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Analysis of Impact of Accessibility on Residential Property Values in Gotri Area of Vadodara City, India Using OLS and GWR

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ABSTRACT

Valuation of residential property is a complex task involving multiple factors. Also, variation in residential property values are so high and diverse that it becomes difficult to analyse which variables are having greater or lesser impact on residential property valuation. The present study uses statistical regression technique to explain the effects of accessibility on residential property values in the Gotri area of Vadodara city, India. The article also includes a comparison between Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) methods. The present study has used shortest distance via a road network to selected facilities/amenities from sample residential properties to assess the accessibility. Data on more than 30 parameters related to structural, locational and amenities were collected for 161 residential properties. One dependent variable i.e. residential property value per sq. ft. and fifteen explanatory (structural and accessibility) variables were considered for the study. Due to high multiple correlation between the variables, three variables were removed and Ordinary Least Square (OLS) regression, a global model applied on one dependent and twelve explanatory variables (R^2 - 0.40 for ln values of variables). GWR, local model was also applied on same number of variables but did not execute. This was due to severe global or local multicollinearity i.e. redundancy among model explanatory variables. Finally, GWR was implemented considering one dependent and eight explanatory variables which executed successfully (R^2 - 0.67 for real values of variables). GWR outperformed the OLS model which suggests that GWR can be favourably used for such applications.

Keywords: Residential property value, Accessibility, OLS, GWR, Network analysis

I. INTRODUCTION

Residential property value and its assessment is a complex and challenging task since it involves the consideration of a variety of underlying factors of the market and the way they affect the value of the property at a given time. Such factors may include governmental policies, geographical factors or even factors such as fashion, season etc. Property values also depends on the purpose for e.g. sale, taxation, financing etc. and the type of the property such as residential or commercial, for which, it is exercised. The property market is shaped by complex spatial and non-spatial processes which exert a combined effect on market value [1]. Each residential unit has a unique bundle of attributes such as accessibility to work, public transport, amenities, structural characteristics, neighbourhood, and environmental quality [2,3,4,5,6,7].

From the list of attributes, location is arguably the most important component affecting property values. It is also commonly accepted that properties are spatially unique and this means that location is an intrinsic attribute of a dwelling that directly determines housing quality and market value. However, modeling locational factors in understanding property values has proved difficult because of the wide range of spatially defined attributes, which may or may not affect value at a particular time and location. A few of these attributes can be numerically measured, but the measures may not always be valid representation of the locational influence, especially because of the complex interaction of these factors.

The accessibility to services, facilities and amenities is an essential factor affecting the residential property development. In many regions, urban plans ensure that individuals have some minimal levels of accessibility to the public sector facilities, such as schools, emergency services, and recreation amenities. At the same time, an essential element of location strategy for housing development is to avoid proximity to noxious facilities (For e.g., waste disposal sites, gas depots, and chemical factories) or noise producing facilities (For e.g. party plots, marriage halls etc.). It is noted that the results of accessibility evaluation depend on the definition of accessibility.

The Multiple Regression Analysis (MRA) is considered a classical and traditional technique for explaining and predicting property values. In implementing MRA, a dependent variable and set of explanatory variables need to be identified and measured in quantitative form. This task becomes more complicated when the location influence in the form of accessibility on property values need to be explicitly identified and modelled.

Various studies have reported that MRA has not been successful in quantifying location influence on property values. The failure of MRA is related to spatial autocorrelation and heteroscedasticity, the two spatial effects inherent in property data [8,9]. Spatial autocorrelation means that the residuals are spatially correlated. Thus, this is the violation of the presumption of OLS (Ordinary Least Square), a global technique for linear regression that the residuals must be uncorrelated and normally distributed with zero mean and constant variance. This makes the OLS estimated coefficients biased and unsuitable for inference. The ending effect is that the predicted property prices are unreliable [10]. An alternative to OLS can be Geographically Weighted Regression (GWR). GWR is a local multiple regression model which considers only a subset of observations nearest to the regression point. These observations are weighted according to some distance decay functions. Observations near the regression point receive higher weight while observations farther from regression point receive lower weight [10].

The presented article uses statistical regression technique to develop a model to explain the effects of accessibility on residential property values in the Gotri area of Vadodara city, India. The article also provides a useful comparison between Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR). In analyzing the effect of accessibility, the rule that higher the accessibility higher is the residential property value and vice a versa is followed. The accessibility is also considered in terms of spatial distribution of the facilities and amenities presently available for residential units in the study area. The larger is the shortest distance to a facility; the lower is the accessibility level to the facility. In the context of housing development, a location may have good access to some useful facilities (e.g., schools), but not to others (e.g., community centers) or be close to noxious facilities. The present study has used shortest distance via a road network to selected facilities/amenities from sample residential properties to assess the accessibility.

II. STUDY AREA

Gotri area located in the western part of Vadodara City, India is selected as a case study for understanding the effects of accessibility on residential property values (fig. 1). Gotri, situated some 5 km west of central transport hub of the city, was once considered a small village situated in the outskirts of the city, it is now being considered as a developing counterpart of Alkapuri, one of the posh locality within Vadodara city. The study area is situated 5 km away from railway station/central bus depot and 9 km from the airport. Gotri is considered as one of the fastest developing reality market of the city. At the same time, the study area is developing fast in terms of social and physical infrastructure. Gotri offers a maximum number of apartments with respect to other residential areas of the city along with other types of residential units. Several schools, hospitals, banks, sub-markets etc. are located within the study area. People have easy access to malls, restaurants and movie theatres situated around race course circle which is only 2 km away from the Gotri. All type of residential options from apartments to bungalows to villas is catering to the middle income, upper middle and higher income groups. A wide range of apartments are available in the price range of INR 2,200 to 3,300 per sq. ft. (adapted from magicbricks.com).

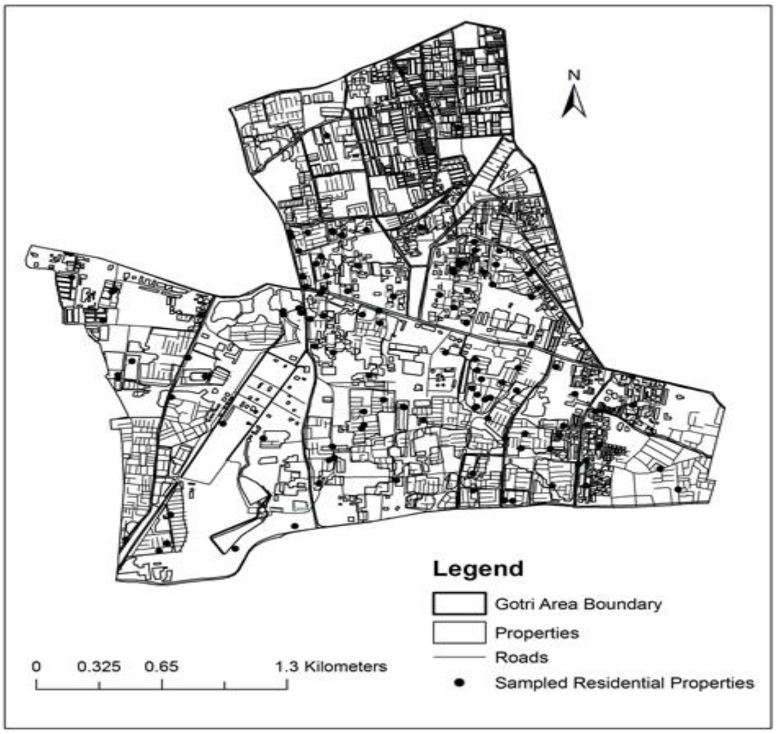

Figure 1. Randomly sampled residential properties in Gotri area

III. DATABASE AND METHODOLOGY

Data on more than 30 parameters related to structural (type of property, carpet area, saleable area, age of the property, no. of bedrooms etc.) locational (location of the property, distance to nearest major road, market, public transport facility, public health service, recreational areas, central bus depot/railway station, central market, noise producing facilities etc.) and amenities (absence/presence of parking - 2/4 wheeler, open/close, common/allotted, club house, open play area/garden, gymnasium, community hall, walking track etc.) were collected for 161 residential properties. The amenities data were collected to understand their effects on property values. The residential properties were selected through stratified random sampling method and in proportion with the number of type of residential properties in the study area. The type of residential properties was considered based on classification used by Vadodara Municipal Corporation for collecting property tax. These types are Flat / Apartment, Apartment Penthouse Flat, Tenament, Row House, Bunglow, Villas, Duplex, Individual Building, Gamtal house (house in original village Gotri), Pole House (old houses in congested locality), Cabin, Chali House (old houses in congested lanes) and Hut.

The data on assessed residential property value per square feet were collected from the property valuers and were normalized based on inputs received from property experts. Also, the contribution of land value to the total property value for each of types of residential property varies greatly and therefore it was adjusted based on property valuer's judgement.

The dependent and explanatory accessibility variables selected for the present work and their descriptive statistics is presented in table 1. Because of skewed distribution of all the variables, natural log of dependent variable i.e. residential property value and natural log of selected explanatory variables (table 2) including structural and accessibility were used in the multiple regression analysis. For calculating natural log of variables, certain modifications were made in the dataset for e.g. for under construction properties, the age was taken as 1 because natural log of 0 cannot be calculated.

Multiple correlation analysis is performed by calculating correlation matrix (table 3) to understand the degree of association between dependent variable i.e. residential property value and explanatory variables and among explanatory variables themselves. This analysis helped in understanding the presence of multicollinearity among the variables. The multicollinearity also suggests data redundancy which may affect the OLS and GWR model building process. Carpet area is the area enclosed within the walls and it is the actual area which can be put to any use within any residential unit. On the other hand, saleable area or super built-up area is inclusive of carpet area, walls with their thickness and area under common spaces like the lobby, staircase, lift, security room etc. Most builders in the study area are using saleable area for selling the properties however, saleable area may significantly differ from carpet area as every residential complex may have unique bundle of common spaces, facilities and amenities. Therefore, the data were collected for both carpet and saleable area as they may have different effects on residential property values.

Table 1. Descriptive statistics of variables from sample residential properties

Sr. No.	Variable	Mean	1st Quartile	3rd Quartile	Standard Deviation
1	Residential property value per square feet (INR) (rpvsf)	3240	2703	3800	734
2	Age of the property in years (pay)	14	3	23	12
3	Carpet area in square feet (casf)	912	700	1037	417
4	Saleable area in square feet (sasf)	1302	1000	1482	598
5	Number of bedrooms (bedr)	2	2	3	1
6	Distance to nearest major road (metres) (disnmr)	178	51	279	156
7	Distance to nearest market (metres) (disnm)	897	361	1107	739
8	Distance to nearest school (metres) (disns)	649	310	747	509
9	Distance to nearest public transport facility (metres) (disnptf)	485	240	585	382
10	Distance to nearest recreational facility (metres) (disnrecf)	653	336	742	483

11	Distance to nearest public health service (metres) (disnphs)	649	310	747	509
12	Distance to central transport facility (metres) (disctf)	4355	3539	5039	995
13	Distance to central market (metres) (discm)	7481	6661	8182	991
14	Distance to highway (metres) (dish)	7338	6751	7726	893
15	Distance to nearest exit point (metres) (disnep)	2065	1568	2656	779
16	Distance to nearest noise producing facility (metres) (disnnpf)	743	471	852	470

Source: authors' calculations

In calculating accessibility, distance was considered with negative impedance i.e. larger the distance from residential properties to selected accessibility variables via a road network, lower is the accessibility and vice versa. An exception is the distance from residential properties to noise producing facilities. Here, lower distance is considered as negative impendence. The distances were calculated based on ArcGIS network model. The "near" function in ArcGIS software was used to find out nearest facility/amenity with a distance from sample residential properties.

Multiple regression is a commonly used analysis in understanding the effects of variety of factors on property valuation. The present study has used Ordinary Least Square (OLS) i.e. a linear multiple regression technique which is a global model and Geographically Weighted Regression (GWR), local model to understand the effect of accessibility on residential property values and to estimate the exact function which can be used for prediction.

Table 2. Variable definition

Sr. No.	Variable	Description
		Dependent variable
1	rpvsfln	Natural log of residential property value per square feet (INR)
		Explanatory variables
2	payln	Natural log of age of the property in years
3	psasfln	Natural log of saleable area in square feet
4	bedrln	Natural log of number of bedrooms
5	disnmrln	Natural log of distance to nearest major road (metres)
6	disnmln	Natural log of distance to nearest market (metres)
7	disnsln	Natural log of distance to nearest school (metres)
8	disnptfln	Natural log of distance to nearest public transport facility (metres)
9	disnrecfln	Natural log of distance to nearest recreational facility (metres)
10	discmln	Natural log of distance to central market (metres)
11	dishln	Natural log of distance to highway (metres)
12	dishgln	Natural log of distance to nearest exit point (metres)
13	disnnopfln	Natural log of distance to nearest noise producing facility (metres)

IV. RESULTS AND DISCUSSION

The correlation matrix suggests that many variables are highly correlated which may hamper the regression modelling process. The result of multiple correlation analysis is presented in table 3. Correlation coefficient of value higher than ± 0.7 was evaluated further to make decision about their inclusion or exclusion in the OLS and GWR model. Almost perfect positive correlation was observed between carpet area and saleable area (+0.99) suggesting very high degree of association. From both the variables, inclusion of saleable area in the model was thought to be more appropriate because the final cost of the residential property is generally arrived at using saleable area and not the carpet area for most of the builders in Vadodara city. Other variables for which higher positive correlation coefficient was observed were between discm and disctf (+0.98), disnrecf and disnm (+0.87), disnptf and disnm (+0.81), disnnpf and disns (+0.77), disnnpf and disnphs (+0.77), disnphs and disnm (+0.77), disns and disnm (+0.77), disctf and disnm (+0.75), disnnpf and disnm (+0.73), disnphs and disnptf (+0.72), disnptf and disns (+0.72), disnnpf and disnrecf (+0.72), disctf and disnrecf (+0.72) and negative correlation between disnep and discm (-0.71) (table 3). Higher positive/negative correlation coefficient necessitated the exclusion of some of the variables so that the issue of multicollinearity could be eliminated. For example, between distance to central market (discm) and distance to central transport facility (disctf), discm was retained because central market may play a decisive role in selecting the residential site than the central transport facility. Also there is strong negative correlation observed between distance to central transport facility (disctf) and distance to nearest city exit point of Gotri area (disnep). Therefore, after considering all above mentioned correlations among various explanatory variables, three variables namely carpet area, disnphs and disctf were removed from fifteen explanatory variables and OLS and GWR analysis was performed. Because of skewed distribution for dependent and all explanatory variables, natural log of selected variables (table 2) has also been incorporated for calculating regression and comparison is made with results obtained from real values of variables.

A. OLS IMPLEMENTATION

OLS was implemented on real and natural log of residential property value (dependent variable) and twelve explanatory variables after removing three highly correlated variables namely carpet area, distance to nearest public health system (disnphs) and distance to central transport facility (disctf). The R2 value achieved was 0.36 (table 4), which is suggesting that only 36% of the variation in the residential property value is explained by the selected twelve explanatory variables which includes structural and accessibility variables. This also implies that around 64% of the variation in the residential property value is not explained by considered explanatory variables. Also, Moran's I was calculated to ensure that residuals are not spatially autocorrelated (table 6). Moran's I suggested that pattern does not appear to be significantly different than random, that means residuals are not spatially autocorrelated. Same OLS analysis was repeated using natural log (ln) values of dependent and explanatory variables. The slight improvement was observed with R2 value of 0.40 (table 4).

It was observed that though data transformation helps in getting more un-skewed distribution, it also kills the real variation present in the data. Therefore, care needs to be taken while using data transformation particularly for model building. Further, OLS was applied to the model after removing some of the explanatory variables to see the improvement in R2 value. But, results did not show any improvement over the results obtained through removal of three explanatory variables (carpet area, disnphs and disctf). The lower R2 value (0.40 for ln values of dependent and twelve explanatory variables) suggest that OLS which is a global model may not be in a position to include some of the local spatial variations existing in the parameters.

Table 3: Correlation matrix for dependent and explanatory variables

Variables	rpvsf	pay	casf	sasf	bedr	disnmr	disnm	disns	disnptf	disnrecf	disnphs	disctf	discm	dish	disnep	disnnpf
rpvsf	1															
pay	0.35	1														
casf	0.08	-0.25	1													
sasf	0.08	-0.26	0.99	1												
bedr	0.27	-0.21	0.64	0.64	1											
disnmr	-0.19	0.00	0.03	0.03	0.04	1										
disnm	-0.32	-0.43	0.15	0.15	0.06	0.44	1									
disns	-0.29	-0.43	0.27	0.27	0.11	0.16	0.77	1								
disnptf	-0.35	-0.42	0.30	0.30	0.18	0.33	0.81	0.72	1							
disnrecf	-0.33	-0.38	0.11	0.11	0.03	0.52	0.87	0.61	0.65	1						
disnphs	-0.29	-0.43	0.27	0.27	0.11	0.16	0.77	1.00	0.72	0.61	1					
disctf	-0.29	-0.51	0.20	0.20	0.07	0.21	0.75	0.65	0.64	0.72	0.65	1				
discm	-0.27	-0.51	0.22	0.22	0.09	0.12	0.68	0.59	0.63	0.64	0.59	0.98	1			
dish	-0.14	-0.04	-0.09	-0.09	-0.07	0.53	0.44	0.36	0.07	0.55	0.36	0.26	0.09	1		
disnep	0.04	0.30	-0.11	-0.11	-0.06	0.16	-0.05	0.05	-0.07	-0.09	0.05	-0.62	-0.71	0.32	1	
disnnpf	-0.31	-0.27	0.14	0.14	0.02	0.45	0.73	0.78	0.64	0.72	0.78	0.52	0.41	0.55	0.27	1

Table 4. OLS analysis results for a dependent and twelve explanatory variables

Regression Statistics	Real Values of variables	Natural log (ln) of variables
Multiple R^2	0.36*	0.40*
Adjusted R^2	0.31*	0.35*
Standard Error	3896.94	3.78
AICc	2540.23	-46.06

Note: *- significant at the 0.05 level

Standard residuals map (figure 2) for sample residential properties is generated to visualize the distribution of over and under predictions using standard deviation of residuals. The map shows the random distributional pattern of standard residuals which suggests that there is no problem with OLS model design. However, some key explanatory variables may be missing because of which the overall result of OLS model is not impressive. Also, modelling the value of the residential property is such a complex phenomenon that only selected structural and accessibility variables may not be sufficient for the modelling purpose. In order to gauge possible influence of local spatial variations in explanatory variables, Geographically Weighted Regression (GWR), a localized model has been implemented and discussed in the following subsection.

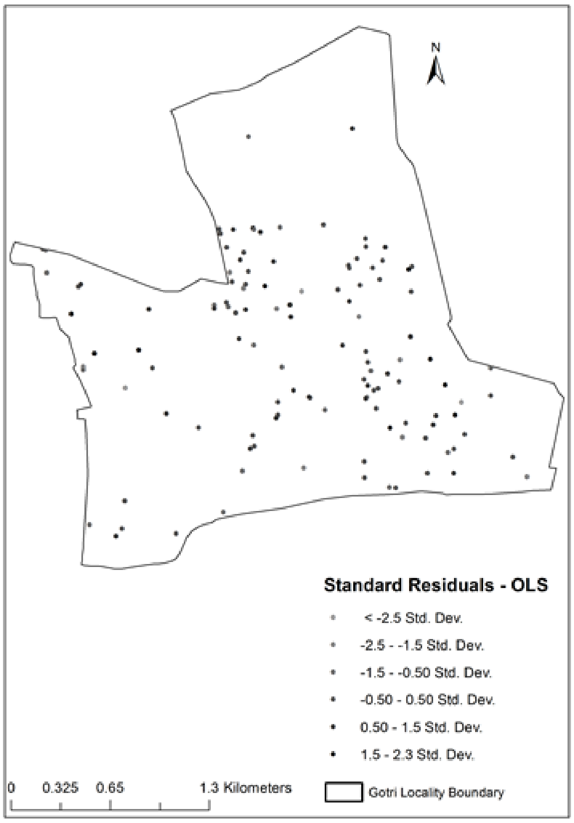

Figure 2. OLS Standard Residuals for Sample Residential Properties

B. GWR IMPLEMENTATION

Geographically Weighted Regression (GWR) is a statistical technique used for modelling of processes that vary over space. In Other words, GWR considers spatial variation in the dependent and explanatory variables which might help in making the model better over simple regression (i.e. OLS). However, GWR cannot be the first choice for all regression tasks. First, one begins with OLS regression analysis and identifies the best model possible. Then after identifying best explanatory variables through OLS, one needs to implement GWR for possible improvement. In the present work, GWR was implemented after unsatisfactory results obtained from OLS model to get more robust local regression model taking into account the spatially uncorrelated variables.

Based on OLS model and the results obtained from it, GWR was implemented considering same dependent and explanatory variables. Here, the assumption was that since OLS has been successfully executed, GWR will follow the same. However, GWR failed to execute for a dependent and twelve explanatory variables because of severe global or local multicollinearity i.e. redundancy among model explanatory variables. To check for global multicollinearity, from the OLS model implemented, variables with larger VIF (Variance Inflation Factor) (generally VIF > 7.5) are redundant that needs to be removed for GWR implementation. Also, variables reflecting categorical/nominal data or variables with only a few possible values (for example, no. of bedrooms in the present study) need to be avoided to run the model successfully. Finally, eight explanatory variables i.e. pay (ln), sasf (ln), disnmr (ln), disnm (ln), disnptf (ln), disnrecf (ln), disnnpf (ln) and disns (ln) satisfying all conditions of non-multicollinearity were used for GWR implementation. In GWR implementation, certain choices are to be made for parameters. For example, kernel type: fixed or adaptive. Fixed kernel type is appropriate for reasonably regularly spaced observations within the selected spatial unit. Since, residential property observations are not regular and are clustered at certain locations within the study area, author used adaptive kernel type. Second is bandwidth method.

There are three methods generally used, AICc (corrected Akaike Information Criterion), CV (Cross Validation) and Bandwidth Parameter. The AICc and CV are automatic methods whereas bandwith parameter is manual in which user defined input is required to compute the analysis. The AICc method finds the bandwidth which minimises the AICc value. This value is calculated from a measure of the divergence between the observed and fitted values and from the complexity of the model. On the other hand, CV decides the bandwidth based on minimization of a Cross Validation Score. There is no absolute advantage or disadvantage in using AICs or CV however, AICc takes into account the complexity of the model and therefore it is more preferred in many applications. This is the reason AICc method is used to decide bandwidth for implementing GWR in the present study. GWR produced R^2 value of 0.67 (table 5) suggesting 67 % of the variation in residential property value is explained by selected explanatory variables. The adjusted R^2 value obtained is 0.60 which is lower than R^2. GWR failed to execute when natural log of a dependent and eight explanatory variables were used. This is expected as problem of multicollinearity persisted due to reduced variation in the ln values of variables. OLS analysis was also performed for the same combination of dependent and eight explanatory variables. The R^2 value of 0.26 (table 5) was obtained for real values of variables and 0.34 (table 5) for ln values of variables.

In comparison to GWR, the OLS R^2 result is slightly lower (for real values) and slightly higher (for ln values) which does not seem to be much significant. AICc value is also almost same for GWR and OLS models when implemented for real values of variables. However, the standard error is low (184.82) for OLS than for GWR (646.18) as given in table 5. Also, Moran's I was calculated (table 6) for standard residuals to ensure that residuals are not spatially autocorrelated. Moran's I suggested that residuals are not spatially autocorrelated.

Table 5. GWR and related OLS results for a dependent and eight explanatory variables

	OLS		GWR	
Regression Statistics	**Real Values of variables**	**Natural log (ln) of variables**	**Real Values of variables**	**Natural log (ln) of variables**
Multiple R^2	0.26*	0.34*	0.67*	Failed to execute
Adjusted R^2	0.22*	0.30*	0.60*	
Standard Error	184.82	0.40	646.18	
AICc	2552.96	-39.64	2555.94	

Note: * - significant at the 0.05 level

Table 6. Moran's I for Standard Residuals of OLS and GWR analysis

	Standard residuals - OLS	**Standard residuals - GWR**
Moran's Index:	-0.024217	-0.046213
z-score:	-0.147860	-0.329322
p-value:	0.882453	0.741913

As in OLS, standard residuals map (figure 3) of sample residential properties for GWR model is also generated to visualize the distribution of over and under predictions using standard deviation of residuals. Like OLS, the map shows the random distributional pattern of standard residuals.

Figure 4 represents local R^2 map of GWR for sample residential properties in the study area. Lower R^2 is observed mainly along the main Gotri Road which connects the study area with rest of the city. This may be because of several reasons. The sample residential properties along the main Gotri road would have lower and similar distances to major road (disnmr) resulting into less variation in the variable disnmr. The less variation might affect the model building. Another important reason is that the prices of residential properties along the main road are always higher and are governed by many other factors than simply structural or accessibility variables. Also, opportunity cost of properties on main road is always higher due to favourable locational and other factors. These opportunity cost is governed more by economic and market forces than any other factors. Local R^2 is higher along the minor roads and in the interior of the study area ranging from 0.22 to 0.32. These areas are away from major road and low on accessibility hence, low property values with less opportunity cost.

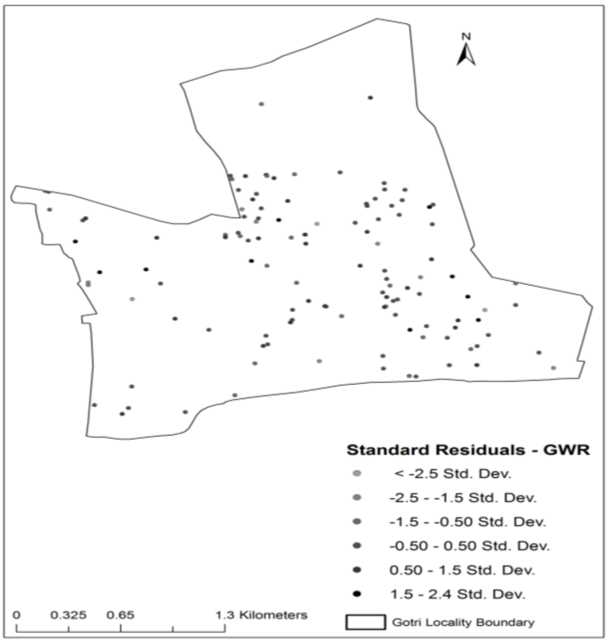

Figure 3. GWR Standard Residuals for Sample Residential Properties

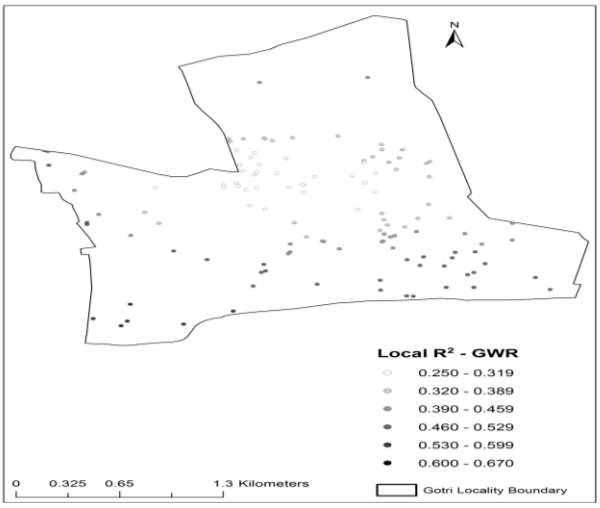

Figure 4. GWR Local R^2 for Sample Residential Properties

V. CONCLUSION

The present study has attempted to assess the effects of accessibility on residential property values and to compare two multiple regression techniques namely OLS and GWR. Initially, OLS was implemented on a dependent variable and twelve explanatory variables after removing three highly correlated variables namely carpet area, distance to nearest public health system (disnphs) and distance to central transport facility (disctf). For same variables GWR did not successfully executed which was because of severe global or local multicollinearity i.e. redundancy among model explanatory variables. Finally, GWR was implemented considering one dependent and eight explanatory variables which executed successfully. GWR outperformed the OLS model which suggest that GWR can be favourably used for such applications.

VI. FUNDING

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