting the real estate value complicates the model, producing a single index for location-specific data such as spatial, demographic and neighbourhood relations make provides ease of use. The produced indexes can be used in different studies. Briefly, a developed methodology for the process steps in mass real estate appraisal can be shown as the generalized solution.

REAL ESTATE APPRAISAL METHODS

Real estate valuation has a wide range of applications ranging as taxation, mortgaged sales, and expropriation in the world countries. Besides it has been used in development practices and planning studies to land management Also, the appraisal issue must be considered based on scientific bases and social justice due to today's changing needs. International Association of Assessing Officers (IAAO) examines the appraisal issue, in two groups, as single and mass real estate appraisal (IAAO, 2013). There are various methods for both single and mass appraisals in literature. These methods have been presented in Figure 1 considering current academic research, today's various requirements for the types of different real estates, and IAAO standards. However, there have been significant changes in the use of these methods and content of appraisal issue with the developing computer technology over time. Furthermore, because valuations of real estate are used in different requirements, single appraisal methods produce temporary solutions. These methods do not provide sufficiently today's requirements. Therefore, the need to appraise many real estates at simultaneously has become popular. According to IAAO, mass appraisal is the process of valuing a group of properties as of a given date and using common data, standardized methods, and statistical testing (IAAO, 2013). Mass appraisal is a subject that our country and many other countries of the world are working on. Although there are differences in the locations and living standards of the countries, the general understanding is the same (Barańska, 2013).

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When Figure 1 is examined, firstly, real estate appraisal methods are divided into two groups as single and mass. The single appraisal methods group includes sales comparison, income, and cost methods, respectively. These methods are also known as traditional methods in the literature and provide temporary solutions in real estate appraisal applications. The group of mass appraisal methods, on the other hand, includes various methods that are quite popular today. Foremost of these methods is machine learning techniques, which are often preferred in the literature. Machine learning methods used and to be used in the mass appraisal are multiple linear and nonlinear regression, Support Vector Machines-Support Vector Regression, Artificial Neural Networks, and ensemble learning-based Decision Trees (e.g. Random Forest), respectively. In addition to these techniques, MCDA-based methods such as Fuzzy Logic, Nominal method, Analytic Hierarchy Process (AHP) and FAHP can also be used effectively in the mass appraisal of real estates (Yalpir, 2018; Aydinoglu et al., 2020; Yilmazer and Kocaman, 2020; Chen et al., 2017; Mete and Yomralioglu, 2019; Yalpir et al., 2013; Selim, 2009).

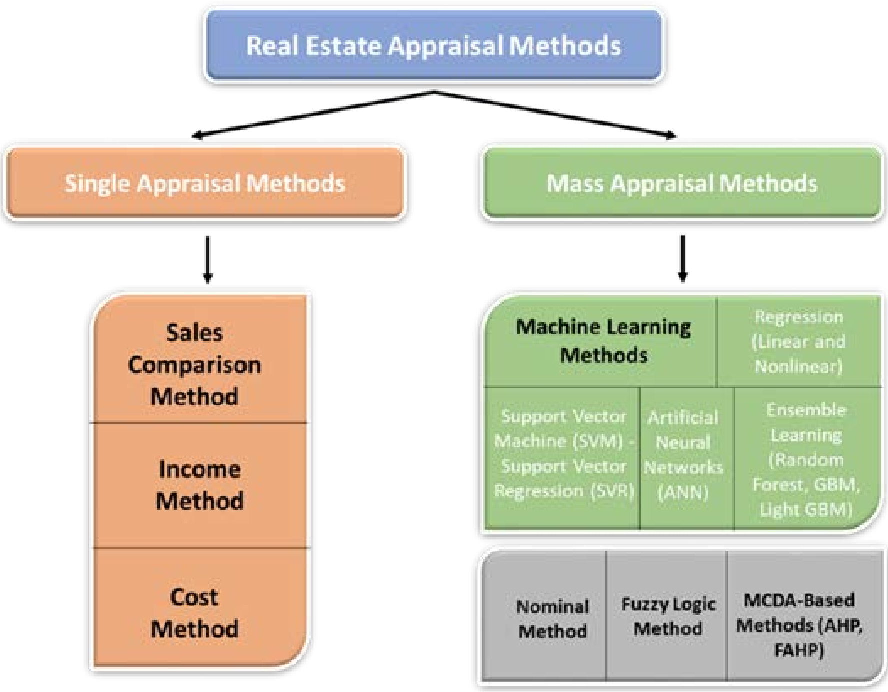

Figure 1. Real estate appraisal methods

Regression Analysis

Regression methods are statistical analysis and estimation techniques used in many different fields such as environment and climate (Sousa et al., 2007), agriculture (Kostov, 2009), electronic (Hong et al., 2010), sustainable energy (Sehgal et al., 2014) and industry (Syazali et al., 2019). On the other hand, regression analysis methods are also currently used in real estate appraisal studies (Božic et al., 2013; Pérez-Rave et al., 2019; Nesticò and La Marca, 2020). Regression

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analysis is divided into two as linear and nonlinear regression methods according to the characteristics of mathematical functions.

Linear Multiple Regression Analysis (Linear MRA)

Linear MRA explains the relationship between the dependent variable and independent variables using a mathematical equation (Zheng et al., 2020) (Equation 1). It is a crucial procedure used for data analysis in many applications. Independent variables can affect each other among themselves. As well as many independent variables can come together and affect another dependent variable (Kilic, 2013).

$$Y_n = a_0 + a_1 X_{n1} + a_2 X_{n2} + \ldots\ldots\ldots + a_m X_{nm} + e_n \quad (1)$$

Y_n = Dependent variable (Real estate value), X_{n1}, X_{n2}, ..., X_{nm} = Independent variables (Base area coefficient, Floor area coefficient, Area,..., etc.), e_n = Random error term, a_0 = Regression constant coefficient, a_1, a_2,..., a_m = Regression (variable) coefficients. In the study, the linear MRA method was used to present the success of the new hybrid model comparatively.

Nonlinear Multiple Regression Method (Nonlinear MRA)

Nonlinear MRA aims to establish a nonlinear relationship between the dependent variable and independent variables. Different model functions can be generated in nonlinear regression and many mathematical equations are involved (Wang et al., 2020). Nonlinear regression function examples include exponential, logarithmic, trigonometric, polynomial and Gauss curves. Some functions can be transformed so that they are linear. When so transformed, linear regression can be performed but must be applied within the check (URL1). For the study, the Cobb-Douglas model application, which is one of the nonlinear approaches, has been used in mass real estate appraisal. Detailed explanations about the Cobb-Douglas model are explained in the sub-heading.

Cobb-Douglas Modelling

The Cobb-Douglas model is an economic mathematical model proposed by Charles W. Cobb and Paul Douglas in early the 1930s. With the Cobb-Douglas model, predictions were made for many production functions and solutions were presented for the problems encountered (Nikkhah et al., 2016; Gorgess and Naby, 2017; Kojić and Lukač, 2018; Mahaboob et al., 2019). Generally, the method is used to predict national and regional industrial production (Zhang et al., 2013). It has a mathematical foundation that provides physical connections between input and output through equations containing dependent and independent variables. Inputs are subject-specific parameters, and output is the result of mathematical equations. The mathematical expression of the model is shown in Equation 2.

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$$Y = A(i)\, f(A_i, A_{ii}) = y_i = a_0\ A_{1,i}^{a_1} A_{2,i}^{a_2} \ldots + u_i \quad (2)$$

Y, y_i = Dependent variable; A_i, A_{ii} = Independent variables; a_1, a_2, …., a_n = Density coefficients (exponential); A(i), a_0 = Constant parameter; u_i = Random error term.

Mass Real Estate Appraisal with Cobb-Douglas Hybrid Model

If we are talking about the concept of mass real estate appraisal, primarily, the methodology put forward should concern the whole real estate. Thus, the methods to be applied should take into account all the real estate and the method should also explain the dependent variable and many independent variables that affect the real estate value. There are many methods of real estate appraisal in the literature. All methods have explained the approach between value of the real estate and attributes with linear and nonlinear models. The most common model is multiple regression model. Multiple regression model is linear and nonlinear models created due to the need to work with multiple criteria in mathematical modelling. In this paper, the hybrid model is proposed for mass real estate appraisal. While the mathematical model for the nonlinear is used as Cobb-Douglas, a model integrated with the linear approach is created. Models created by using linear and nonlinear mathematical models (Equation 3):

$$y = \underbrace{a_0 * (M_1^{a^1} * M_2^{a^2} * \ldots)}_{1^{st}\ Group\ Attributes} + \underbrace{b_0 * (K_1^{b^1} * K_2^{b^2} * \ldots)}_{2^{nd}\ Group\ Attributes} + \ldots\ldots + \underbrace{e_0 * (A_1^{e^1} * A_2^{e^2} * \ldots)}_{n.\ Group\ Attributes} \quad (3)$$

are expressed. Here, the constants of the model are the weights that a_0, b_0,…, e_0 attribute groups (Main-group: local, spatial, physical and legal in this study) add to the model. M_1, K_1….., A_1 attribute groups (Sub-attribute: Base area coefficient, floor area coefficient, number of floors, area of residential land, building layout, , corner/intermediate land, facade length, facade number, geometric shape, infrastructure services, roadway type, healthcare centres, education facilities, shopping centres, public facilities, cultural centres, security units, entertainment centres, green areas, city centre, insanitary areas, transportation, other attributes, population density, education level, favourite neighbourhood, building density, development potential, slope of neighbourhood, geological condition, climate condition, air pollution, noise pollution in this study) and a_1, a_2,...b_1, b_2,..e_1, e_2,… values within the group contain the effect intensities of the attribute within the group. While the basic mathematical expression and coefficients in the model are Cobb-Douglas method, different attribute group's sums include the linearity model. In the study, each group was brought together according to the attribute of real estate. The C-DHM has been created in a way that counts the attribute of local, spatial, physical and legal groups and the sub-attributes of these groups.

Local and Spatial Indexing

AHP simplifies and analyses a complex multi-criteria decision process. In doing so, it uses numerical scale values in binary comparisons to determine the importance of each criterion. Despite its advantages, the method is short of modelling the fuzziness caused by decision-makers' preferences. Therefore, methods should be developed to assist in deciding fuzzy judgments. It is more possible to use fuzzy methods in a complex and indefinite loop (Goguen, 1967).

Fuzzy logic theory, one of the fuzzy methods, is an approach put forward by Zadeh in 1965 (Zadeh, 1965). The basic principle in the method is that answer to be given about whether an element belongs to a set or not is not based on precise judgments. Consequently, the probability of this element belonging to the respective set is demonstrated by a continuous membership function that can take values between 0 and 1. FAHP is also the method suggested for a similar purpose. The method offers alternatives to select the best option or order the options in a multi-criteria environment using fuzzy sets theory and hierarchy structure. FAHP utilizes triangular fuzzy numbers (TFNs) to model the complexity or fuzziness of decision-makers (Nyimbili and Erden, 2020). TFNs is a peculiar type of number whose membership function is characterized by l, m and u parameters in Figure 2.

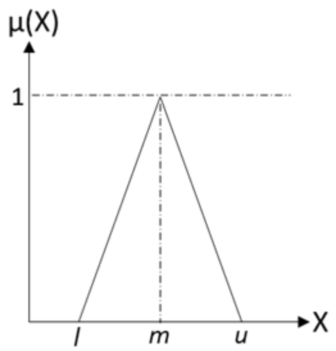

Figure 2. Triangular fuzzy number (l, m, u)

l, m and u parameters represent the lower, mean and upper bounds of the TFN (Mu et al., 2008). Linear representations of each TFN can be defined by the following membership functions (Equation 4).

$$\mu(x; l, m, u) = \begin{cases} \dfrac{x-l}{m-l}; & l \leq x \leq m \\ \dfrac{u-x}{u-m}; & m \leq x \leq u \\ 0; & otherwise \end{cases} \quad (4)$$

These TFNs are used to create a fuzzy pairwise comparison matrix. TFNs related to FAHP have been used differently by different

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practitioners (Laarhoven and Pedrycz, 1983; Buckley, 1985; Chang, 1996). In our study, it is proposed to use Buckley's (1985) geometric mean method, which is a unique solution and ease of calculation to develop indexes in mass real estate appraisal.

Geometric mean method

The geometric mean method proposed by Buckley was used in this study. TFNs were used to express expert opinions, generating a triangular fuzzy comparison matrix (Table 1).

Table 1. Fuzzy Comparison Matrix

$A = (\tilde{a}_{ij})_{nxn} =$

(1,1,1)	l_{12}, m_{12}, u_{12}	…	…	l_{1n}, m_{1n}, u_{1n}
l_{21}, m_{21}, u_{21}	(1,1,1)	…	…	l_{2n}, m_{2n}, u_{2n}
…	…	(1,1,1)	…	…
…	…	…	(1,1,1)	…
l_{n1}, m_{n1}, u_{n1}	l_{n2}, m_{n2}, u_{n2}	…	…	(1,1,1)

Where, $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ and $\tilde{a}_{ij}^{-1} = (1/u_{ji}, 1/m_{ji}, 1/l_{ji})$ for i, j = 1, …, n and i ≠ j is represents. Fuzzy set operators of multiplication, addition and subtraction, used in the fuzzy pairwise comparison approach computation for fuzzy sets M_1 ($\tilde{a}_i$) and M_2 ($\tilde{a}_j$) are demonstrated from (Equation 5-7) as follows:

$$M_1 \times M_2 = [(l_1, m_1, u_1). (l_2, m_2, u_2) = (l_1.1_2, m_l.m_2, u_1. u_2)] \quad (5)$$

$$M_1 + M_2 = [(l_1, m_1, u_1) + (l_2, m_2, u_2) = (l_1 + 1_2, m_l + m_2, u_1 + u_2)] \quad (6)$$

$$M_1 - M_2 = [(l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - 1_2, m_l - m_2, u_1 - u_2)] \quad (7)$$

TFNs transformed from linguistic variables representing scores of pairwise comparisons are presented in Table 2.

Table 2. TFN correspondence of linguistic variables

Linguistic Variables	Fuzzy scale	Inverse fuzzy scale
Equally important	(1, 1, 1)	(1, 1, 1)
Moderate	(2, 3, 4)	(1/4, 1/3, 1/2)
Fairly strong	(4, 5, 6)	(1/6, 1/5, 1/4)
Very strong	(6, 7, 8)	(1/8, 1/7, 1/6)
Absolutely more important	(9, 9, 9)	(1/9, 1/9, 1/9)
Intermediate values	(1, 2, 3)	(1/3, 1/2, 1)
	(3, 4, 5)	(1/5, 1/4, 1/3)
	(5, 6, 7)	(1/7, 1/6, 1/5)
	(7, 8, 9)	(1/9, 1/8, 1/7)

Where $\acute{r}_{ij}$ is the **fuzzy geometric mean** value given via (Equation 8),

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$$ŕ_{ij} = (ã_{i1} \times ã_{i2} \times \ldots \times ã_{in})^{1/n} \quad (8)$$

Normalization of the weights, w_i is then performed (Equation 9).

$$w_i = [\ (\ l + m + u\ )\ /\ 3\ ] \quad (9)$$

After the weights are determined, the process is completed by performing a consistency analysis. If there is any inconsistency, transactions are repeated.

Model Performance Analyses

In order to evaluate the model performance, outputs obtained from the nonlinear hybrid model have been compared with the market values. In comparing, R^2 (Equation 10), Mean Absolute Percentage Error-(MAPE) (Equation 11), Standard Deviation (SD) (Equation 12), Standard Deviation Percentage (SD%) (Eqn. 13) statistical performance methods were used.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_p - x_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (10)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|x_p - x_i|}{x_p} \quad (11)$$

$$SD = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{(n-1)} \quad (12)$$

$$SD\% = 100 * \frac{SD_{model}}{SD_{market}} \quad (13)$$

Where = x_p is market value; x_i is model value; $= 1, 2, 3, \ldots . n$; n is number of total parcel in the dataset; $\bar{x}$ mean market values. R^2 is a measure of the success of the equation obtained from the regression analysis. MAPE shows that the predicted value is how closer to market value. The low MAPE ratio is recommended for the high prediction accuracy of a model. In studies where methods are developed especially for real estate appraisal, these error rates and model performances were examined (Lin, 2010; Sarac, 2012; Kavas, 2014). SD is the deviation of the approximations in market and model values.

APPLICATION

In this study, first of all, the definition of the problem has been made. After the definition of the problem, the study objective(s) have been determined for its solution. The main objective(s) is;

a-) Mass appraisal of real estates using the developed Cobb-Douglas Hybrid model,

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b-) Creating indexes for real estate attribute groups (spatial and local) with FAHP,

c-) Developing real estate appraisal determining methodology.

Respectively, the prepared flowchart to achieve the objectives has given below (Figure 3.).

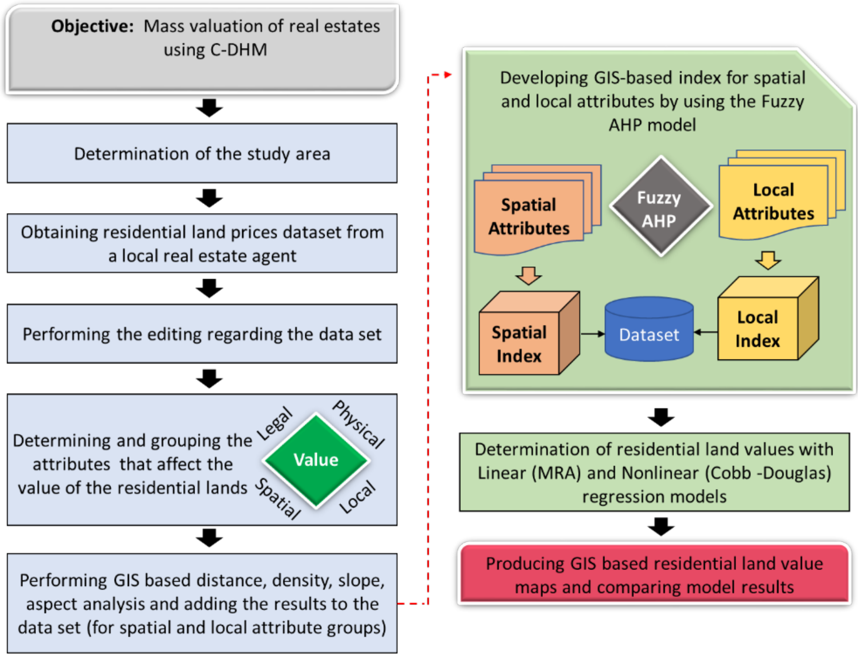

Figure 3. Flowchart for process of mass real estate appraisal

Study Area, Market Samples and Data Obtaining

The Konya province is located in the Central Anatolia Region, which is one region of seven in Turkey. Konya neighbours Ankara province which is the capital of Turkey in the north, Eskisehir province in the northwest, Antalya and Karaman province in the south, Nigde and Aksaray province in the east, Isparta and Afyonkarahisar province in the west (Figure 4). In 2020, the total population of the province is 2.232.374 (URL2). Although it has 31 districts in total, Meram, Selcuklu and Karatay districts are central districts and quite close to the city centre. The intersection of these three district boundaries is the city center. The study area is located in the neighbourhoods of three districts (Meram, Selcuklu and Karatay) that are close to the city centre and where housing is concentrated. The study area covers 269 neighbourhoods with 82.868 residential lands and 30.395 buildings. The study area is approximately 260 km^2. Maps of the study area have been presented in Figure 4.

The market samples were gathered to use in modelling from real estate purchase/sale websites, and local real estate agents, which is located in the study area. A data storage was created with obtained market samples. After data(s) editing, the last remaining dataset includes 457 real estates in residential land type. The sales values belong to the 2019 year in the dataset. The location of market samples throughout the study area is shown in Figure 4 using the red dot markers. Market sample prices range from a minimum of 55.000 ₺ to a maximum of 2.350.000 ₺. Besides, some descriptive statistics regarding market samples have been presented in Table 3.

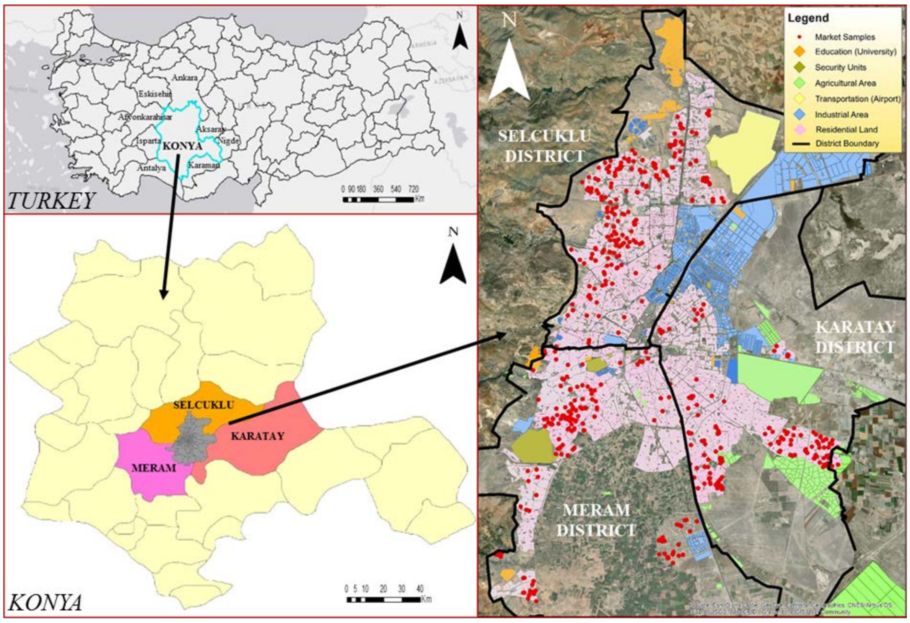

Figure 4. The study area and market samples

Table 3. Descriptive statistics of the dataset (Legal-Physical)

Attribute	Units	Mean	SD	Min	Max
Market value	₺	326253	341912	55000	2350000
Base area coefficient	Rate	0.24	0.07	0.08	0.90
Floor area coefficient	Rate	0.59	0.34	0.15	3.60
Number of floors	Number	2.44	0.93	1.00	8.00
Area of residential land	m^2	868	639	117	5462
Building layout	Text	2.92	0.35	1.00	3.00
Facade length	Meter	25.36	13.26	4.00	100
Facade number	Number	1.46	0.62	1.00	4.00
Infrastructure services	Rate	0.66	0.21	0.25	1.00
Corner/Intermediate Land	Text	1.36	0.48	1.00	2.00
Roadway type	Text	1.36	0.48	1.00	2.00
Geometric shape	Text	1.97	0.17	1.00	2.00

Note: *Attributes in the text (categorical) unit were transformed to numeric values. Building layout (Discrete-3, Contiguous-2, Block-1), Position of residential land in the building block (Corner-2, Intermediate -1), Geometric shape (Regular-2, Irregular-1), Roadway type (two-way-2, one-way-1).*

In hybrid mathematical modelling, scaling was performed on the dataset to more accurately determine the attributes activities and to eliminate the unit differences of the dataset record fields. Scaling the dataset provides both ease of multiple modelling and interpreting the result of models. Therefore, we performed a scaling to the dataset by using Equation 10. These equations were implemented in the dataset for each attribute record field respectively (BAC, FAC, Number of floors, Building layout etc.). In Equation 14, X_{scale} is scaled value for any attributes, X_i is value of i^{st} attributes in the dataset and $i = 1,2,3, \dots, n$, X_{max} is the maximum value of an attribute in column of the dataset.

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$$X_{scale} = \frac{X_i}{X_{max}} \tag{14}$$

In other words, since the mathematical model will be developed from a scaled dataset, the dataset was divided into the highest value of the relevant attribute in the study area. This scaling process was performed for other attributes, which is explained in Section 3.2. After the scaling process, the final dataset for modelling included the scaled value of all attributes. In this manner, the dataset was prepared for linear and nonlinear combination modelling.

Determination of Attributes for Mass Appraisal

The most important part of the real estate value model production is determination of the attributes that affect the value. In determining the value attributes, first, the attributes were grouped under four main categories as local, spatial, physical and legal. In this context, 5 attributes under legal group, 7 attributes under physical group, 12 attributes under spatial group and 10 attributes under local group were determined (Table 4). For local and spatial attributes, respectively, 10 attributes and 12 attributes were examined and an index was created from these attributes. The indexes for the attributes are explained in the next section. Looking at the attributes as a group, **legal attributes** are data arising from the usage rights granted to the property. It includes the property status and easement rights registered in the land registry and the construction information in the Implementation Zoning Plans. The least required to be made on the parcel granted to the real estate owners under the plan conditions is building floor area, floor area ratio, total number of floors and type of construction. Since the area of the parcel where these conditions will be realized is also a legal right, it is included in this group. **Physical attributes** include the feature that arises from the physical conditions where the parcel is located spatially.

Spatial attributes of all subtitles are based on data from plans (Table 4). Spatially, by determining the locations of these attributes, proximity analyses were performed and map bases were used. Each of the features has been transferred to ArcGIS software in separate layers. Proximity analysis was applied considering the impact service areas of the attributes. With the help of proximity analysis, the weights of each of the spatial attributes were determined as a result of the survey study. **Local attributes** were taken from the Turkey Statistical Institute (TUIK) and also, from the local government for use in small-scale mapping (Table 4). Taking into consideration the central neighbourhoods in Meram, Selcuklu and Karatay districts, a map base with neighbourhood borders on a small map scale was arranged (Figure 4). Based on this map, attribute data such as population density, structure density and level of education regarding local attributes were taken from TUIK. These data were associated with neighbourhood boundaries in ArcGIS and analysis maps of attributes specific to central neighbourhoods were created. Development potential, slope of neighbourhood and geological situation were obtained from the local government and datasets were created with GIS integration. Data of five stations belonging to the meteorological institution in the region were used for climate conditions and air pollution. Noise data were used by integrating into the map according to the data obtained from the Municipalities as a result of the measurements in the related areas (ring roads and crossroads on main streets, train and tramlines, industries, airport noise measurements). In favourite neighbourhoods, factors such as trade mobility and frequency of preference taken from local managers are handled in an integrated way. In determining these attributes, the results of the studies conducted in The Scientific and Technological Research Council of Turkey (TUBITAK) projects have been handled (Unel, 2017; Unel and Yalpir, 2019(b)).

Table 4. Grouping of real estate appraisal attributes

	Attributes (Sub-attributes)	Abb	Description	References
Legal Attributes (5)	Base area coefficient	BAC	Building base area.	Antipov and Pokryshevskaya, 2012; Unel and Yalpir, (2019b)
	Floor area coefficient	FAC	Total building area.	Kontrimas and Verikas, (2011); Unel and Yalpir, (2019b)
	Number of floors	NF	Number of floors ≥10m; Number of floors <10m.	Portnov, (2005)
	Building layout	BL	The state of the building layout being discrete, block or contiguous.	Kontrimas and Verikas, (2011)
	Area of residential land	ARL	Area of the parcel.	Schulz, 2003; El-Gohary, (2004)
Physical Attributes (6)	Corner/Intermediate land	CIL	The parcel's corner or intermediate parcel status.	Ong, (2013); Antipov and Pokryshevskaya, 2012
	Facade length	FL	Garden distances (m).	Lin, (2010)
	Facade number	FN	Number.	Lin, (2010); Antipov and Pokryshevskaya, 2012
	Geometric shape	GS	Geometric status of the parcel.	Dmytrów and Gnat, 2019
	Infrastructure services	IS	Parcel's utilize of technical infrastructure services.	Wilkowski and Budzyński, (2006)
	Roadway type	RT	Whether the road is one-way or two-way.	Portnov, (2005); Comertler, (2007)
Spatial Attributes (12)	Healthcare centres	HC	Distance to healthcare centres (m).	Unel and Yalpir, (2019a)
	Education facilities	EF	Distance to primary, secondary, high school and university facilities (m).	Casas, (2014)
	Public facilities	PF	Distance to facilities belonging to official institutions (m).	Kisilevich et al., (2013)
	Security units	SU	Distance to facilities belonging to security units (m).	Wilkowski and Budzyński, (2006)
	Shopping centres	SC	Distance to shopping centres	Yomralıoglu, (1993);

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			(malls, grocer) (m).	Demircioglu, (2004)
	Cultural centres	CC	Cinema, tourist attraction fields etc. distance (m).	Kisilevich et al., (2013)
	Entertainment centres	EC	Sports, entertainment centres etc. distance (m).	Kryvobokov, 2005
	Green areas	GA	Distance to park, playground, picnic area and forest (m).	Damigos and Anyfantis, (2011); Hammer et al., (1974)
	Transportation	T	Distance to bus, tram and train stations and bus terminal (m).	Son et al., (2012); Dmytrów and Gnat, 2019
	Insanitary areas	IA	Distance to industrial and waste discharge areas etc. (m).	Klaiber and Gopalakrishnan, (2012); Bennet, 2013
	City centre	CiC	Distance to city centre (m).	Antipov and Pokryshevskaya, (2012); Mora-Esperanza, 2004
	Other attributes	OA	Trade, bazaar, industrial commercial areas etc.	Portnov, (2005); Damigos and Anyfantis, (2011)
Local Attributes (10)	Population density	PD	The ratio of the total population of the neighbourhood to the area of the neighbourhood.	Casas, (2014)
	Education level	EL	The total number of persons with primary, secondary, high school and higher education in the neighbourhood.	Casas, (2014); Unel and Yalpir, (2019a)
	Favourite neighbour.	FN	Neighbourhood value according to individuals' income status, real estate purchase and sale density and infrastructure facilities.	Dmytrów and Gnat, 2019; Kryvobokov, 2005
	Building density	BD	The ratio of the total number of buildings in the neighbourhood to the area of the neighbourhood.	Antipov and Pokryshevskaya, 2012
	Development potential	DP	Completion rate of infrastructure facilities in the neighbourhood.	Kryvobokov, 2005
	Slope of neighbour.	SN	Slope map of the neighbourhood (%).	Cellmer et al., (2012); Mora-Esperanza, 2004
	Geological condition	GC	Construction cost according to the ground geological condition of the neighbourhood.	Cellmer et al., (2012); Yomralıoglu, (1993)
	Climate condition	CliC	Temperature, humidity and wind speed-direction meteorological station measurements.	Bennet, 2013; Casas, (2014)
	Air pollution	AP	SO_2 and PM_{10} station measurements from air pollution criteria.	Klaiber and Gopalakrishnan, (2012); Kelly, (2013)
	Noise pollution	NP	Noise data measured from specific strategic points.	El-Gohary, (2004); Kelly, (2013)

Note: *Abb: Abbreviation, ** The real estate appraisal attributes used in the literature have been given above with their references.*

Indexing Attributes with GIS Analysis and Fuzzy AHP

This section explains the proposed attribute indexing to include similar (quantitative) attributes in the model more easily and simply while determining value of the real estate in mass appraisal. Index groups created for the study are as in Figure 5. Here, indexing has been performed only for local and spatial attributes.

The GIS-based analysis is needed (1) to include spatial and local attributes determined in Section 3.2 into modelling and (2) to develop indexes. Therefore, various GIS analyses such as distance, density, slope, and aspect were performed for spatial and local attribute groups. ArcGIS 10.5.1 software was used for analyses. Raster-based maps were produced for each of the spatial and local attributes and these raster maps were reclassified in the 1-5 class range. On the other hand, to develop spatial and local index FAHP method was used. Relative importance of attributes was determined by using this method. The pairwise comparison matrices were developed based on the expert's opinions.

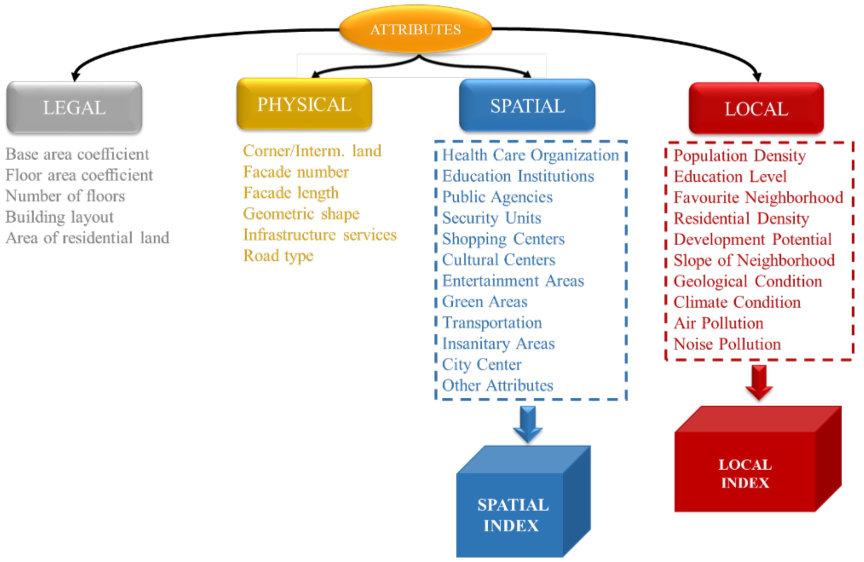

Figure 5. Indexes created for local and spatial attributes

In order to create the pairwise comparison matrices, the survey study within the scope of the project numbered TÜBİTAK-115Y769 was used. The survey was completed with 559 experts. These are the expert participants consisting of experienced people; 2.3% Real Estate Valuation, 29.1% Geomatics Engineer, 6.6% City and Regional Planning, 2.3% Architect, 10.2% Construction Engineer, 1.1% Agriculture Engineer, 0.4% Lawyer, 1.8% Economics and Administrative Sciences, 0.7% National Real Estate Specialist, 0.9% Land Registry and Cadastre Specialist, 6.8% Civil Servants (Land Registry/Cadastre), 6.3% Contractors and 30.7% Real Estate Agents (Yalpir et al., 2017). It was observed that the age of the experts was in the 30-39 age range with a rate of 35%. It was determined that 85% of the participants were male and 72.1% of them were university graduates. Expert participants in the survey study may have more than one task in real estate valuation. Considering this situation, 5% of the expert participants are members of the valuation commission, 5% are academicians, 12% are real estate appraisers, 32% are employed in public institutions, 2% are expropriation expert certificate holders, and 9% are contractors and 28% are real estate agents working in local real estate buying and selling offices.

Namely, the weight coefficients were calculated for each of attributes with FAHP. For each of spatial and local attributes calculated these

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normalized weights were shown in Section 4.1. Then, above-mentioned reclassified raster maps and these weight coefficients were multiplied in the GIS environment by using Raster Calculator tools. In this manner, GIS-based spatial and local indexes were obtained. The developed index values were re-assigned by scaling in the range of 1-10 classes (Figure 6-7 inside Section 4.1). The latest, developed indexes were joined to the dataset, which includes legal and physical attributes as well as market values. Briefly, for the developed hybrid modelling, the final dataset contains legal attributes, physical attributes, spatial index and local index.

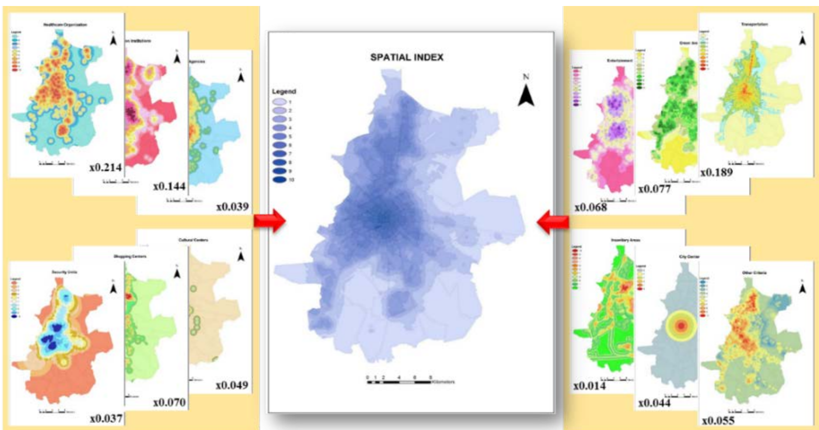
RESULTS

Fuzzy AHP Weights Obtained for Indexing

It is an important approach that the sub-attributes of spatial and local attributes are quantitatively similar and included in the mass appraisal model as an index. Spatial and local attributes in achieving the goal have been examined in detail. Fuzzy pairwise comparison matrices were created according to the relative importance of the attributes (Table 5-6). Spatial attributes chosen for indexing are Healthcare centres (HC), Education facilities (EF), Public facilities (PF), Security units (SU), Shopping centres (SC), Cultural centres (CC), Entertainment centres (EC), Green areas (GA), Transportation (T), Insanitary areas (IA), City centre (CiC), Other attributes (OA).

Local attributes chosen for indexing are Population density (PD), Education level (EL), Favourite neighbour. (FN), Building density (BD), Development potential (DP), Slope of neighbour. (SN), Geological condition (GC), Climate condition (CliC), Air pollution (AP), Noise Pollution (NP). Attribute weights were calculated using fuzzy AHP method in Section 2.1.4. (Table 7).

After the attribute weights were found, reclassified raster maps and these weight coefficients were multiplied in the GIS environment by using Raster Calculator tool. The last stage, in the region where spatial and local indexes are created, index values were made usable for the value prediction model. 12 spatial attributes and 10 local attributes have been converted to a single value map as a whole (Figure 6-7).



Note: Dark-colored numbers are normalized weights obtained via Fuzzy AHP

Figure 6. Spatial index map produced by using weighted combination of spatial attributes

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Table 5. Fuzzy pairwise comparison matrix for spatial attributes

	HC	EF	PF	SU	SC	CC	EC	GA	T	IA	CiC	OA
HC	(1,1,1)	(3,4,5)	(2,3,4)	(4,5,6)	(5,6,7)	(3,4,5)	(4,5,6)	(2,3,4)	(1,1,1)	(6,7,8)	(4,5,6)	(2,3,4)
EF	(1/5,1/4,1/3)	(1,1,1)	(3,4,5)	(3,4,5)	(4,5,6)	(2,3,4)	(3,4,5)	(2,3,4)	(1,1,1)	(5,6,7)	(1,2,3)	(1,2,3)
PF	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1,1,1)	(1,1,1)	(1/3,1/2,1/1)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/7,1/6,1/5)	(4,5,6)	(1/3,1/2,1/1)	(1,1,1)
SU	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(1,1,1)	(1,1,1)	(1/5,1/4,1/3)	(1,1,1)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(3,4,5)	(1,1,1)	(1/3,1/2,1/1)
SC	(1/7,1/6,1/5)	(1/6,1/5,1/4)	(1,2,3)	(3,4,5)	(1,1,1)	(1,1,1)	(1,1,1)	(1,2,3)	(1/4,1/3,1/2)	(3,4,5)	(1,2,3)	(1,2,3)
CC	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1,2,3)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(4,5,6)	(1/3,1/2,1/1)	(1/3,1/2,1/1)
EC	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(2,3,4)	(2,3,4)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1/5,1/4,1/3)	(4,5,6)	(1,2,3)	(1,2,3)
GA	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(2,3,4)	(1,2,3)	(1/3,1/2,1/1)	(1,2,3)	(1,1,1)	(1,1,1)	(1/5,1/4,1/3)	(5,6,7)	(2,3,4)	(1,2,3)
T	(1,1,1)	(1,1,1)	(5,6,7)	(3,4,5)	(2,3,4)	(3,4,5)	(3,4,5)	(3,4,5)	(1,1,1)	(6,7,8)	(3,4,5)	(3,4,5)
IA	(1/8,1/7,1/6)	(1/7,1/6,1/5)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(1,1,1)	(1/6,1/5,1/4)	(1/5,1/4,1/3)
CiC	(1/6,1/5,1/4)	(1/3,1/2,1/1)	(1,2,3)	(1,1,1)	(1/3,1/2,1/1)	(1,2,3)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1,1,1)	(1,2,3)
OA	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1,1,1)	(1,2,3)	(1/3,1/2,1/1)	(1,2,3)	(1/3,1/2,1/1)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(3,4,5)	(1/3,1/2,1/1)	(1,1,1)

Note: λ_{max} = 12.92850, Consistency Ratio (CR) = 0.05703 < 0.10, Accepted

Table 6. Fuzzy pairwise comparison matrix for local attributes

	PD	EL	FN	BD	DP	SN	GC	CliC	AP	NP
PD	(1,1,1)	(3,4,5)	(1/5,1/4,1/3)	(1,2,3)	(1/4,1/3,1/2)	(2,3,4)	(3,4,5)	(4,5,6)	(3,4,5)	(1,2,3)
EL	(1/5,1/4,1/3)	(1,1,1)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,2,3)	(1,2,3)	(2,3,4)	(1,1,1)	(1/3,1/2,1/1)
FN	(3,4,5)	(2,3,4)	(1,1,1)	(1,2,3)	(1,1,1)	(2,3,4)	(3,4,5)	(3,4,5)	(2,3,4)	(3,4,5)
BD	(1/3,1/2,1/1)	(2,3,4)	(1/3,1/2,1/1)	(1,1,1)	(1/3,1/2,1/1)	(1,2,3)	(2,3,4)	(2,3,4)	(2,3,4)	(1,2,3)
DP	(2,3,4)	(2,3,4)	(1,1,1)	(1,2,3)	(1,1,1)	(3,4,5)	(4,5,6)	(3,4,5)	(3,4,5)	(3,4,5)
SN	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(1,1,1)	(1,1,1)	(1,2,3)	(1,1,1)	(1/3,1/2,1/1)
GC	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1/6, 1/5,1/4)	(1,1,1)	(1,1,1)	(1,1,1)	(1/3,1/2,1/1)	(1/4,1/3,1/2)
CliC	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
AP	(1/5,1/4,1/3)	(1,1,1)	(1,1,1)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(1,1,1)
NP	(1/3,1/2,1/1)	(1,2,3)	(1,2,3)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(1,2,3)	(2,3,4)	(1,1,1)	(1,1,1)	(1,1,1)

Note: λ_{max} = 10.59232, Consistency Ratio (CR) = 0.04417 < 0.10, Accepted

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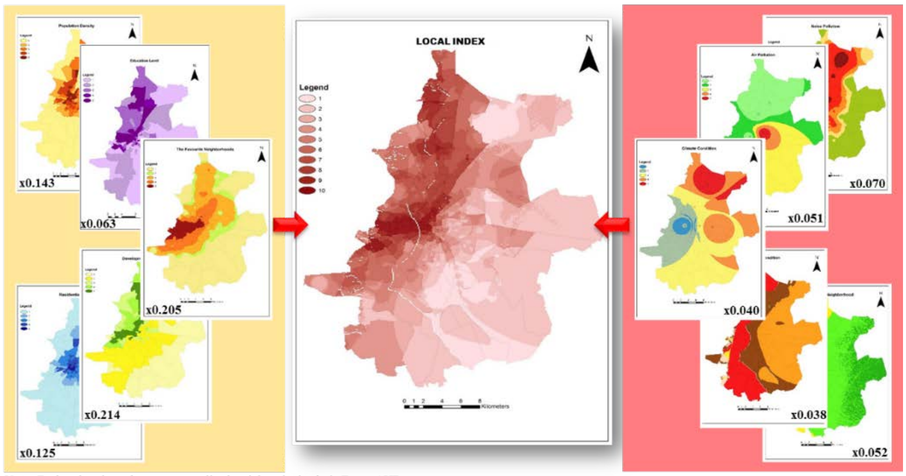
Table 7. Fuzzy and normalized weights for spatial and local attributes

Attribute	Fuzzy weights	Normalized weights (w_i)
Spatial Attributes		
HC	(0.15381, 0.24134, 0.37176)	**0.214**
EI	(0.09511, 0.16161, 0.25891)	**0.144**
PA	(0.02572, 0.04156, 0.07155)	**0.039**
SU	(0.02686, 0.03948, 0.06710)	**0.037**
SC	(0.04495, 0.07634, 0.12737)	**0.070**
CC	(0.03333, 0.05163, 0.09184)	**0.049**
EC	(0.04760, 0.07486, 0.11969)	**0.068**
GA	(0.04663, 0.08403, 0.14560)	**0.077**
T	(0.13975, 0.21333, 0.32239)	**0.189**
IA	(0.01079, 0.01581, 0.02494)	**0.014**
CiC	(0.02557, 0.04584, 0.08463)	**0.044**
OA	(0.03098, 0.05554, 0.10863)	**0.055**
Local Attributes		
PD	(0.07870, 0.14436, 0.25395)	**0.143**
EL	(0.03346, 0.06145, 0.11403)	**0.063**
FN	(0.11852, 0.21038, 0.35265)	**0.205**
RD	(0.05887, 0.11880, 0.23751)	**0.125**
DP	(0.12703, 0.21998, 0.36724)	**0.214**
SN	(0.02879, 0.04793, 0.09533)	**0.052**
GC	(0.02287, 0.03552, 0.06662)	**0.038**
CliC	(0.02552, 0.04081, 0.06662)	**0.040**
AP	(0.03408, 0.05137, 0.08541)	**0.051**
NP	(0.03868, 0.06940, 0.12579)	**0.070**



Note: Dark-colored numbers are normalized weights obtained via Fuzzy AHP

Figure 7. Local index map produced by using weighted combination of local attributes

The Results of C-DHM and Performance

SPSS 20 software package was used for C-DHM (Equation 3) used in the study. First of all, the dataset was arranged and scaled. The model was established with the dataset formed by 13 attributes (5 legal, 6 physicals, 1 spatial index, 1 local index) belonging to 457 parcels collected from the central districts of Konya. The accuracy of created mathematical model was tested with the mentioned software package. C-DHM was applied in multiple nonlinear regression model approach

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and MRA. After The weights of the variables that affect the value of the real estate have been found. Results showed that R^2 value for the C-DHM used as indexes (local/spatial) was found to be 85% (Table 8). Among the coefficients, A0, B0, C0, D0 are related to the local, spatial, physical and legal attribute weights and others indicate the densities of the sub-attributes.

Table 8. Nonlinear Regression Parameter Estimates and ANOVA[a] Results

Attributes	Parameter	Estimate	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
LEGAL	A_0 (constant)	1,009	,527	-,027	2,045
BAC	A_1	-,199	,088	-,372	-,026
FAC	A_2	,272	,076	,123	,421
NF	A_3	,261	,085	,093	,429
BL	A_4	-,014	,077	-,164	,137
ARL	A_5	,728	,054	,621	,835
PHYSICAL	B_0 (constant)	11,627	7,016	-2,161	25,415
CIL	B_1	-,040	,062	-,161	,080
FL	B_2	-,024	,038	-,099	,050
FN	B_3	,078	,057	-,033	,189
GS	B_4	,110	,083	-,054	,274
IS	B_5	,096	,038	,022	,171
RT	B_6	,032	,027	-,021	,085
SPATIAL	C_0 (constant)	,547	1,544	-2,487	3,580
Index	C_1	,785	,566	-,327	1,897
LOCAL	D_0 (constant)	2,861E-13	,000	-3,033E-12	3,606E-12
Index	D_1	6,848	1,288	4,317	9,380

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	1947253,416	17	114544,319
Residual	14532,377	440	33,028
Uncorrected Total	1961785,794	457	
Corrected Total	96740,965	456	

Dependent variable: Market Value

R^2 = 0, 85

The developed hybrid model expansion is in Equation 15.

$$\textit{Model value (Y)} = \mathbf{A_0} * (BAC^{A1} * FAC^{A2} * NF^{A3} * BL^{A4} * ARL^{A5}) + \mathbf{B_0} * (CIL^{B1} * FL^{B2} * FN^{B3} * GS^{B4} * IS^{B5} * RT^{B6}) + \mathbf{C_0} * (Spatial^{C}{}_1) + \mathbf{D_0} * (Local^{D}{}_1) \quad (15)$$

The model coefficients specified as "A_0, B_0, C_0, D_0" have been related associated with local, spatial, physical and legal main attributes. In this model "A_1, A_2, A_3, A_4, A_5" coefficients contain the effect intensities of the legal attributes (sub-attributes). "B_1, B_2, B_3, B_4, B_5, B_6" coefficients contain the effect intensities of the physical attributes (sub-attributes). "C_1" coefficient contains the effect intensities of the spatial index and "D_1" coefficient contains the effect intensities of the local index.

When looking at the model coefficients in Table 8, it is seen that the physical attributes are the most effective from main attributes in model. It can be said that the local attributes make the lowest contribution to

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the model, but the value from the local indexing has effective in terms of impact intensity. Moreover, attributes that are also effective in other groups stand out. For the part of legal attribute, the most effective one has ARL (Area of Residential Land) attribute. Here the size of the parcel significantly affects the real estate value. For the part of physical attribute, the most effective one has GS (Geometric Shape) attribute. It is seen that whether the geometric state of the parcel has regular or irregular affects the value.

Legal attribute from the exponential number values obtained as a result of C-DHM; From BAC and BL and physical properties; CIL and FL were found to be negative. Considering the market conditions, the effects of these attributes are expected to be positive and linear. However, a new modelling result based on the dataset and the study area was obtained in this way. If there is an attribute added to or removed from the dataset, it changes the exponential results and group weights. This result is completely related to which attribute are included in the model.

The power to measure the real estate value of the above equation obtained from the C-DHM, which was created to determine the value of the real estate, was found to be at the rate of R^2 0.85. This ratio shows that the C-DHM predicts the market value with high success according to most of the calculations made with real estate value estimation model approaches (Yakub et al., 2020; Yildirim, 2019; Abidoye et al., 2019).

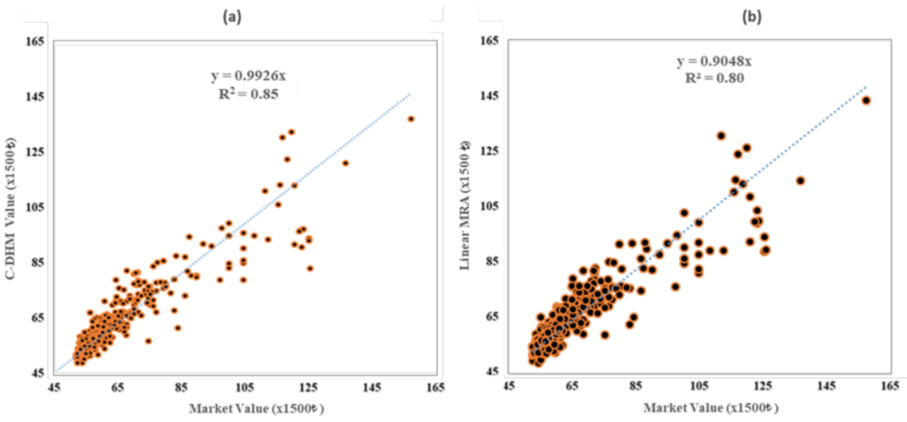

Figure 8. Comparison of C-DHM and market value (a) C-DHM and (b) Linear MRA model

Accordingly, in performance calculations C-DHM was applied to the dataset of the study area. As the graphic, the trend line was formed C-DHM and Linear MRA values with market values, and R^2 were calculated. The distribution and scattering of the model values were also examined (Figure 8). In addition, the 0.9926 multiplier coefficient of the trend line equation indicates that the model is very successful in finding market values with predicted values. Linear MRA was found to be lower than C-DHM with a value of 0.9048 (Figure 8). MAPE values were calculated to compare the models values and market values. If we look at the performance, it has shown that the C-DHM can be used in real estate appraisal, the MAPE rate in the C-DHM approach is 4.84% and Linear MRA is 7.56%. In addition, the error rates (MAPE) between the

C-DHM calculated according to dataset of the real estates in the study area and the market value are calculated and compared in maps.

Consequently, in the calculations, SD_{market} in market values of the real estate was 14.57, while it was found as 13.43 of the $SD_{modelC\text{-}DHM}$ and 13.09 of the $SD_{modelLinearMRA}$. In this case, it shows that the C-DHM catches SD % 92 and Linear MRA catches %90 successful. The fact that the models captures this deviation interval also shows the estimated power in the value range of max and min between the samples. It was seen that C-DHM estimated the value of more successful plot than Linear MRA. For this reason, the results of the application with C-DHM and the market values were used in the mapping.

Value Maps in GIS

GIS was used for generating real estate value maps. The market values of parcels and C-DHM value results were added to the ArcGIS software. Different value maps were produced for market values, and the model results. The maps were utilized for comparison of the models, determining spatial distribution of values and information on parcel values (Figure 9).

MAPE average calculated in the model performance was found to be 4.84%. According to literature implements and Turkey national appraisal standards need to be reconsidered error estimate max 15%. For this reason, GIS was used to determine where these real estates are located spatially and real estates with more than 15% error. With the MAPE calculation was mapped using the relationship in C-DHM and market values (Figure 10). It was determined that 25 of the 447 real estates in dataset had a MAPE value greater than 15%. It has been observed that these real estates are located in the north of the city in areas where reconstruction is intense and they are located in the western part near the city core. It can be said that the MAPE value of a 6% real estate is high in study area.

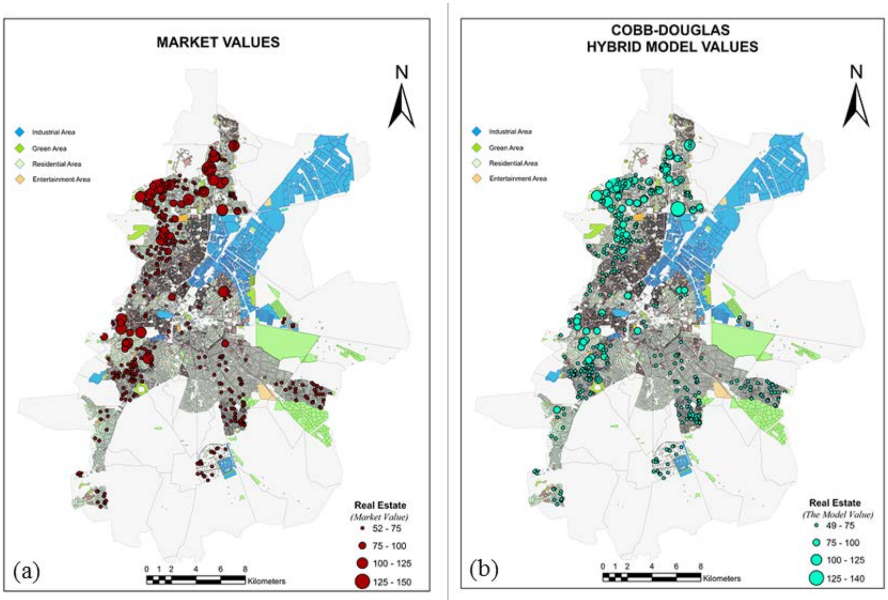

Figure 9. Value maps of sampling parcels: (a) Market value map, (b) Cobb-Douglas hybrid value map

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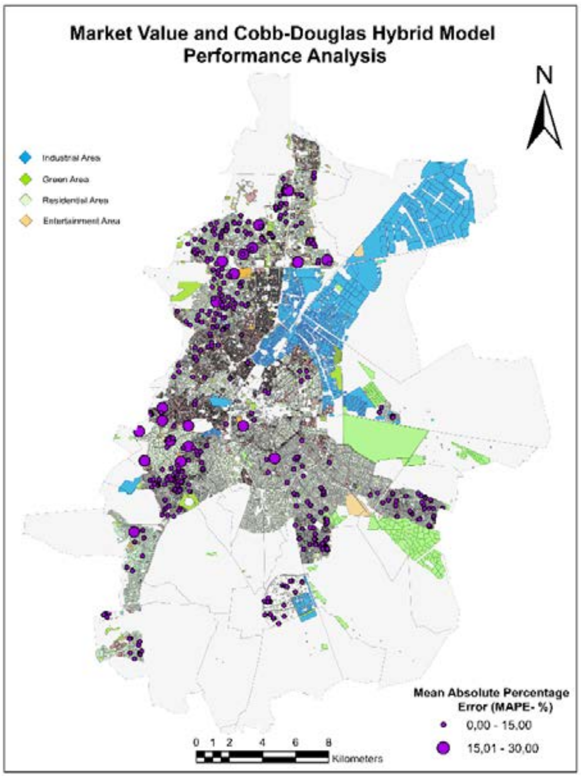

Figure 10. C-DHM and market value spatial MAPE distribution in sampling parcels

CONCLUSIONS

Real estates that have a serious share in economy; are used in different fields such as taxation, investment, zoning implements, project development, etc. Accurate and mass recognition of values of these properties (real estates) is important in the relations of government agencies, even citizens with real estates and private companies. Therefore, the value model should be established for the appraisal of real estates. In this study, hybrid model (residential land as a function) was used for performing mass real estate appraisal applications. C-DHM was applied on the parcels where conditions favourable for construction occurred, in the region covering centre neighbourhoods in Konya. Hybrid model can meet user's (from local manager to citizen) needs to get accurate value information for applications such as mass real estate appraisal especially.

While creating an optimal appraisal model, some topics should be taken into consideration. First of all, the dataset that will be used in the model should be prepared well. In non-hybrid traditional models such as single appraisal or some mass appraisal, some problems arise when building the model on dataset. Encountered the most common problem is the inability to get data for all attributes that affect the real estate value, or the same type of variables are separately entered into the model. For example, it is a reasonable assumption that the variables belonging to residential land located close to each other and their immediate surroundings have similar values. Namely, these variables are spatially auto-correlated. This means that the variables affect the real estate value by the same size. Consequently, it is unnecessary to insert data of the same value and size into the model separately.

Therefore, in the study, it is presented to use Fuzzy AHP method and GIS software together for the spatial and local part of the model. So with the use of this technique, the model will avoid the complex structure and the data-based incompatibilities will be reduced with the developed indexes.

After preparing the dataset for value determining, real estate values were obtained with the C-DHM and Linear MRA in study. It has been observed that the performance results of C-DHM are more successful than Linear MRA. In addition, the fact that MAPE errors between the C-DHM and market values can be analysed by integrating the results into the map has added privileges to the study. The use of the developed C-DHM in real estate value determining has its advantages. In making value estimations, grouping the attributes of the real estate made the model more understandable. Besides, if the attribute in the created model does not have real estate whose value will be determined in the region, it can be used without the need to change the model.

In this study real estate appraisal estimation methodology, it will be able to contribute a great contribution to activities such as fair taxation of real estate, the creation of small and large-scale value maps in applications involving appraisal, and the development of urbanization policies with city-based value maps.

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