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# A Novel Perspective on The Analysis of Residential Property Prices Near Transportation Investments: Wide-Range Vs Narrow-Range Factors

Onur Sahin[1,*], Ilgin Gokasar[2],

[1] Civil Engineering Department, Transportation Department, Yildiz Technical University, Istanbul Turkiye
[2] Department of Civil Engineering, Bogazici University, Istanbul Turkiye

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**ABSTRACT**

A new perspective on the relationship between transportation systems and property prices is available, "evaluation by considering bandwidths." "bandwidth" indicates the number of neighbor data points influencing the target point. The main motivation of this research is to eliminate the restricted effects of spatial analysis. When a single bandwidth value is defined for all models, indicate that an equal number of neighbor data in GWR influences all model factors for target points. When the multiscale geographically weighted regression (MGWR) is used, a unique bandwidth value can be defined for each factor. This study, by using MGWR, allows researchers to distinguish the effects of factors and classify them as either wide-range or narrow-range. 3487 geographical data were collected for a study area covering Esenyurt and Beylikduzu Counties in Istanbul, Turkey. As a result, when considering different bandwidths, factors are recognized as either narrow-range or wide-range. The output of this study proved that the researchers strongly recommended considering the bandwidth effects while performing a spatial regression analysis. Hence, the gap in selecting factors for spatial analyses in different study areas is likely to be filled.

## 1. Introduction

Transportation systems provide some benefits to their vicinity, such as economic growth, shorter travel times, lower commuter costs, and so on. They also affect the prices of residential properties in the vicinity [1-11].

There are various factors affecting the prices defined in the literature for investigation of the relationship between the transportation systems and residential property prices, such as neighborhood quality, locational amenities, size of the property, number of rooms, number of bedrooms, number of bathrooms, age, green area ratio, credit viability of the residential property,

*Corresponding author: tigremiens@hotmail.com
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parking area, floor level, existence of elevator, storage place, fireplace, air conditioning, sea view, distance to each of CBD (Central business district), hospitals, schools and shopping malls, the transportation modes, education level of the neighborhood, orientation of the residential property (sunny, corner and front), and so on [9-20]. These factors can vary from city to city because some of them are peculiar to the investigated study area. However, some factors such as age, floor level, existence of parking area, etc. are taken into consideration in most studies.

The most commonly used analysis model is the hedonic price model due to its simplicity and capability of easy adjustments [2,4,5,7, 9, 10, 11, 12, 13-17]. The hedonic price model can be analyzed by many different techniques such as OLS, SAR, SAC, SDM, GWR and MGWR [2-7,9-26]. The number of neighbor data points that have an effect on each other is called the bandwidth. Geographically weighted regression (GWR) is mostly used in order to obtain a single optimum bandwidth for the model. However, this assumption creates a problem in obtaining significant results because all the factors in the model do not necessarily take the same bandwidth value. Depending upon its narrow-range or wide-range type, each factor might be affected by a different number of nearby data points in order to reach its optimum bandwidth value. This problem is overcome by the introduction of the multiscale geographically weighted regression (MGWR) technique which provides the opportunity of obtaining specific optimum bandwidths for each variable in the model [27-28].

After introduction this high capability model MGWR to the literature, it has been used in different areas by researchers. Especially when the spatial effects are counted as the main factors affecting the outcomes, MGWR is considered as an effective tool [29-42].

Klar & Rubensson [43] identified MGWR as the successor of traditional GWR method [43]. The popularity of MGWR increased among the researchers at transportation field especially for the studies concerning about the relation between transportation and regional effects [44-60].

In this study, a total of 3,487 data points, including the structural and environmental characteristics of the residential properties in the selected study areas of Esenyurt and Beylikduzu Counties, in Istanbul, Turkey is analyzed utilizing a hedonic price model through GWR and MGWR methods. Some factors in the model reached their optimum bandwidth values by using a large number of nearby data points while the remaining factors were affected by fewer nearby data points. According to this concept, as the size of the region, which includes the neighbor data points that affect the selected factor, increases, the factor gets closer to being evaluated as a wide-range factor. This output depends upon the related factor’s optimum bandwidth value obtained from MGWR analysis. In this study, it is assumed that if the optimum bandwidth value of a factor is obtained by using a large region in the neighborhood, the factor and its effects should be considered as a wide-range factor. This study provides the following contributions:

(1) Instead of using a single optimum bandwidth value obtained by GWR, a new method MGWR, which provides different optimum bandwidth values for each variable in the model, is used in order to evaluate the range of the factors that affect the residential property prices.

(2) Some factors are classified as wide-range factors and others as narrow-range factors based on the optimum bandwidth values in MGWR analysis.

(3) MGWR is applied to real data collected from the study area, and the wide-range and narrow-range factors are defined through an analysis of an actual geographical dataset.

## 2. Theory

### *2.1 Multiscale Geographically Weighted Regression (MGWR)*

In the analysis of datasets which have geographical dependence, the GWR technique has mostly been used [61-66]. However, the main assumption of GWR, which accepts that all factors in the model have the same bandwidth value, motivated the researchers to search for a solution to this limitation. Thus, a new model was developed, the multiscale geographically weighted regression MGWR [28]. By the help of MGWR, it is possible to provide specific bandwidth values for each factor in the model. The geographically linear regression model is provided in equation 2. Addition of a bandwidth calibration term to equation 2 is provided in equation 7 for MGWR:

$$y_i = \sum_{j=0}^{m} \beta_{bwj}(u_i, v_i)x_{ij} + \varepsilon_i \tag{7}$$

where the term $\beta_{bwj}$ is the bandwidth calibration term for the j th experimental condition. There are alternatives for the calibration process. The bandwidth values can start from “0” or start with taking the bandwidth value of the GWR analysis for the same model. Afterwards, these bandwidth values are adjusted based on comparison with the residual sum of squares (RSS) and Akaike information criterion (AIC) values of the previous model. This advantage, providing specific bandwidth values for each factor in the model compared with GWR, made MGWR a superior model to GWR [28]. On the other hand, MGWR analysis requires a relatively large amount of time for the iterations and its computational process requires very high computer performance [28].

## 3. Methodology

### *3.1 Data*

The selected study area includes two counties of Istanbul, namely Esenyurt and Beylikduzu. These counties are selected because they are far away from the city center and they are relatively new counties, both of which were established in 2008 by the government. There is a bus rapid transit (BRT) system providing service on D100 Highway, which lies on the border between the two counties. Also, an ongoing metro line project exists in Esenyurt County. These transportation systems connect the two counties to the city center. In Figure 1, the borders of Beylikduzu and Esenyurt Counties are presented.

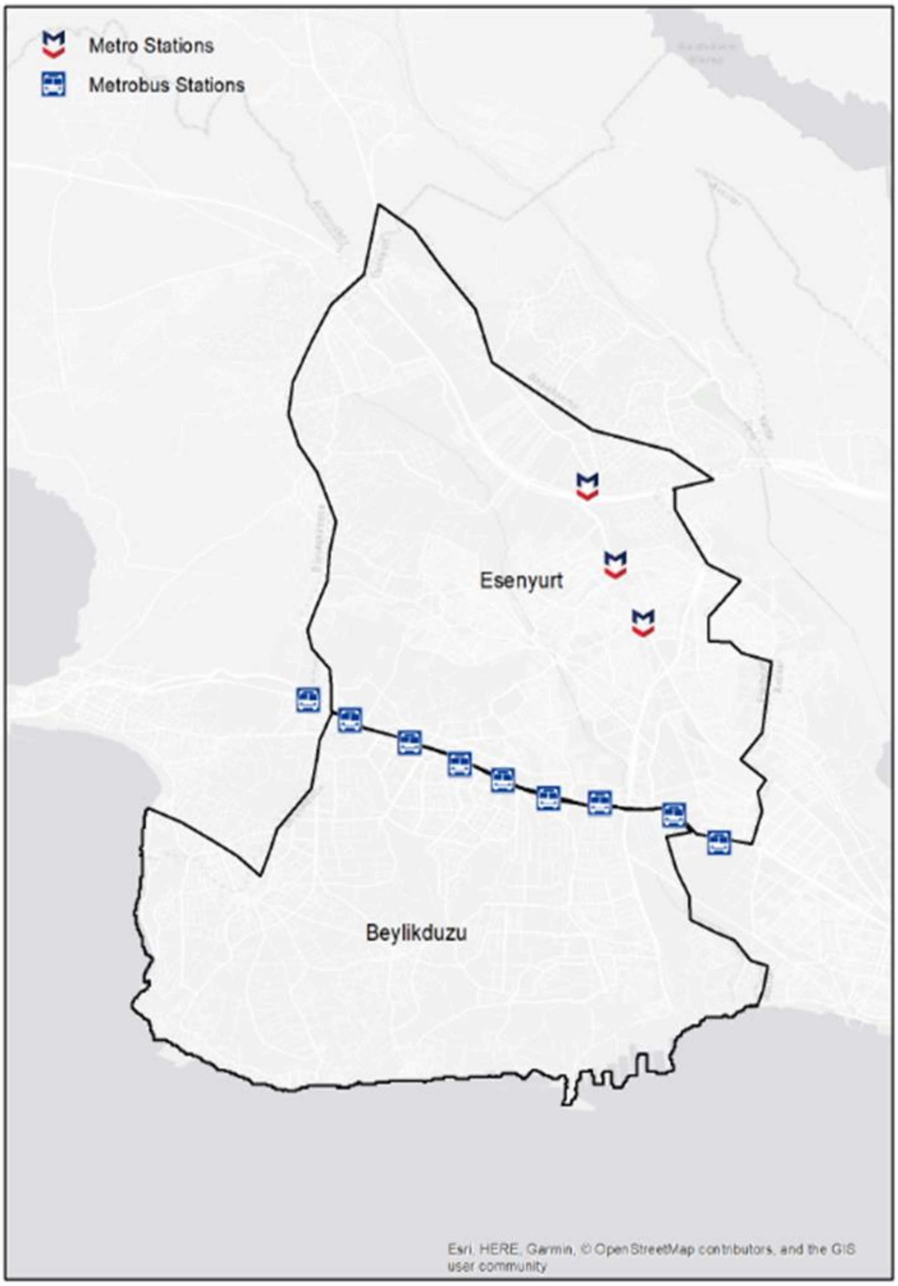


**Fig. 1.** Beylikduzu and Esenyurt Counties (Google Maps, Esenyurt and Beylikduzu, www.googlemaps.com)

Beylikduzu County lies between D100 Highway (the route of the BRT line) and the Marmara Sea, whereas the Esenyurt County is located between the D100 Highway and the TEM Highway (Figure 1). The BRT line has four phases, the fourth of which actually takes place between Esenyurt and Beylikduzu Counties. In Figure 1, the BRT line and its stations are also presented. The fourth phase was completed in 2012 with 9.7 km length and 11 stations connecting Avcilar County to Beylikduzu County. The BRT line is currently the most important public transportation mode for the people in Esenyurt and Beylikduzu. The regions to the north of Esenyurt County mostly prefer to use TEM Highway because public transportation services are not available in this region. Therefore, the ongoing metro line project will likely to contribute to the transportation services. This Metro line aims to connect Esenyurt County to Mahmutbey and, via another Metro line, to the city center. Therefore, it will serve as an alternative transportation mode to the BRT line, which is currently considered as the main public transportation system that connects Esenyurt County to the city center. There will be a total of 12 stations on the Metro line. The total length will be 18.6 km and the predicted passenger capacity of the Metro line is 70,000 passengers per day. The total travel time from Esenyurt terminal to Mahmutbey terminal on the Metro line is estimated as 25 minutes. The project started in 2017 and will start to provide service in August, 2020. As presented in Figure 1, the last 3 stations namely, Esenkent, Ardicli and Esenyurt Meydan stations are within the selected study area. The data was collected from both the Esenyurt and Beylikduzu Counties. The data points are marked on the map in GIS program (Figure 2).

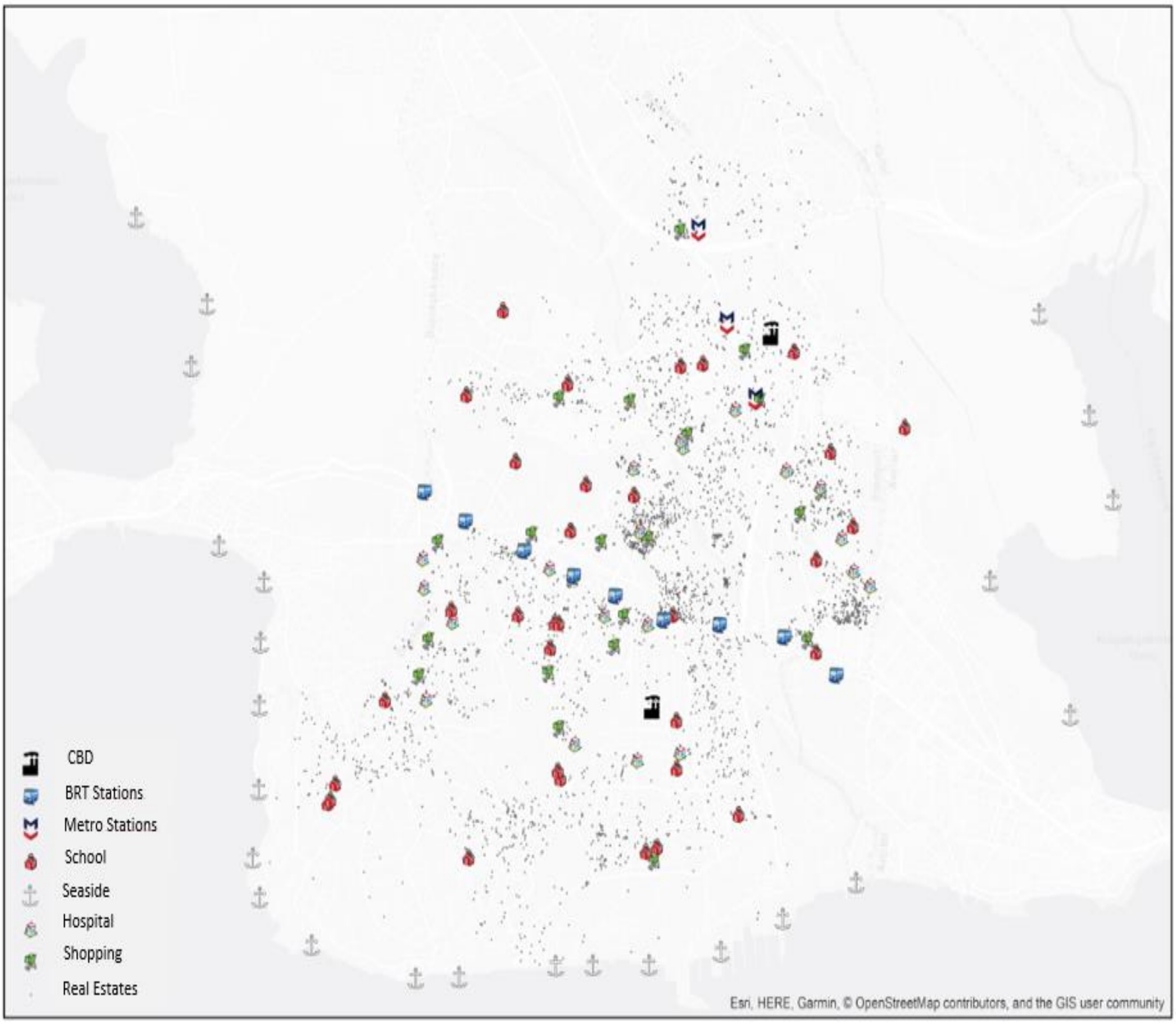


**Fig. 2.** Study area in GIS program

In Figure 2, the residential property points, BRT stations, Metro stations, schools, seaside points, hospitals, CBD and shopping malls are indicated.

### *3.2 The established model*

In order to estimate the optimum bandwidth values, the study area is analyzed in 4 different datasets. Region 1 includes the data points only inside the Esenyurt County, Region 2 includes the data points only inside the Beylikduzu County, Region 3 includes the data points that are inside the neighborhood quarters of Esenyurt and Beylikduzu Counties nearby the BRT line (considered as a transition zone) and Region 4 includes all data points collected from the study area. The hedonic price model established and analyzed in this study is as follows in Eq. 2.:

$$y_i = \alpha + \beta_1(size) + \beta_2(age) + \beta_3(creditvia) + \beta_4(floorlev) + \beta_5(facility) + \beta_6(rooms) + \beta_7(distHosp) + \beta_8(distMall) + \beta_9(distBRT) + \beta_{10}(distMetro) + \beta_{11}(distSchool) + \beta_{12}(distCBD) + \beta_{13}(distSea) \quad \textbf{(2)}$$

where y is the average price (TL/m$^2$), $\alpha$ is the constant value, $\beta_i$ (i = 1, 2, 3…i) is the coefficient of each explanatory variable in the model, “size” is the size of the residential property in m$^2$, “age” is the age of the residential property in terms of years, “creditvia” is the credit viability condition of the residential property, “floorlev” is the floor level of the residential property, “facility” is the term for the existence of parking and other facilities for the residential property, “rooms” is the number of rooms of the residential property. “distHosp” is the distance to closest hospital, “distMall” is the distance to closest shopping mall, “distBRT” is the distance to closest BRT station, “distMetro” is the distance to closest Metro station, “distSchool” is the distance to closest school, “distCBD” is the distance to closest central business district and “distSea” is the distance to the closest seaside point.

## 4. Analysis Results

The datasets of all regions were analyzed using GWR and MGWR in order to compare the bandwidth value of each factor in different regions. According to the results, presented in Table 1, in the first region the total number of observations is 2,230 and for the second region, the total number of observations is 1,156.

**Table 1**
Bandwidth Values (Regions 1 & 2)

| | Region 1 | | | | Region 2 | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | GWR | MGWR | | | GWR | MGWR | | |
| | 8.40% | | % of all data | Adj. α | 18.80% | | % of all data | Adj. α |
| Area (m²) | 189 | 1111 | 49.8 | 0.002 | 217 | 1155 | 99.9 | 0.049 |
| Rooms | 189 | 2228 | 99.9 | 0.049 | 217 | 1151 | 99.5 | 0.044 |
| Age | 189 | 1268 | 56.8 | 0.005 | 217 | 356 | 30.7 | 0.002 |
| Floor | 189 | 193 | 8.7 | 0.003 | 217 | 123 | 10.6 | 0.006 |
| Facility | 189 | 2102 | 94.2 | 0.001 | 217 | 1155 | 99.9 | 0.048 |
| DistShop (m) | 189 | 373 | 16.7 | 0.013 | 217 | 1155 | 99.9 | 0.049 |
| DistHospital (m) | 189 | 193 | 8.7 | 0.006 | 217 | 1155 | 99.9 | 0.044 |
| DistBRT (m) | 189 | 277 | 12.4 | 0.013 | 217 | 102 | 8.8 | 0.011 |
| DistSchool (m) | 189 | 621 | 27.8 | 0.025 | 217 | 1155 | 99.9 | 0.049 |
| DistCBD (m) | 189 | 102 | 4.6 | 0.002 | 217 | 105 | 9.1 | 0.001 |
| DistSea (m) | 189 | 706 | 31.6 | 0.009 | 217 | 1155 | 99.9 | 0.046 |
| DistMetro (m) | 189 | 104 | 4.7 | 0.002 | 217 | 1155 | 99.9 | 0.049 |
| Number of Observations | | | | 2230 | | | | 1156 |

The bandwidth value of the GWR analysis is 189, which is a relatively small number compared to 2,230 whereas the factors took different values in the MGWR analysis. The bandwidth values of GWR and MGWR for Region 1 are shown in Figure 3.

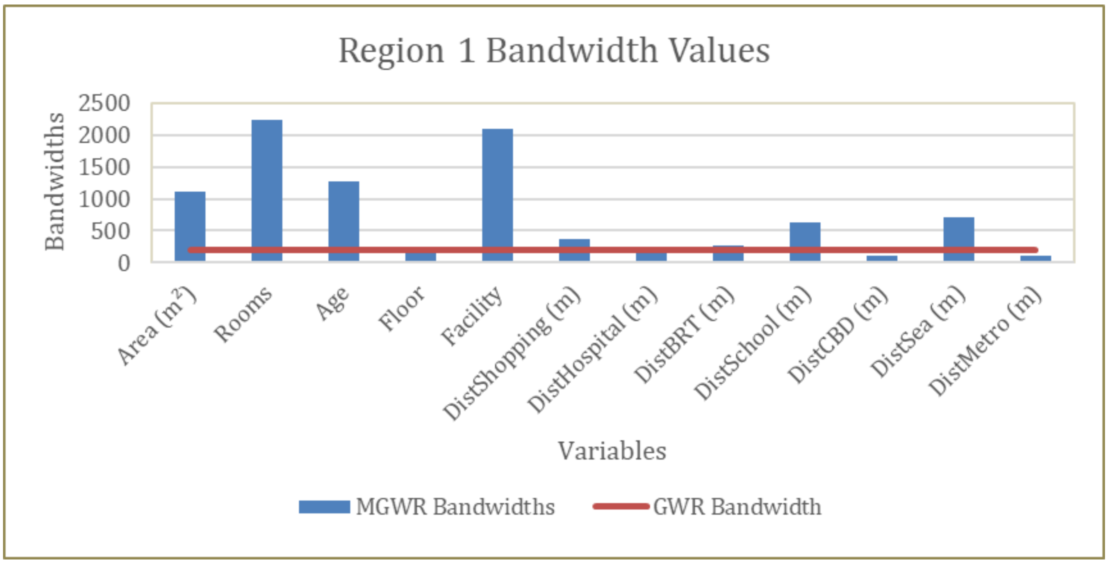


**Fig. 3.** MGWR and GWR bandwidth values for Region 1

The bandwidth values of the factors “Area” (1111, 49.8%), “Rooms” (2228, 99.9%), “Age” (1268, 56.8%), and “Facility” (2102, 34.2%) are relatively higher than the optimum bandwidth value of the GWR analysis (189, 8.4%) for Region 1. The bandwidth values of GWR and MGWR for Region 2 are demonstrated in Figure 4. The bandwidth value of the GWR analysis is 217, which is assumed to be equal for all factors whereas the MGWR analysis provided different optimum bandwidth values for each factor.

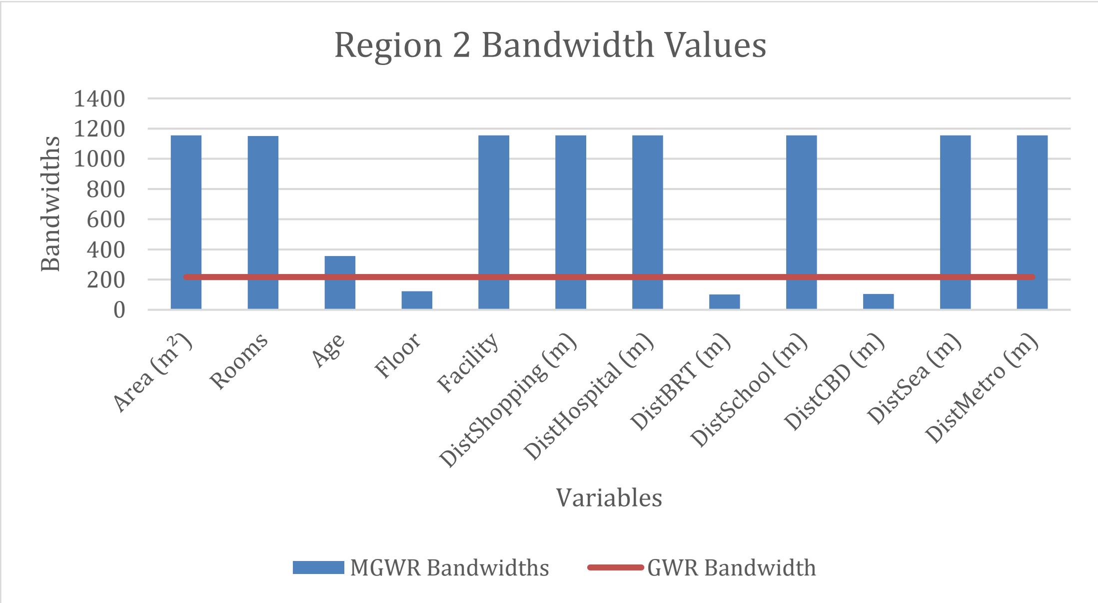


**Fig. 4.** MGWR and GWR bandwidth values for Region 2

The “Area” (1155, 99.9%), “Rooms” (1151, 99.5%), “Facility” (1155, 99.9%), “DistShopping” (1155, 99.9%), “DistHospital” (1155, 99.9%), “DistSchool” (1155, 99.9%), “DistSea” (1155, 99.9%) and “DistMetro” (1155, 99.9%) factors have relatively higher values than the GWR bandwidth value (217, 18.8%) for Region 2. For the third region, the total number of observations is 1,553 and for the fourth region, the total number of the observations is 3,487, as presented in Table 2.

**Table 2**
Bandwidth Values (Regions 3 & 4)

| | Region 3 | | | | Region 4 | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | GWR | MGWR | | | GWR | MGWR | | |
| | 9.00% | | % of all data | Adj. α | 7.90% | | % of all data | Adj. α |
| Area (m²) | 140 | 1525 | 98.2 | 0.046 | 277 | 2016 | 57.8 | 0.026 |
| Rooms | 140 | 1552 | 99.9 | 0.047 | 277 | 3485 | 99.9 | 0.049 |
| Age | 140 | 1102 | 71 | 0.002 | 277 | 2262 | 64.9 | 0.013 |
| Floor | 140 | 176 | 11.3 | 0.003 | 277 | 303 | 86.9 | 0.002 |
| Facility | 140 | 1102 | 71 | 0.002 | 277 | 2252 | 64.6 | 0.009 |
| DistShopping (m) | 140 | 429 | 27.6 | 0.021 | 277 | 673 | 19.3 | 0.021 |
| DistHospital (m) | 140 | 1552 | 99.9 | 0.048 | 277 | 3447 | 98.9 | 0.046 |
| DistBRT (m) | 140 | 347 | 22.3 | 0.017 | 277 | 1216 | 34.9 | 0.003 |
| DistSchool (m) | 140 | 236 | 15.2 | 0.010 | 277 | 2133 | 61.2 | 0.018 |
| DistCBD (m) | 140 | 521 | 33.5 | 0.030 | 277 | 268 | 7.7 | 0.001 |
| DistSea (m) | 140 | 1101 | 70.9 | 0.003 | 277 | 3485 | 99.9 | 0.049 |
| DistMetro (m) | 140 | 102 | 6.6 | 0.003 | 277 | 485 | 13.9 | 0.007 |
| Number of Observations | | | | 1553 | | | | 3487 |

The GWR analysis provided the bandwidth value of 140 for the model. However, the MGWR analysis results revealed that the optimum bandwidth values are different for every factor. The bandwidth values of GWR and MGWR for Region 3 are illustrated in Figure 5.

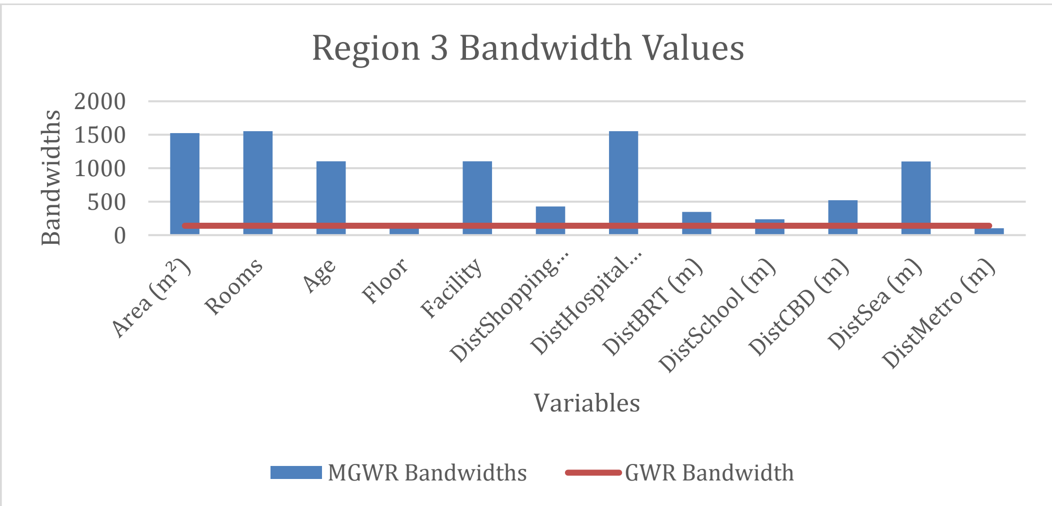


**Fig. 5.** MGWR and GWR bandwidth values for Region 3

The factors "Area" (1525, 98.2%), "Rooms" (1552, 99.9%), "Age" (1102, 71%), "Facility" (1102, 71%), "DistHospital" (1552, 99.9%) and "DistSea" (1101, 70.9%) have higher bandwidth values compared to the bandwidth value obtained from the GWR analysis (140, 9.0%) for Region 3. The bandwidth values of GWR and MGWR for Region 4 are presented in Figure 6. The bandwidth value obtained from the GWR analysis is 277 and as the main assumption of the GWR technique, it is accepted for all factors. However, the MGWR technique again provided different optimum bandwidth values.

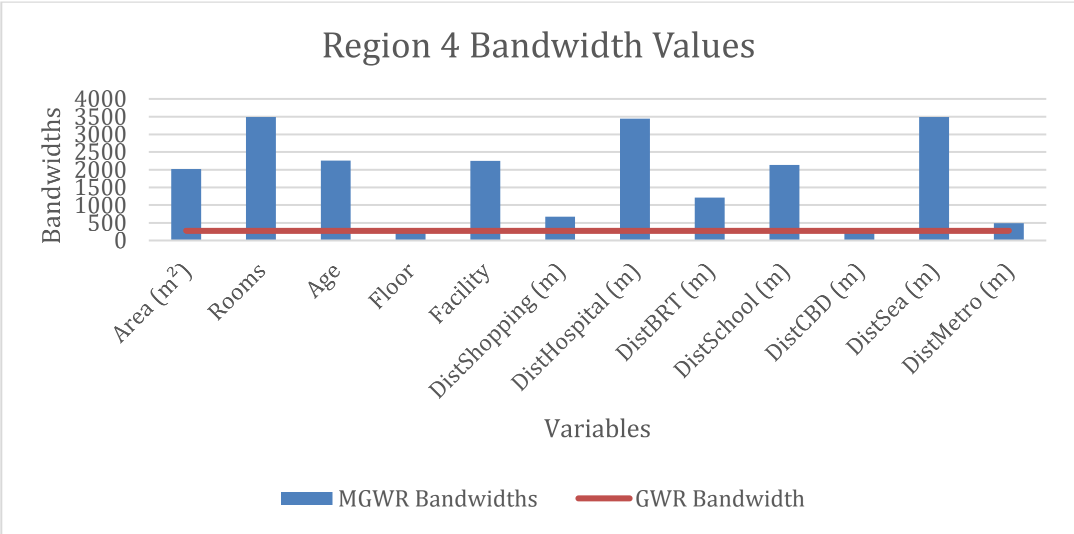


**Fig. 6.** MGWR and GWR bandwidth values for Region 4

The factors "Area" (2016, 57.8%), "Rooms" (3485, 99.9%), "Age" (2262, 64.9%), "Facility" (2252, 64.6%), "DistHospital" (3447, 98.9%), "DistSchool" (2133, 61.2%) and "DistSea" (3485, 99.9%) are higher than the optimum bandwidth value of the model (277, 7.9%) which is provided by GWR analysis for Region 4. In general, as presented in Table 3, the bandwidth values of "Area", "Rooms", "Age", "Facility", "DistSchool", "DistSea" and "DistHospital" factors increased more than 400 % with respect to GWR bandwidth values, which indicates that these factors should be considered as wide-range factors rather than narrow-range.

**Table 3**
Change in Bandwidth Values GWR– MGWR Comparison

| | Region 1 | | | Region 2 | | | Region 3 | | | Region 4 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variables | GWR | MGWR | Change % | GWR | MGWR | Change % | GWR | MGWR | Change % | GWR | MGWR | Change % |
| Area ($m^2$) | 189 | 1111 | 487.8 | 217 | 1155 | 432.3 | 140 | 1525 | 989.3 | 277 | 2016 | 627.8 |
| Rooms | 189 | 2228 | 1078.8 | 217 | 1151 | 430.4 | 140 | 1552 | 1008.6 | 277 | 3485 | 1158.1 |
| Age | 189 | 1268 | 570.9 | 217 | 356 | 64.1 | 140 | 1102 | 687.1 | 277 | 2262 | 716.6 |
| Floor | 189 | 193 | 2.1 | 217 | 123 | -43.3 | 140 | 176 | 25.7 | 277 | 303 | 9.4 |
| Facility | 189 | 2102 | 1012.2 | 217 | 1155 | 432.3 | 140 | 1102 | 687.1 | 277 | 2252 | 713.0 |
| DistShopping (m) | 189 | 373 | 97.4 | 217 | 1155 | 432.3 | 140 | 429 | 206.4 | 277 | 673 | 143.0 |
| DistHospital (m) | 189 | 193 | 2.1 | 217 | 1155 | 432.3 | 140 | 1552 | 1008.6 | 277 | 3447 | 1144.4 |
| DistBRT (m) | 189 | 277 | 46.6 | 217 | 102 | -53.0 | 140 | 347 | 147.9 | 277 | 1216 | 339.0 |
| DistSchool (m) | 189 | 621 | 228.6 | 217 | 1155 | 432.3 | 140 | 236 | 68.6 | 277 | 2133 | 670.0 |
| DistCBD (m) | 189 | 102 | -46.0 | 217 | 105 | -51.6 | 140 | 521 | 272.1 | 277 | 268 | -3.2 |
| DistSea (m) | 189 | 706 | 273.5 | 217 | 1155 | 432.3 | 140 | 1101 | 686.4 | 277 | 3485 | 1158.1 |
| DistMetro (m) | 189 | 104 | -45.0 | 217 | 1155 | 432.3 | 140 | 102 | -27.1 | 277 | 485 | 75.1 |
| Number of Observations | | | 2230 | | | 1156 | | | 1553 | | | 3487 |

Also, the GWR analysis provided bandwidth values of 189, 217, 140 and 277 for Region 1, Region 2, Region 3 and Region 4, respectively. The total number of observations for these regions is 2230, 1156, 1553 and 3487, respectively. According to these results, one can say that the bandwidth values obtained from the GWR analysis are not proportional to the number of observations used for the analysis.

## 5. Discussion

The results of this study revealed that some factors have bandwidth values of over half of the total data points. That is, in all regions, estimations of the coefficients of “Area”, “Rooms” and “Facility” factors were influenced by more than half of the data points. Therefore, these three factors have the highest possibility of being considered as wide-range factors in all types of analyses. In terms of the “Area” factor, the price increases as the size of a house increases [2, 4, 7, 8, 9, 11, 17, 21, 68]. Therefore, this factor can be defined as a wide-range one in this study. Considering the “Rooms” factor, although in some studies the number of rooms can be linearly dependent on the size of the real estate property, in most cases a larger number of rooms adds a premium to the prices of residential properties [10, 11, 68, 69]. Also, people are willing to pay more for residential properties with facilities such as parking area, gym, pool and other social activities within the living area [9, 11, 17, 18, 19, 23, 68-69, 71]. Therefore, the facility condition of the residential properties can also be considered as a wide-range factor. However, the factors, namely “Floor”, “Proximity to the BRT line” and “Proximity to central business district” have bandwidth values lower than half of the total data points in each region. Estimation of the coefficients of these factors was influenced by fewer nearby data points compared to that of the “Area”, “Rooms” and “Facility” factors. Hence, these three factors can be considered as narrow-range factors and they should be included into analysis models after careful consideration. The “Floor” factor shows narrow-rangiest because in city centers where crowds and noise might cause a disturbance, people may prefer to live on upper floors. However, in rural areas where the amount of green areas is larger and residential properties have gardens, people are willing to pay more for lower floors [5, 7, 14, 17, 22, 69]. Therefore, the floor level and its effect on residential properties change over the space, which indicates that the floor level can be considered as a narrow-range factor. On the other hand, proximity to locations such as schools, hospitals, shopping malls, transportation facilities and the seaside is mostly considered as an important factor when choosing a place to live. The outcomes of this study also revealed that the proximity to the BRT line should be considered as a narrow-range factor. In general, proximity to a transportation system can be considered as a wide-range factor, however, the effect of a transportation system is limited up to some specific distances from that system [10-11, 15- 21, 71]. The bandwidth of the factor “Proximity to central business district” was lower than that determined by GWR in all regions except Region 3. That is, the location of the central business district is important only to its specific vicinity, which makes it a narrow-range factor. Similarly, proximity to the central business district can be considered as a narrow-range factor because people would like to have rapid access to their job [ 1-2, 4-5, 10-11, 18-19, 21-22, 69-71].

## 6. Concluding Remarks

The effect of regional factors is considered in many studies in the literature as mentioned above. However, in traditional regression models all factors are defined and taken into consideration as they are all affected by equal number of neighbor data. In this study, it is hypothesized that some factors and their effects are subject to change across larger regions. In order to test this claim, a total of 3,487 geographical data points, including the characteristics and environmental features and coordinates of residential properties, were collected from a study area in Istanbul, Turkey (Esenyurt and Beylikduzu Counties). Then, the dataset was analyzed by geographically weighted regression (GWR) as well as a new technique, namely multiscale geographically weighted regression (MGWR). A single optimum bandwidth value was obtained from GWR analysis. Then, this value was compared to the optimum bandwidth values of each factor obtained from MGWR analysis in order to define newly proposed narrow-range and wide-range factors of the study area. In the analyzed model, the factors, size, age, floor level, number of rooms of the residential properties, existence of facilities such as parking, gym, pool, etc., and proximity to school, seaside, central business district, shopping malls, metro line, BRT line and hospitals, were investigated. The bandwidth values of these factors within the analyzed models were estimated by GWR and MGWR with the purpose of identifying the factors as either narrow-range or wide-range. The findings of this study are transferrable through careful implementation of an analysis model including the selected factors for a new study area. With the help of this study, it is possible to generalize the outcomes regarding the factors depending on whether they are considered as narrow-range or wide-range. In this type of investigation, studies are limited by the size of the data. By providing a larger amount of data, it is possible to achieve more reliable bandwidth values for each specific factor in the model. Further studies with commercial and industrial properties are also recommended in different study areas considering narrow-range and wide-range factors. It would be an interesting research topic to include the demographic effects of the population living in the research area. The isolated effect of demographic profile may reflect the price changes of the residential properties mostly based on the income level actually.

## Author Contributions

Conceptualization, Sahin and Gokasar.; methodology, Sahin and Gokasar; software, Sahin; validation, Gokasar; formal analysis, Sahin and Gokasar; investigation, Sahin and Gokasar; resources, Sahin; data curation, Gokasar; writing—original draft preparation, Sahin; writing—review and editing, Gokasar; visualization, Sahin; supervision, Gokasar; project administration, Gokasar. All authors have read and agreed to the published version of the manuscript."

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## Conflicts of Interest

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

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