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Revisiting Urban Immovable Property Valuation: An Appraisal of Spatial Heterogeneities in Punjab Using Big Data

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This study employed big data and spatial analysis to assess property values in two cities, Lahore and Faisalabad. Traditional housing price models overlook spatial nuances, focusing solely on structural attributes. To address this, we constructed valuation models using ordinary least square regression and Fast Geographic Weighted Regression (FastGWR), implemented through Python and MPI, based on spatial variables. The models explained up to 75 percent of variance in Faisalabad and around 85 percent in Lahore. Factors like floor area, proximity of health facilities, recreational sites, and marketplaces add a premium to prices, while the nearness of educational institutions, worship places, and solid waste transfer stations or dumping sites lessen the property values in both cities. However, the proximity of industrial units and graveyards affects property values negatively in Lahore but positively in Faisalabad. This study highlights the critical significance of spatial factors in urban immovable property appraisal. As a result, it is recommended to integrate these factors into the process of policy formulation and urban planning.

Keywords: Urban Immovable Property Valuation, Location Specific Parameters, Spatial Heterogeneity, Big Data, Ordinary Least Square Regression (OLS), FastGWR.

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1. INTRODUCTION

Pakistan's real estate market emerges as a potential economic powerhouse, with a substantial portion of the nation's wealth concentrated within its real estate assets, estimated at 60-70 percent. While the sector contributes around 2 percent to the GDP, the combined impact of housing and construction reaches nearly 9 percent. The value of Pakistan's real estate sector, evaluated at approximately $700 billion by the Federal Board of Revenue, signifies its economic significance. Impressively, returns on investment can soar beyond 100 percent (Ouattara et al., 2018). However, this promising market is juxtaposed against a backdrop of challenges and disparities. Pakistan's population, surpassing 225 million, expands annually at a 2.4 percent rate, characterised by an average household size of 6.5 (Pakistan Bureau of Statistics, 2019). With a yearly housing requirement of 700,000 units, merely half of this demand is met, leading to an alarming gap of roughly 10 million units (Rizvi, 2018). This housing shortage necessitates innovative strategies, particularly in the realm of low-cost housing schemes. The intricacies of property valuation further complicate the real estate landscape. Government land acquisitions relying on DC valuation tables often incite public protests due to perceived undervaluation (Sabir et al., 2017). The importance of precise valuation for equitable compensation is underscored by research (Malaitham et al., 2020). Notably, property valuation is not just pivotal for buyers and sellers; it resonates with stakeholders such as investors, banks, agents, and insurers. The geographical location holds substantial influence over a property's price, further emphasising the necessity for accurate valuation (Mankad, 2021).

In dynamically growing cities, the accurate prediction of urban land use evolution plays a pivotal role in fostering sustainable urban planning (Liang et al., 2018) such as Lahore and Faisalabad in Pakistan. Notably, vast untapped potential resides within public properties, including Government Officers Residences (GORs) and railway lands, representing latent avenues for wealth creation. Leveraging these assets effectively can substantially contribute to economic prosperity. The implications of this study extend to policymakers, offering insights to navigate the intricate domains of housing and urban development. A robust housing market stands as a linchpin of a resilient economy; however, Pakistan's housing sector faces an intricate array of challenges. Urbanisation and migration galvanise demand within urban centers, an issue compounded by insufficient supply catalysed by diverse factors. Shortcomings in land usage, planning, and property rights impede progress, while inadequate revenue collection from property taxes curtails infrastructure financing. The labyrinthine regulations further stall land development, exacerbating housing availability discrepancies, particularly pronounced in megacities like Karachi and Lahore. Notably, housing construction trails behind the meteoric pace of population expansion. Skyrocketing market conditions render housing unattainable for many, channeling them towards informal settlements (Dowall & Ellis, 2009; Haque, 2015; Wani et al., 2020; Yuen & Choi, 2012). The challenges are particularly pronounced within Punjab's housing markets, accentuated in cities like Lahore and Faisalabad, grappling with deficits in affordable housing (Malik et al., 2020; Wajahat, 2012). A glaring obstacle lies in the hands of speculative investors who control 75 percent of residential plots, perpetuating this complex issue (Zaman & Baloch, 2011). This practice thrives on secure real estate investments and tax loopholes, compounding the predicament. Although plot prices surge significantly (Gul et al., 2018), official valuations lag behind, generating volatility in Pakistan's property prices. The repercussions of such fluctuations extend to the public, shouldering the burden of investor gains. Despite intermittent housing policies, the issue remains inadequately addressed, emphasising the urgency of public sector interventions to stabilise spiraling prices (Ahmed et al., 2021).

This investigation delves into the spatial disparities within real estate property values, aiming to underpin a refined and scientific valuation model. A motivation underpinning this study is the inefficiency, non-scientific nature, and inconsistency of the prevailing valuation systems employed by government entities, including DC and FBR rates. Notably, these methods disregard spatial attributes, leading to valuations far below the market values of immovable properties. The absence of mechanisms to record actual market transactions exacerbates the issue, fostering illicit practices and revenue loss for the nation. There arises an imperative to establish a sophisticated valuation system hinged upon spatial variables. Such a framework could not only bridge the gap between official and market rates, but also deter market speculation, which artificially inflates property prices. Annually, the FBR mandates RTOs across Pakistan to constitute committees, including stakeholders such as Chief Commissioners, RTO officers, property dealers, and representatives from the Builders and Developers Association of Pakistan (ABAD). These committees evaluate and adjust valuation tables for tax purposes, a process prone to subjectivity (FBR, 2020). Such a subjective approach underscores the need for scientific calculation methodologies. The persistently lower District Collector's valuation rates (DC rates) in comparison to FBR rates further highlight the shortcomings. Until 2019, DC rates were based on average property transaction prices, often underreported to evade taxes. Although some progress is noted in Lahore's 2020 DC rates, transparency remains questionable. The striking differences highlighted in the

Table 1 & Table 2, underscore the significant gap between market rates and government agency rates.

Table 1

Price per Marla (PKR) of FBR and the Property Portal of Zameen.com

	2016			Feb-19			Jan-20		
DHA Lahore	FBR	Zameen.com	Difference	FBR	Zameen.com	Difference	FBR	Zaineen	Difference
Phase I	672000	1903900	184%	S06400	2140200	165%	360000	2144250	149%
Phase II	552000	1935900	251%	662400	2240325	238%	sooooo	2183400	173%
Phase III	552000	3243600	488%	662400	2909250	339%	300000	3176325	297%
Phase IV	525525	2095S75	299%	630630	2482650	294%	S50000	2478150	192%
Phase V	420000	2733250	563%	504000	3072150	510%	900000	3313350	268%
Phase VI	405000	2184975	440%	486000	2400750	394%	350000	2450025	188%

Source: Zameen.com and FBR.

Table 2

Price per Marla (PKR) of DC Rates and the Property Portal of Zameen.com

	2016			2017			2020		
DHA Lahore	DC Rate	Zameen.com	Difference	DC Rate	Zameen.com	Difference	DC Rate	Zameen.com	Difference
Phase I	560000	1773000	217%	600000	1773400	196%	962500	2144250	123%
Phase EE	460000	1967S50	328%	520000	2026500	2903-4	962500	21S3400	127%
Phase HI	460000	3118975	582%	520000	3GB6550	494%	1100000	3176325	189%
Phase EV	420000	2249325	436%	490000	2255400	360%	825000	2478150	200%
Phase V	250000	2606175	831%	450000	2801250	523%	962500	3313350	244%
Phase VI	270000	2141325	693%	420000	2230875	431%	687500	2450025	256%

Source: Zameen.com and Board of Revenue Punjab.

The objective of this study is to build a valuation model for urban immovable properties based on spatial attributes by utilising big data ($n \geq 1.2$ million) in two big cities of Punjab, i.e., Lahore and Faisalabad.

1.1. Literature Review

The economic value of a commodity is its estimated value based on individual benefits and utility. Quantifying this value is challenging, often relying on market prices and features of both perceptible and imperceptible nature (Fisher et al., 2015; Gabrielli & French, 2020; Lovett, 2019). Hedonic valuation, a prevalent method, uses attributes and past transactions to determine a commodity's utility and market price while the relevant models establish relationships between price and attributes (Baranzini et al., 2008, 2010; Bateman et al., 2001). The hedonic approach identifies factors influencing urban property value, including area, structure, walkability, security, and amenities such as electricity & water supplies, etc. (Boza, 2015; Erickson et al., 2011; Gilderbloom et al., 2015). Models use techniques like ordinary least squares (OLS) or geographically weighted regression (GWR) (Machin, 2011; Pace & Gilley, 1998; Pagourtzi et al., 2003; Shabana et al., 2015). Four sets of variables—structural, locational, environmental, and neighbourhood—are typically used for valuation, with selling prices as the response variable (Freeman, 1981). Mapping urban property values is vital for real estate insights, price monitoring (Brown et al., 2020; Gaffney, 2009), and future city planning (Barreca et al., 2020). Valuation maps benefit buyers, sellers (Goix et al., 2019; Wang et al., 2020), and government agencies for property tax assessments (Chapman et al., 2009; Larson & Shui, 2020). Taxes based on fair market values consider urban services, enhancing tax fairness and benefiting property owners. Urban service provision positively impacts property value, funded by government resources. Hedonic models are essential for estimating real estate property market prices, factoring in various influences. These models provide crucial insights for understanding housing preferences and assume perfect market competition and information symmetry among buyers and sellers (Freeman, 1981; Taylor, 2008). However, housing markets differ due to distinctive features, resulting in product range discontinuities and complexities in assessing price-determining features (Knight, 2008). Residential property value hinges on floor area, structural attributes, and location (Xiao et al., 2017). Spatial hedonic valuation models, accounting for location, prove effective (Helbich et al., 2013; Koschinsky et al., 2012). Proximity to amenities and urban services impacts house prices, with mixed findings – positive correlations for factors like transport access and negative correlations for aspects like waste stations (Seo et al., 2014; Tian et al., 2017). House values are also linked to factors like government policies, infrastructure, water supply, and security (De & Vupru, 2017; Xiao et al., 2017; Yang et al., 2018). Real estate valuation methods encompass spatial dependence and heterogeneity models (Krause & Bitter, 2012).

The utilisation of spatial dependence in property valuation research has a rich history and substantial literature. Spatial dependence refers to the degree of similarity among observation values in geographic space (Crawford, 2009). Positive spatial autocorrelation implies similar values cluster together, while negative autocorrelation indicates dissimilar values cluster (Griffith, 2004; Hubert et al., 1981). Hedonic price theory suggests that utility-bearing features influence the value of commodities, with their impact estimated through hedonic price indices (Lancaster, 1966; Rosen, 1974). A user's willingness to pay for a commodity feature reflects its hedonic price under consumer utility maximisation. Historical transactions can establish a price function between commodity attributes and price, enabling estimation of implicit hedonic prices for specific features. Notably diverse house attributes warrant separate hedonic models to assess their values. Landscape features significantly affect housing prices, necessitating location-specific valuation (Goodman, 1978). Studies like Can (1990) found spatial attribute inclusion improved urban property appraisal accuracy. Can and Megbolugbe (1997) highlighted that hidden spatial dependence in residential real estate data substantially influenced value estimation accuracy. Liao and Wang (2012) identified a U-shaped spatial dependence pattern in Changsha's house prices, where proximity of high- and low-priced houses positively impacted implicit prices, while medium-priced houses had a comparatively lesser effect. House prices were lower in densely built-up areas, counter to Western city market trends where central properties were usually pricier.

Spatial heterogeneity is a recognised challenge in real estate datasets, often addressed by segmenting the area of interest into functionally homogeneous regions for valuation (Kauko, 2003). Spatial heterogeneity signifies variability in values across space (Dutilleul & Legendre, 1993). In this context, it refers to properties with similar characteristics being valued differently across different areas within the study space. Spatial heterogeneity exploration has historical roots with techniques like Casetti's expansion method (Casetti, 1972), which broadens a mathematical model by redefining parameters through spatial variables (Casetti, 1997). Can (1990) applied the spatial expansion method to construct a hedonic model for residential property valuation, considering neighbourhood attributes. Anselin (1995) used local indicators of spatial association (LISA) to explain spatial heterogeneity and spatial dependence, indicating a potential link between nearby values. Brunsdon et al. (1996) developed geographically weighted regression (GWR) to address spatial non-stationarity by modifying parameters in Kernel Regression. GWR provides localised spatial statistics, offering visual analysis. Fik et al. (2003) used an interactive variable approach for spatial heterogeneity in house prices, highlighting location's interactive effect with other variables. Bitter et al. (2007) compared GWR with spatial expansion methods, concluding GWR's better accuracy in capturing varying attribute effects. Wen et al. (2017) noted GWR's advantages, offering accurate and visually distributive implicit values. Spatial heterogeneity is crucial for accurate house price appraisal due to varying property prices within urban centres influenced by urban facilities (Redfearn, 2009; Yuan et al., 2020). Wu et al. (2020) favoured spatial heterogeneity over spatial dependence in identifying housing submarkets due to urban complexity. (Jiang, 2018) advocated using spatial heterogeneity over spatial dependence for geospatial analysis, especially with large data, suggesting a shift from Euclidean to fractal geometry. Addressing spatial heterogeneity in property valuation is vital as real estate prices vary across locations within urban areas, influenced by varying urban facilities. Techniques like GWR provide accurate insights into such variations and aid in accurate valuation.

Big data refers to vast, intricate datasets accumulating over time on platforms like social media, organisational transactions, and machine-generated sources. When coupled with geographic information, it becomes spatial-big data or geo-big data (Dalton & Thatcher, 2015; Gao et al., 2017; Goodchild, 2013; Guo et al., 2014). C. Wu et al. (2016)

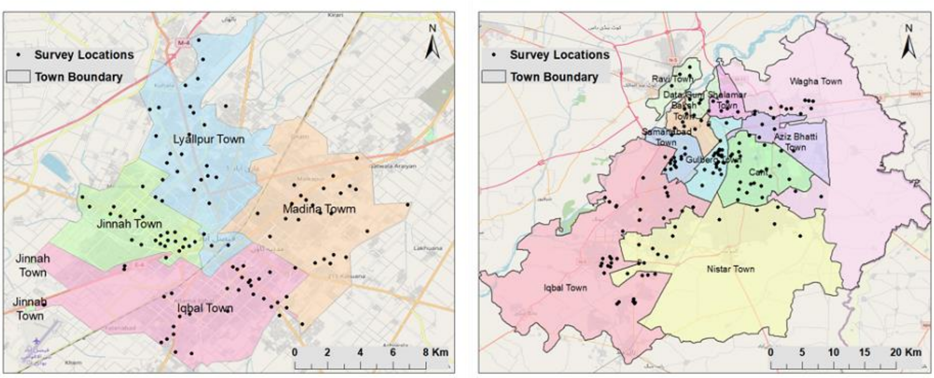
analysed check-in data from Sina Visitor System to gauge urban amenity influence on homebuyer preferences in Shenzhen, China. Yang, et al. (2020) studied the impact of a bus rapid transit system on property values using data from Fang.com. Singh et al. (2020) used software packages including gdata and caret to mine housing sale prices from web sources. Ma et al. (2020) noted big data's advantage in real estate appraisal due to its richness in factors and robustness in analysis compared to traditional methods.

Ordinary least square (OLS), a linear regression type, estimates relationships between dependent and explanatory variables (Dismuke & Lindrooth, 2006; Frost, 2019). It assumes constant relationships across all locations (Wooldridge, 2016). Global techniques like Moran's I and GI* detect spatial patterns and association (Getis, 2008; Getis & Ord, 2010). Local spatial statistic Oi identifies hotspots, considering global spatial structure (Ord & Getis, 1995, 2001). GI* and K-means assess spatial non-stationarity (Peeters et al., 2015). Spatial dependence in real estate is modeled with SLM, SEM (Kim et al., 2003) and GSM which combines both SLM & SEM (Brasington & Hite, 2005; LeSage, 2008). GWR explores spatial heterogeneity, estimating location-specific parameters (Brunsdon et al., 1996; Fotheringham et al., 2015; Scott & Janikas, 2010). Larger datasets challenge traditional GWR (Harris et al., 2010). MGWR relaxes assumptions with unique spatial scales (Fotheringham et al., 2017). MGWR's Python-based mgwr offers efficiency (Z. Li & Fotheringham, 2020; Oshan et al., 2019). FastGWR handles millions of observations, outperforming other packages, it reduces memory constraints and employs parallel diagnostic calculations (Z. Li et al., 2019).

2. MATERIAL AND METHODS

This study covered two major cities of Punjab, Pakistan i.e., Lahore and Faisalabad.

Fig. 1. Study Area



2.1. Data and Sources

Data for the study were gathered from diverse sources including governmental and non-governmental entities and web scraping programs. Property price data, house parcels, road networks, urban land use, and key locations were among the data types used. Property portals in Pakistan such as zameen.com were utilised, with zameen.com being the largest, covering numerous cities. Through web scraping, data on 3,526 houses in Faisalabad were collected from zameen.com and geocoded. These prices serve as approximations, typically 3-5 percent higher than actual transactions (Wahid et al., 2021). While the property listing data does not provide transactional history, it serves as a proxy for market prices (C. Wu et al., 2016). In Lahore and Faisalabad, property data from zameen.com, encompassing 26,031 properties and 3,526 properties respectively, were employed. As official transaction records tend to understate actual prices, web-based data was used for estimation. Although sellers' asking prices are used, they closely correlate with actual transactional prices in certain markets (Ibeas et al., 2012; Salon et al., 2014). While listed properties might not always be sold, they offer insights into seller perceptions. The study also utilised land use parcels datasets from Urban Units in Lahore and Faisalabad. Deficiencies in the property parcels dataset were resolved through digitisation and geo-referencing.

2.2. Processing Operations

Using ArcGIS 10.8 software, processing operations were performed. Selected properties were displayed using coordinate values, creating price surfaces for entire cities. Raster price surfaces were generated via geo-referenced property points using Inverse Distance Weighted (IDW) interpolation with barriers. IDW computes values of unknown points based on weighted averages of known values, giving more weight to nearby points (Hu et al., 2013; L. Li & Revesz, 2004; S. Li et al., 2017). Raster price surfaces were converted to point layers, shifting price field from point feature layers to property parcels. Resultant parcels were converted to points. Near tables within attribute tables of property point layers were generated for selected spatial amenities, containing Euclidean distances to nearest relevant spatial amenity points.

2.3. The Spatial Hedonic Valuation Model

A hedonic house property valuation model based on various attributes was constructed as follows:

$$\begin{aligned} y = \; & \beta_0 + \beta_1(\mathrm{A}) + \beta_2(\mathrm{d.WP}) + \beta_3(\mathrm{d.HR}) + \beta_4(\mathrm{d.Rec}) + \beta_5(\mathrm{d.Mar}) \\ & + \beta_6(\mathrm{d.Ind}) + \beta_7(\mathrm{d.HF}) + \beta_8(\mathrm{d.Gy}) + \beta_9(d.\mathrm{Edu}) + \beta_{10}(d.\mathrm{Ban}) \\ & + \beta_{11}(d.\mathrm{Com}) + \beta_{12}(d.\mathrm{SCom}) + \beta_{13}(d.SW) + \beta_{14}(d.\mathrm{AF}) + \epsilon \qquad \ldots \quad 2.1 \end{aligned}$$

In Equation 2.1 the variables are defined as follows:

(1) y is the estimated value of a house;
(2) β_0 is the intercept;
(3) A is the floor area of the house;
(4) d.WP is the proximity distance to the nearest worship place;
(5) d.HR is the proximity distance to the nearest hotel or restaurant;
(6) d.Rec is the proximity distance to the nearest recreational site such as a park, playground or other recreational site;
(7) d.Mar is the proximity distance to the nearest market, a shopping centre, or a supper store;
(8) d.Ind is the proximity distance to the nearest industrial unit;
(9) d.HF is the proximity distance to the nearest health facility such as a hospital or clinic;
(10) d.Gy is the proximity distance to the nearest graveyard;

(11) d.Edu is the proximity distance to the nearest educational institute such as a school, college, university or technical training institute;
(12) d.Ban is the proximity distance to the nearest bank or automated teller machine (ATM);
(13) d.Com is the proximity distance to the nearest commercial building;
(14) d.SCom is the proximity distance to the nearest semi-commercial building;
(15) d.SW is the proximity distance to the nearest solid waste dumping site/collection or transfer station;
(16) d.AF is the proximity distance to the nearest animal farm; and
(17) ϵ represents the error term.

2.4. Variable Selection

After an extensive literature review, we initially selected fourteen covariates for analysis. The prime structural attribute, floor area, a significant determinant of property value (Gluszak & Zygmunt, 2018), was included along with other spatial regressors. Through elimination, multicollinearity was addressed, leading to exclusion of variables like commercial places, semi-commercial buildings, banks and ATMs, restaurants, and animal farms due to multicollinearity. This resulted in a final model with nine explanatory variables.

2.5. Interpolation of Property Values

Before computing the property valuation model, the inverse distance weighting (IDW) interpolation was performed to obtain the predicted surface of property prices. The IDW interpolation with barriers and without barriers was applied to the data to avoid under- or over- prediction. The results of the interpolation with barriers and without barriers for property prices are shown in Figure 2 and Figure 4.

Fig. 2. Interpolation of property prices (A) IDW interpolation (B) IDW interpolation with barriers (Faisalabad)

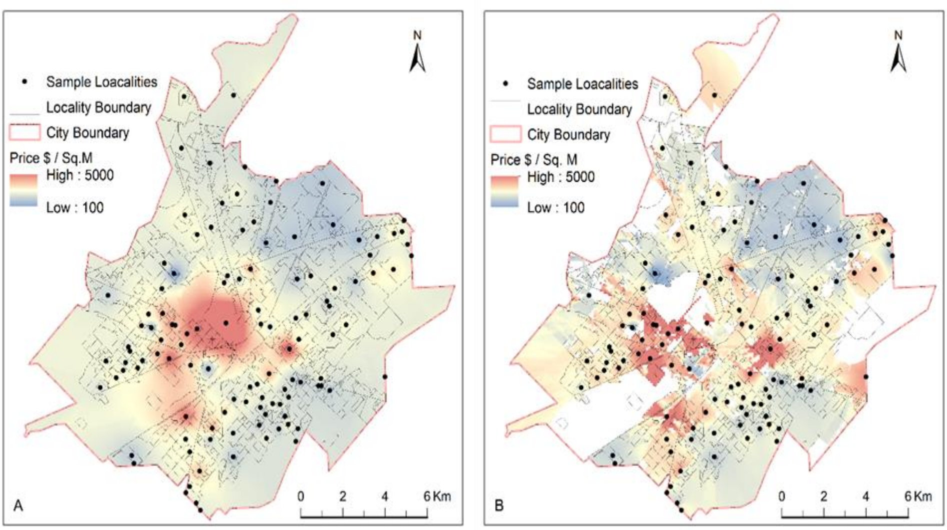


Fig. 3. Transferring Interpolated Values of House Prices to the Locality Boundary and the Individual House Parcel

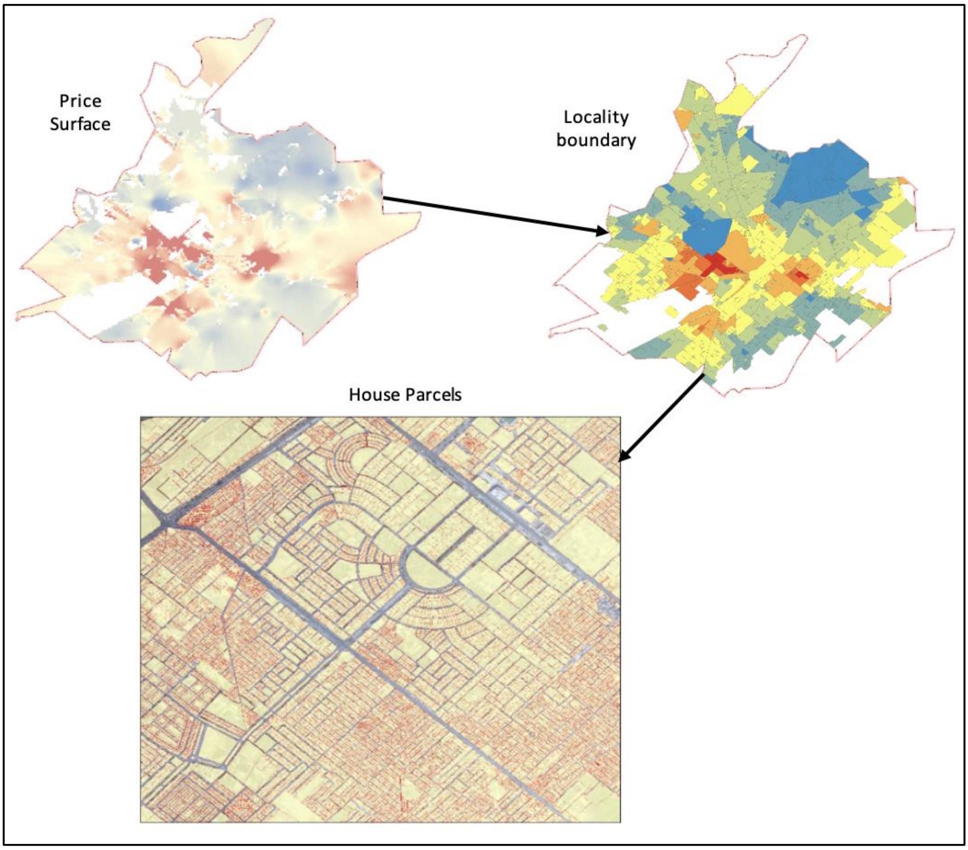
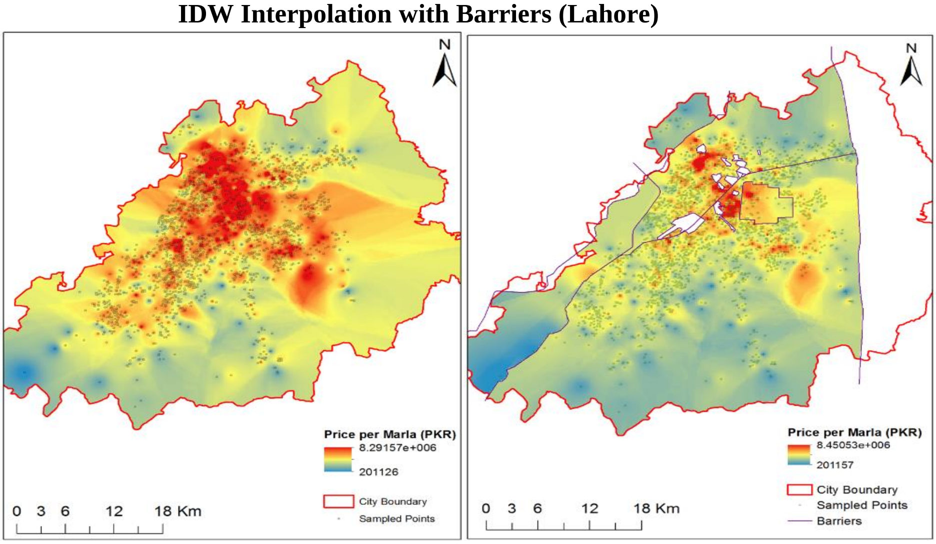


Fig. 4. Interpolation of Property Prices (A) IDW Interpolation (B) IDW Interpolation with Barriers (Lahore)



2.6. Analyses

We first performed the hedonic valuation analysis using the OLS model. The OLS is considered the best technique among all the regression methods and is used as a proper initial procedure before conducting any other regression-based spatial analysis. The OLS in the spatial statistics toolset of ArcGIS desktop can be used to discover, inspect, and model the linear spatial relationship between a dependent and one or more explanatory variables with a global approach. This means that OLS computes the relationship between the variables using a single equation for the whole area under study and assumes that the relationship remains consistent and stationary at all locations (Mitchell, 2005; Scott & Janikas, 2010).

GWR model was then employed to capture the spatial heterogeneity. It is a valuable tool for studying spatial variability. It focuses on estimating site-specific parameters, enhancing calibration. GWR addresses spatial non-stationarity, where traditional linear regression fails in explaining variable relationships across a geographic area. Local GWR analyses residential property values for each area, incorporating regional variation in the model (Getis & Ord, 2010; Mitchel, 2005). Unlike a single model for the entire study area, GWR runs regressions for each location. However, the open-source GWR software is limited, processing around 15,000 data points on a standard computer. This constraint hampers GWR's application, especially in large areas like cities. To overcome this, FastGWR, a Python-based application developed by Li et al. (2019), is utilised. FastGWR employs Message Passing Interface (MPI) for parallel computing, boosting performance and memory usage. This enables processing of millions of observations, surpassing existing GWR software. FastGWR improves memory efficiency through enhanced linear algebra in GWR calibration. Memory requirements are reduced from O(n^2) to O(nk), with k (covariates) typically much smaller than n (observations). FastGWR offers parallel model diagnostics for massive datasets, significantly reducing GWR calibration time. OpenMPI and the "mpi4py" Python wrapper are employed for implementation.

3. RESULTS AND DISCUSSION

3.1. Global Model Implementations

Linear model implementation produced adjusted R^2 values of 0.85 for Lahore and 0.75 for Faisalabad. The values were slightly lower than R^2 values and there were no big differences, which indicates that the models were properly specified. The joint-F test result is not interpretable because the associated p-value of the Koenker BP test was statistically significant. Therefore, the joint-Wald test statistic was used to determine the overall model significance. Since the p-value of the joint Wald statistic was statistically significant and smaller than 0.05 at a 95 percent confidence level, there was enough evidence to reject the null hypothesis and accept the alternative hypothesis that the regressors in the model were effective. The P-value associated with the Koenker BP test was also much lower than 0.05 at a 95 percent confidence level, which points toward the conclusion that the relationship between the response and explanatory variables was not consistent and stationary implying that spatial heterogeneity exists. That result was expected as the relevant literature confirms that the occurrence of spatial non-stationarity in the housing data is a common real-life phenomenon because the degree of the effect contributed to the house prices by different externalities is always unique at different locations. Spatial heterogeneity can be reported using a global model like OLS but could further be measured using some local models, such as GWR (Bitter et al., 2007; Brunsdon et al., 1996; Fik et al., 2003; Wen, Jin, et al., 2017). A statistically significant p-value of the Jarque-Bera test is the indication of the presence of non-normality in the distribution of the residuals and that the model is not unbiased and could not be trusted fully. However, the relevant literature suggests that a model with a significant p-value of the Jarque-Bera test can be trusted when working with a large dataset because it is a proven fact that the assumption of normality for response as well as explanatory variables is not required in an OLS linear model when the sample size is too large. Since the distribution of regression residuals depends on the distribution of regression variables, the normality assumption can be ignored for residual distribution as well in case of large sample size (Lumley et al., 2002). When a regression model has non-normally distributed residuals, one needs to check robust standard errors and robust p-values to check if the variable coefficients are significant statistically instead of standard errors and probabilities (Mitchell, 2005; Scott & Janikas, 2010). Since Koenker statistics were statistically significant in the model diagnostics, only those robust p-values (probabilities) were checked that were smaller than 0.05 for all explanatory variables. There was sufficient evidence to reject the null hypothesis and accept the alternative hypothesis that all the coefficients were significant. The coefficient values reflect the nature and strength of the relationship of each regressor with the response variable.

The results of the linear model for the entire cities of Faisalabad and Lahore are presented in Table 3. The adjusted R^2 value explained the relationship of explanatory variables to the house prices up to 75 percent for Faisalabad and around 85 percent for Lahore in the linear model. However, the robustness of the model was improbable since residential property prices were less normally distributed. Most of the coefficients for the explanatory variables were as expected and explained the relation between the response variable and explanatory variables.

Total floor area (in Marlas for Lahore and m2 for Faisalabad) showed a positive relationship with the house price, which indicates that every additional Marla in the floor area increased the house price by PKR 2,202,216.09 in Lahore, while every additional m2 in floor area increased the house price by PKR 86,256.45 in Faisalabad. Spatial variables, i.e., distance to the nearest health facility, marketplace, and recreational facility, such as a park, lowered the house price by PKR 2,614.52, 1,149.4, 1,105.2, respectively, with a one-meter increase in the Euclidean distance. It implies that people value these facilities and like to live near them. On the other hand, the results show that as the distance between the house and the nearest industrial unit, educational institution, graveyard, solid waste dumping site/transfer station, and worship place increased, the house price also increased by PKR 1,921.57, PKR 647.83, PKR 563.58, PKR 429.79 and PKR 234.92 per metre, respectively. It indicates that the residents do not prefer to reside near these features in Lahore. In Faisalabad, the dynamics, however, are somewhat different from Lahore.

In Faisalabad, as the Euclidean distance to the nearest health facility, park, marketplace, industrial unit and graveyard decreased by one metre, the house price increased by PKR 1,495.64, PKR 1460.89, PKR 517.08, PKR 130.66, and PKR 45.87, respectively. On the other hand, as the distance to the nearest educational institution, solid waste dumping site/transfer station and worship place decreased by one metre, the house price also decreased by PKR 504.57, PKR 393.37, PKR 355.84, respectively. Unlike Lahore, the proximity to industrial units and graveyards contributed positively to house prices in Faisalabad. A possible reason for this contradiction may be the presence of small industrial units, such as power looms, and graveyards within residential areas, especially in the central parts of Faisalabad. This pattern is not present on such a large scale in Lahore.

Table 3

Description of the Variables for the Spatial Hedonic Valuation Model

Category	Features	Description	Faisalabad	Lahore
Parcel counts	Parcels	Number of total parcels in the study area	416,168	808,710
House counts	House Parcels	Number of residential properties in the study area	268,911	780,178
House Attributes	Area (m^2)	Total area of the residential properties in square metres	30.22	116.04
	Area (Marla)	Total area of the residential properties in Marlas	1.20	5.55
Valuation	Total worth	Total worth of residential properties	PKR 2.97 trillion ($ 17.52 billion)	PKR 11.36 trillion ($ 66.83 billion)
	Average Price	Average price per square meter (per Marla)	PKR 98,279 (PKR 2.47 million)	PKR 97,897 (PKR 2.04 million)
Amenities	Solid Waste	Number of solid waste facilities and transfer stations	70	1,091
	Graveyard	Number of graveyards	72	166
Cultural	Worship Places	Number of worship places (i.e., mosques, churches, and temples)	1,409	2,281
Education and Health Facilities	Institutes	Number of educational institutions (schools, colleges, and universities)	1,705	4,329
	Health Facility	Number of health facilities (hospitals, clinics, and dispensaries)	318	2,902
Recreation	Parks and Recreation	Number of public parks and recreational sites	368	1,381
Industrial and Commercial	Industries	Number of industrial units	9,319	8,901
	Market Places	Number of market places	141	5,439
	Commercial	Number of commercial buildings	66,769	96,685
	Semi-Commercial	Number of semi-commercial buildings	2,679	68,967
	Bank and ATMs	Number of banks and automated teller machines	229	2,153
	Restaurants	Number of restaurants and cafes	612	2,793
	Animal Farms	Number of animal farms (poultry and dairy farms)	1,224	2,015

The results are per our expectations and in line with the findings of relevant previous studies. Some of the supporting references are discussed here. The floor area of a real estate property is the most important factor that determines its price (Ma et al., 2020), while the proximity of shopping facilities adds a premium to house prices (De & Vupru, 2017; Xiao et al., 2017; Yang et al., 2018b; Yang, Chau, et al., 2020; Zhang et al.). The presence of worship places in the vicinity of every religion contributes to house prices positively. However, some housing properties that are near worship places may experience price devaluation because of noise and a higher number of visitors that create disturbances for the residents (Brandt et al., 2014; Thompson et al., 2012). On the other hand, urban green spaces, public parks, playgrounds, and other recreational sites add a premium to the housing properties (Crompton & Nicholls, 2020; Liao & Wang, 2012; Shabana et al., 2015). Residential properties close to graveyards fetch lower values due to superstitions linked to the burial grounds (Hassan et al., 2021). Similarly, an industrial neighbourhood is a negative influence on residential property prices in most of the research findings (Grislain-Letrémy & Katossky, 2014; Munshi, 2020).

3.2. Local Model Implementation

The FastGWR model estimation produced an adjusted R squared of 78 per cent for Faisalabad, which shows a strong relationship between the house value and predictors. Table 4 presents the results of the FastGWR model estimation for the entire city. The coefficients of the FastGWR are positively correlated except for the distance to a solid waste facility, which deceptively indicates that the house values decreased as the distance increased from the solid waste facility. Since these coefficients are the average values that are affected by the high negative values in the results, we also examined the results locally. Figure 4c depicts the significant parameter estimates for the distance to a solid waste facility. The map shows that the house parcels coloured in blue had a converse effect of distance to solid waste facility, meaning that the values of these houses decreased as the distance from solid waste facility increased. One possible reason for this inverse coefficient could be that earlier the solid waste facilities were established away from the settlements but with time, the settlements have grown around these facilities and the land prices near these facilities have also increased. The low variance inflation factor (less than 7.5 for each regressor) indicates that there is no multicollinearity as we had already eliminated the muiltcollinear explanatory variables, while the regression residuals are random and not spatially autocorrelated.

In the OLS results table, we need to understand the t-statistics value that evaluates the statistical significance of the explanatory variables. The higher the t-statistic, the more significant the variable is. This value explains that the area of the house is the most important structural variable for house price in the entire city, while the other significant variables are the distance to a solid waste facility, distance to worship places, and distance to educational institutes, respectively. These accessibility variables have positive coefficients indicating that the house price increased as the distance from these features increased. The other significant variables with negative coefficients are the distance to parks, distance to markets, distance to hospitals, distance to graveyards, and distance to industries respectively. The negative coefficients suggest that residential property prices decreased as the distance from locational features increased. These findings are similar to that of Li et al., (2019), who studied the city of Los Angeles, California.

Table 4

Explanatory Variables

Variables	Faisalabad	Lahore
Mean Area (Marla)	4.46	7.11
Mean Area (m^2)	111.87	148.62
Mean Distance to Worship places (Metres)	127.15	352.23
Mean Distance to Solid Waste Facilities (Metres)	798.70	696.50
Mean Distance to Parks (Metres)	520.96	397.55
Mean Distance to Markets (Metres)	1,769.26	495.77
Mean Distance to Institutions (Metres)	129.66	287.90
Mean Distance to Industrial Units (Metres)	165.34	408.30
Mean Distance to Health Facilities (Metres)	388.75	440.37
Mean Distance to Graveyards (Metres)	860.15	978.85
Mean Distance to Commercial buildings (Metres)	31.18	1,464.49
Mean Distance to Semi Commercial buildings (Metres)	1343.56	1654.77
Mean Distance to Banks & ATMs (Metres)	1,004.45	811.83
Mean Distance to Hotel / Restaurant / Café (Metres)	434.17	443.11
Mean Distance to Animal farms (Metres)	283.94	2332.94

The results of the OLS model for the FD-I rating area are presented in Table 5. The semi-log model explains the relationship up to 77 percent, while the linear model explained it up to 80 percent. The coefficients are as expected but the distances to worship places, parks, markets, educational institutes, and hospitals were negative. This indicates that the house price decreased as the distance from these variables increased. The worship places are key cultural features in the city that appear to impact the prices of residential houses positively (Brandt et al., 2014; De & Vupru, 2017). In the FD-I zone, the average price per square metre was US$875 and the average house price was US$81,320 with an average area of 95 square meters. The t-statistics are suggestive of the order of significance for these negative coefficients, which indicates that the distance from places of worship, distance from parks, distance from health facilities, and distance from the market were the most significant locational features influencing prices, respectively. The coefficient of distance to a solid waste facility is negative in the linear model, while in the semi-log model, this coefficient is positive. However, they are not statistically significant.

3.3. Model Implementation for different rating areas in Faisalabad

These values indicate that in the FD-I rating area, the distance to solid waste facilities did not influence the prices of residential properties, while all other explanatory variables had an impact on the house prices positively or negatively. The results of the FastGWR are presented in Table 8. The R-squared value for FD-I is 0.61, indicating that the model explained a 60 percent variance based on the explanatory variables. As suggested by the coefficients of all the predictive variables, there existed a positive correlation. This zone comprises the central business district (CBD) where most of the properties are commercial and semi-commercial and there are only 28,090 residential properties.

Table 5

Results of the Linear Model

	Lahore				Faisalabad			
	Adjusted R^2 =0.85				Adjusted R^2 =0.75			
Variable	Coeff.	t-stat	p-Value	VIF	Coeff.	t-stat	p-Value	VIF
Intercept	356,219.99	20.36	0.000*	-----	3,280,398.6	199.14	0.000*	----
Floor Area	2,202,216.09	2,050.22	0.000*	1.04	86,256.45	881.22	0.000*	1.04
D_Worship Places	234.92	6.95	0.000*	3.14	355.84	5.99	0.000*	1.11
D_SolidWaste Site	429.79	24.80	0.000*	2.82	393.37	34.48	0.000*	1.62
D_Parks	-1105.20	-48.86	0.000*	1.85	-1,460.89	-119.19	0.000*	1.18
D_Market	-1149.40	-46.33	0.000*	4.68	-517.08	-94.11	0.000*	1.55
D_Institutes	647.83	15.85	0.000*	3.39	504.57	8.30	0.000*	1.20
D_Industries	1,921.57	73.14	0.000*	1.54	-130.66	-3.04	0.002*	1.23
D_Hospitals	-2,614.52	-109.91	0.000*	3.10	-1,495.64	-73.75	0.000*	1.30
D_Graveyards	563.58	39.45	0.000*	1.26	-45.87	-4.51	0.000*	1.51

Table 6

Results of the FastGWR Model for Faisalabad

	Faisalabad	
	R^2 = 0.78	
Predictor	Coeff.	SE
Area	0.00480	0.00015
D_Worship Places	0.00052	0.00041
D_Solid Waste Facilities	-0.00038	0.00089
D_Parks	0.00094	0.00064
D_Markets	0.00443	0.00065
D_Institutes	0.00042	0.00043
D_Industry	0.00057	0.00049
D_Hospitals	0.00039	0.00062
D_Graveyards	0.00283	0.00076

The FD-II rating area is characterised by small- and medium-scale industries, timber market, and wholesale businesses. Although the average house area in this zone was smaller, the average price per square metre was 22.6 percent higher than the FD-I rating area and the average house price was also 20.32 percent higher (i.e., US$102,063). The higher prices of small houses in this area are due to the ease of access to workplaces and proximity to the city centre. The results of the valuation model for this region are dissimilar to the results of the FD-I rating area. All the explanatory variables are statistically significant except the distance from worship places. Although the average distance to the places of worship was much smaller (93.4 metres), worship places did not seem to influence the residential property prices in this particular zone. This effect is possibly due to the socio-economic conditions of the area since the average house size and the income level were lower than other residential districts. The worship places give the impression of being less important for the residents possibly due to the degree of adherence to religion and the level of noise from the loudspeakers of mosques. Researchers have found the negative effects of places of worship on adjacent house prices but this effect declines with the increasing distance and diminishes after 300 metres (Brandt et al., 2014; Do et al., 1994).

Table 7

Results of the Linear Model for Different Rating Areas in Faisalabad

	Semi-Log OLS Model R^2 =0.77			Linear Model R^2 =0.80			
Rating Area FD-I	Coeff.	t-stat	p-Value	Coeff.	t-stat	p-value	VIF
Intercept	10.35575	1307.87	0.0000*	14,688.14	25.88	0.0000*	–
House Area	0.00985	301.19	0.0000*	793.34	338.31	0.0000*	1.06
D_Worship Places	-0.00063	-30.30	0.0000*	-47.65	-31.82	0.0000*	1.12
D_SolidWaste Facility	0.000002	0.27	0.7859	-0.24	-0.41	0.6831	1.22
D_Parks	-0.00038	-30.17	0.0000*	-30.39	-33.18	0.0000*	1.13
D_Market	-0.00005	-10.15	0.0000*	-6.38	-17.09	0.0000*	1.18
D_Institutes	-0.00012	-5.19	0.0000*	3.95	2.35	0.0186*	1.12
D_Industries	0.00028	18.32	0.0000*	25.08	22.32	0.0000*	1.14
D_Hospitals	-0.00016	-13.58	0.0000*	-16.28	-18.45	0.0000*	1.10
D_Graveyards	0.00016	30.30	0.0000*	12.22	31.22	0.0000*	1.30
	Semi-Log Model R^2 =0.78			Linear Model R^2 =0.81			
Rating Area FD-II	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value	VIF
Intercept	10.16367	852.36	0.0000*	-10,913.75	-10.54	0.0000*	----
House Area	0.01060	187.93	0.0000*	1,015.18	207.08	0.0000*	1.07
D_Worship Places	-0.00007	-1.82	0.0680	-2.52	-0.72	0.4705	1.11
D_SolidWaste Facility	-0.00023	-27.30	0.0000*	-21.46	-29.28	0.0000*	1.53
D_Parks	0.00015	7.21	0.0000*	9.03	4.98	0.0000*	1.44
D_Market	0.00005	7.27	0.0000*	0.72	1.20	0.2305	1.54
D_Institutes	0.00016	4.77	0.0000*	19.52	6.70	0.0000*	1.31
D_Industries	-0.00032	-11.34	0.0000*	-22.13	-8.90	0.0000*	1.59
D_Hospitals	0.00026	16.44	0.0000*	16.89	12.07	0.0000*	1.32
D_Graveyards	0.00047	49.54	0.0000*	38.72	46.48	0.0000*	1.69
	Semi-Log Model R2 =0.71			Linear Model R2 =0.79			
Rating Area FD-III	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value	VIF
Intercept	10.39261	5,323.04	0.0000*	17,254.89	135.38	0.0000*	----
House Area	0.00761	726.77	0.0000*	612.54	896.17	0.0000*	1.04
D_Worship Places	0.000141	22.37	0.0000*	8.88	21.66	0.0000*	1.12
D_SolidWaste Facility	0.000048	40.00	0.0000*	2.66	34.25	0.0000*	1.60
D_Parks	-0.00012	-98.16	0.0000*	-8.76	-106.34	0.0000*	1.15
D_Market	-0.00002	-32.97	0.0000*	-1.72	-42.69	0.0000*	1.53
D_Institutes	0.000011	1.79	0.0741	1.03	2.47	0.0134*	1.21
D_Industries	-0.00005	-10.94	0.0000*	-1.25	-4.15	0.00003*	1.24
D_Hospitals	-0.00008	-37.37	0.0000*	-7.11	-50.95	0.0000*	1.31
D_Graveyards	-0.000045	-41.54	0.0000*	-1.77	-24.89	0.0000*	1.53

Table 8

Results of the FastGWR Model for Rating Area FD-I, FD-II, and FD-III

	FD-I (R^2=0.61)		FD-II (R^2=0.59)		FD-III (R^2=0.80)	
Predictors	Coeff.	SE	Coeff.	SE	Coeff.	SE
Area	0.00511	0.00020	0.00524	0.00021	0.00475	0.00015
D_Worship Places	0.00072	0.00053	0.00181	0.00056	0.00049	0.00039
D_Solid Waste Facility	0.00516	0.00043	0.00025	0.00065	-0.00101	0.00093
D_Parks	0.00044	0.00062	0.00515	0.00043	0.00078	0.00064
D_Market	0.00498	0.00050	0.00205	0.00057	0.00449	0.00066
D_Institutes	0.00047	0.00054	0.00086	0.00053	0.00038	0.00041
D_Industry	0.00220	0.00061	0.00109	0.00063	0.00038	0.00048
D_Hospitals	0.00165	0.00050	0.00442	0.00048	0.00006	0.00064
D_Graveyards	0.00539	0.00053	0.01000	0.00049	0.00209	0.00079

Fig. 5. Maps of Significant Parameter Estimates for the Predictive Variables: Area of the House (a), Distance To Worship Places (b), Distance to Solid Waste Sites (c) Distance to Parks (d)

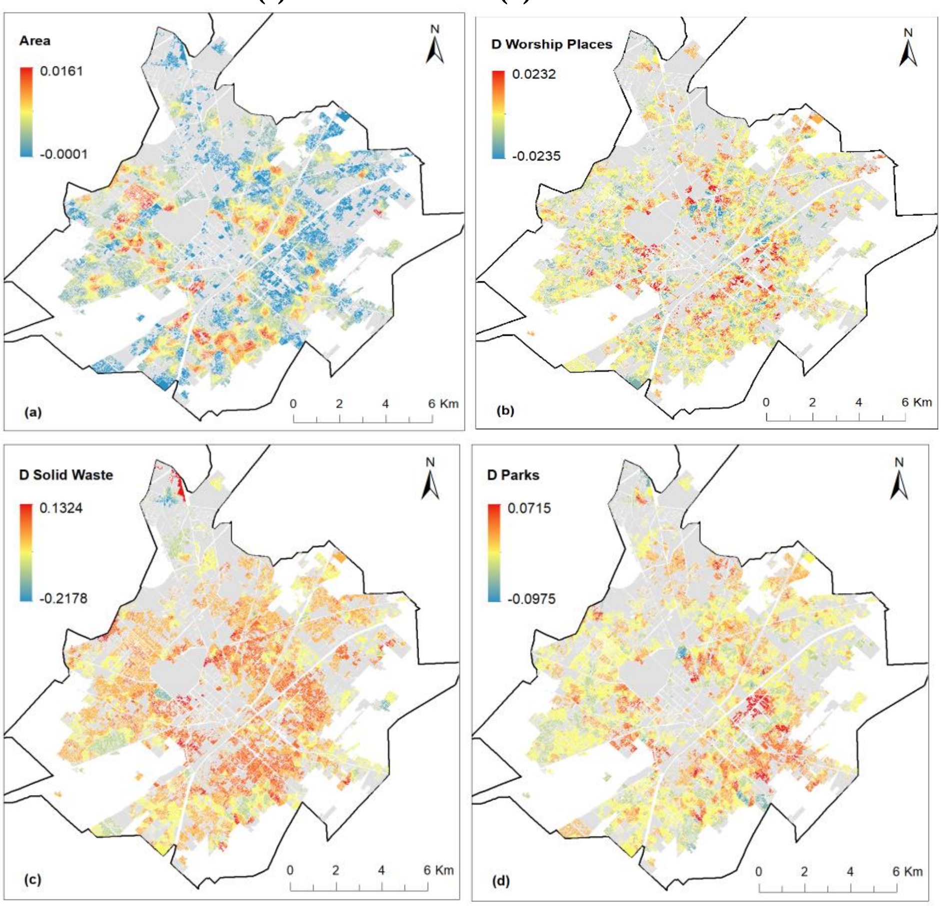
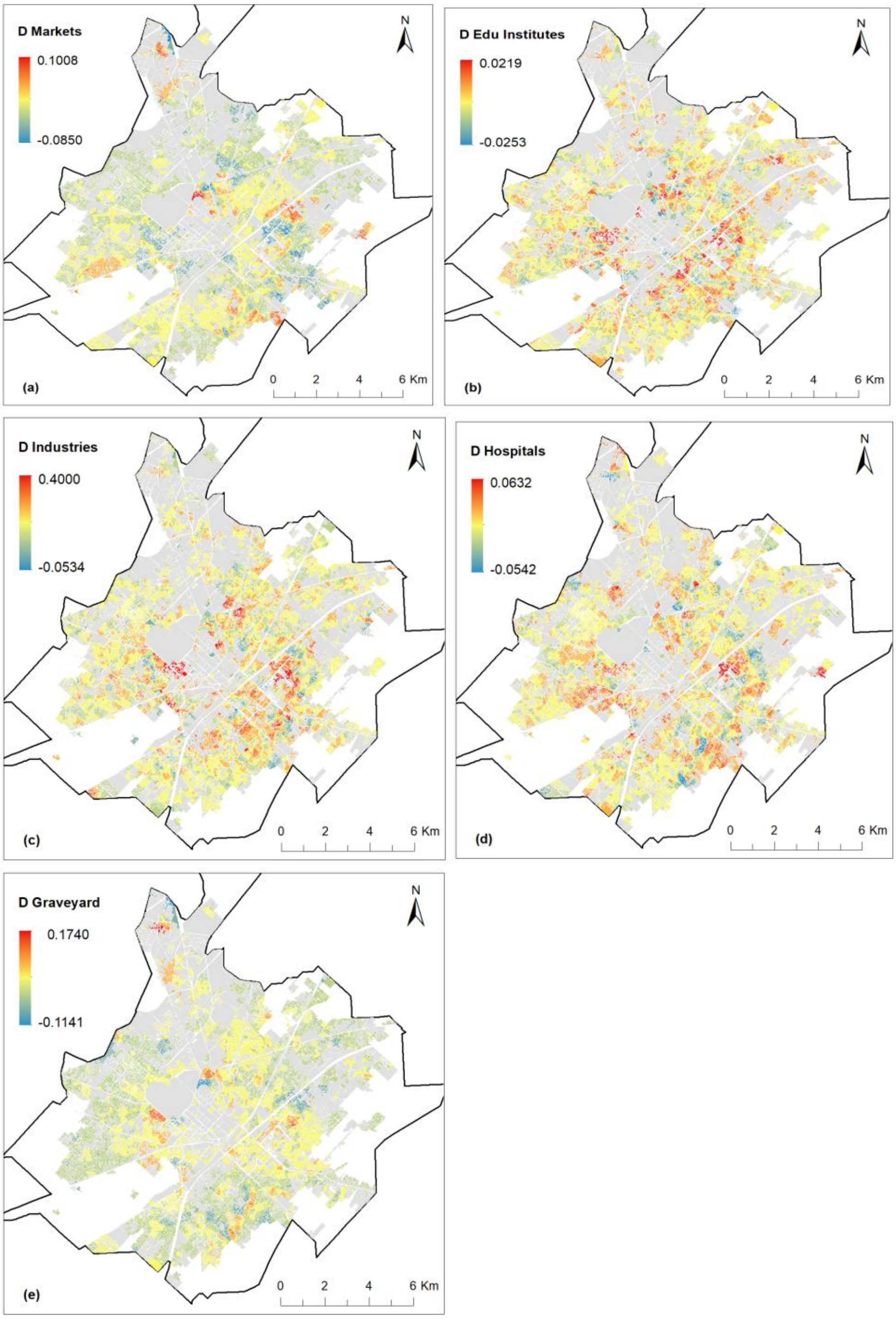


Fig. 6. Maps of Significant Parameter Estimates for Predictive Variables: Distance to Markets (a), Distance to Educational Institutions (c), Distance to Industries (c), Distance to Hospitals (d), Distance to Graveyards (e)



The coefficients for distance to solid waste facilities and distance to industries are negative and statistically significant (99 percent confidence). Solid waste transfer stations provide opportunities for scavengers and scrap dealers to collect recyclable materials to earn their living. Small- and medium-scale industries, like power looms, garment factories, embroidery units, plastic products, leather factories, paper, and chemical factories exist in this area, thus, offering employment opportunities to the residents. Distance to market is statistically significant in the semi-log model but the results of the linear model were not statistically significant. There are only 4.13 percent (n = 11,107) houses present in this zone, whereas 75.7 percent of the houses in the FD-II are exempted from the property tax as per the policy of the revenue department and 24.27 percent of the houses are responsible property tax collection. The results of the semi-log model explain the relationship between house price and explanatory variables by up to 78 percent, while the linear model explained it by up to 80 percent. In this zone, the results of the FastGWR are also positively correlated and the R-squared value is 0.59, which shows an intermediate to high performance by the model. Though the FastGWR model explains a relatively smaller variance as compared to the linear models (59 percent vs. 80 percent), the consideration of spatial aspects in the FastGWR makes it more reliable when applied to analyse geographical disparities. One possible reason for this weak relationship is that there are only 11,107 residential buildings situated in this zone, while most of the buildings are commercial and semi-commercial.

The third zone, the FD-III rating area, is the largest among all other zones in the city, which holds a total number of 339,420 properties of which 229,714 (85.42 percent) are residential. In this zone, only 22 percent of the residential properties are liable to pay the property tax and the rest 78 percent are exempt from any kind of property tax. The results for the FD-III rating area are significant for all the explanatory variables except the distance from educational institutions, which is insignificant under the semi-log model but significant under the linear model. Several studies have demonstrated the effects of schools and educational institutions on property prices (Sah et al., 2016; Wen, Xiao, et al., 2017; Yang et al., 2018a). However, in this zone, the educational institutions did not impact the residential property prices. One explanation for this could be the fact that the schools do not have strict zonal boundaries and the students are willing to travel longer distances to study in educational institutions that offer better quality education. Distances to parks, hospitals, markets, graveyards, and industries have negative coefficients. The results of the FastGWR demonstrate that all the predictive variables have positive coefficients, while the distance to solid waste facilities had a negative effect, suggesting that the residential parcels closer to these facilities have higher values, while the residential properties away from a solid waste facility have lower values. The FastGWR model estimation for Lahore was not possible due to the unavailability of the required high computing power.

4. CONCLUSION

4.1. Summary

This study explored residential property prices in Lahore and Faisalabad using a spatial hedonic approach. It employed spatial hedonic models, OLS, and FastGWR regression to assess the link between explanatory factors and property prices. Nine locational features were considered, revealing significant positive and negative correlations with housing prices. House size emerged as a key positive influencer, consistently displaying a strong coefficient. Other positively linked variables included proximity to worship places, solid waste facilities, and educational institutions. Conversely, negative associations were observed with distances to public parks, markets, hospitals, graveyards, and industries.

As urban development transforms Punjab's cities into multi-center patterns, property reevaluation is essential for boosting property tax revenues. This study underscores the critical importance of spatial determinants in property valuation. Consequently, integrating these determinants into policy formulation and future urban planning is recommended.

4.2. Limitations

Several limitations are notable in this study. Although it emphasised locational factors, socio-economic determinants could also impact housing prices across various spatial scales. However, their inclusion faced two challenges. Firstly, housing-level socio-economic data is severely limited not only in Pakistan but also in many developing nations, precluding their incorporation. Secondly, the study's primary focus was on analysing locational attributes to underscore their influence on housing prices, a neglected aspect in prior Pakistani research. Lastly, unavailability of the necessary high computing power prevented the application of the FastGWR model to Lahore. These limitations underscore the need for caution when interpreting the findings and highlight avenues for future research.

4.3. Recommendations and Policy Implications

This study's outcomes hold implications for policymakers, investors, real estate developers, and urban planners. Our reliable model explains residential property values, vital for decision-makers seeking insights into local housing markets. This informs refined policies and better comprehension of house price variations. The adaptable approach suits various Pakistani regions. To establish accurate property values, we propose:

(1) Waive property transfer fees to encourage transparent property deal prices, compensating via increased annual property tax.
(2) Institute property valuation desks in revenue departments to assess property values at a nominal fee. These desks would gather property details and values, benefiting both assessment seekers and public funds.
(3) Embrace a uniform valuation method, incorporating structural attributes and real-time spatial amenities updates. Federal and provincial revenue bodies can adopt this approach.
(4) Make residential property data accessible to researchers, enabling comprehensive exploration of real estate dynamics and informed policy formulation.

REFERENCES

Ahmed, R., Jawaid, S. T., & Khalil, S. (2021). Bubble Detection in Housing Market: Evidence From a Developing Country. *SAGE Open*, *11*(2). https://doi.org/10.1177/21582440211006690

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Baranzini, A., Schaerer, C., Ramirez, J., & Thalmann, P. (2008). Basics of the Hedonic Price Model. In A. Baranzini, C. Schaerer, J. Ramirez, & P. Thalmann (Eds.), *Hedonic Methods in Housing Markets, Pricing Environmental Amenities and Segregation*. Springer Science+Business Media, LLC, 233 Spring Street, New York,NY 10013, USA. https://doi.org/10.1007/978-0-387-76815-1

Baranzini, A., Schaerer, C., Ramirez, J., & Thalmann, P. (2010). Feel it or measure it-perceived vs. measured noise in hedonic models. *Transportation Research Part D: Transport and Environment*, *15D*(8), 473–482.

Barreca, A., Curto, R., & Rolando, D. (2020). Urban vibrancy: An emerging factor that spatially influences the real estate market. *Sustainability (Switzerland)*, *12*(1), 346. https://doi.org/10.3390/su12010346

Bateman, I. J., Day, B., & Lake, I. (2001). The Effect of Road Traffic on Residential Property Values: A Literature Review and Hedonic Pricing Study. *Bateman, Ian Day, Brett Lake, Iain Lovett, Andrew, January*, 208.

Bitter, C., Mulligan, G. F., & Dall'erba, S. (2007). Incorporating spatial variation in housing attribute prices: A comparison of geographically weighted regression and the spatial expansion method. *Journal of Geographical Systems*, *9*(1), 7–27. https://doi.org/10.1007/s10109-006-0028-7

Boza, E. (2015). *Investigation of Housing Valuation Models based on spatial and non-spatial techniques*. Middle East Technical University (METU), Ankara, Turkey.

Brandt, S., Maennig, W., & Richter, F. (2014). Do Houses of Worship Affect Housing Prices? Evidence from Germany. *Growth and Change*, *45*(4), 549–570. https://doi.org/10.1111/grow.12066

Brasington, D. M., & Hite, D. (2005). Demand for environmental quality: A spatial hedonic analysis. *Regional Science and Urban Economics*, *35*(1), 57–82. https://doi.org/10.1016/j.regsciurbeco.2003.09.001

Brown, G., Reed, P., & Raymond, C. M. (2020). Mapping place values: 10 lessons from two decades of public participation GIS empirical research. In *Applied Geography* (Vol. 116, p. 102156). Elsevier Ltd. https://doi.org/10.1016/j.apgeog.2020.102156

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically weighted regression: a method for exploring spatial nonstationarity. *Geographical Analysis*, *28*(4), 281–298. https://doi.org/10.1111/j.1538-4632.1996.tb00936.x

Can, A. (1990). The measurement of neighborhood dynamics in urban house prices. *Economic Geography*, *66*(3), 254–272. https://doi.org/10.2307/143400

Can, A., & Megbolugbe, I. (1997). Spatial Dependence and House Price Index Construction. *Journal of Real Estate Finance and Economics*, *14*(1–2), 203–222. https://doi.org/10.1023/A:1007744706720

Casetti, E. (1972). Generating Models by the Expansion Method: Applications to Geographical Research. *Geographical Analysis*, *4*(1), 81–91. https://doi.org/10.1111/j.1538-4632.1972.tb00458.x

Casetti, E. (1997). The expansion method, mathematical modeling, and spatial econometrics. *International Regional Science Review*, *20*(1–2), 9–33. https://doi.org/10.1177/016001769702000102

Chapman, J. I., Johnston, R. J., & Tyrrell, T. J. (2009). Implications of a land value tax with error in assesed values. *Land Economics*, *85*(4), 576–586. https://doi.org/10.3368/le.85.4.576

Crawford, T. W. (2009). Scale Analytical. In *International Encyclopedia of Human Geography* (pp. 29–36). Elsevier. https://doi.org/10.1016/B978-008044910-4.00399-0

Crompton, J. L., & Nicholls, S. (2020). Impact on property values of distance to parks and open spaces: An update of U.S. studies in the new millennium. *Journal of Leisure Research*, *51*(2), 127–146. https://doi.org/10.1080/00222216.2019.1637704

Dalton, C. M., & Thatcher, J. (2015). Inflated granularity: Spatial "Big Data" and geodemographics. *Big Data and Society*, *2*(2). https://doi.org/10.1177/2053951715601144

De, U. K., & Vupru, V. (2017). Location and neighbourhood conditions for housing choice and its rental value: Empirical examination in an urban area of North-East India. *International Journal of Housing Markets and Analysis*, *10*(4), 519–538. https://doi.org/10.1108/IJHMA-10-2016-0072

Dismuke, C. E., & Lindrooth, R. (2006). Ordinary least squares. In E. Chumney & K. N. Simpson (Eds.), *Methods and Designs for Outcomes Research* (pp. 93–104). American Society of Health-System Pharmacists.

Do, A. Q., Wilbur, R. W., & Short, J. L. (1994). An empirical examination of the externalities of neighborhood churches on housing values. *The Journal of Real Estate Finance and Economics*, *9*(2), 127–136.

Dowall, D. E., & Ellis, P. D. (2009). Urban land and housing markets in the Punjab, Pakistan. *Urban Studies*, *46*(11), 2277–2300. https://doi.org/10.1177/0042098009342599

Dutilleul, P., & Legendre, P. (1993). Spatial Heterogeneity against Heteroscedasticity: An Ecological Paradigm versus a Statistical Concept. *Oikos*, *66*(1), 152. https://doi.org/10.2307/3545210

Erickson, D. L., Lovell, S. T., & Méndez, V. E. (2011). Landowner willingness to embed production agriculture and other land use options in residential areas of Chittenden County, VT. *Landscape and Urban Planning*, *103*(2), 174–184. https://doi.org/10.1016/j.landurbplan.2011.07.009

FBR. (2020). *Circular; C.No. 1(121)R&S/2017-15297-R, Constitution of Committees for Updation of Valuation Tables of Immoveable Property under Sub-Section (4) of Section 68 of the Income Tax Ordinance, 2001* (p. 1). Revenue Division, Federal Board Of Revenue, Government of Pakistan.

Fik, T. J., Ling, D. C., & Mulligan, G. F. (2003). Modeling Spatial Variation in Housing Prices: A Variable Interaction Approach. In *Real Estate Economics* (Vol. 31, Issue 4, pp. 623–646). John Wiley & Sons, Ltd. https://doi.org/10.1046/j.1080-8620.2003.00079.x

Fisher, B., Naidoo, R., & Ricketts, T. (2015). *A Field Guide to Economics for Conservationists*. Macmillan Learning.

Fotheringham, A. S., Crespo, R., & Yao, J. (2015). Geographical and Temporal Weighted Regression (GTWR). *Geographical Analysis*, *47*(4), 431–452. https://doi.org/10.1111/gean.12071

Fotheringham, A. S., Yang, W., & Kang, W. (2017). Multiscale Geographically Weighted Regression (MGWR). *Annals of the American Association of Geographers*, *107*(6), 1247–1265. https://doi.org/10.1080/24694452.2017.1352480

Freeman, A. M. (1981). Hedonic Prices, Property Values and Measuring Environmental Benefits: A Survey of the Issues. In *Measurement in Public Choice* (pp. 13–32). Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-05090-1_2

Frost, J. (2019). *Introduction to Statistics: An intuitive guide* (First Edit). Statistics by Jim publishing: State College, PA, USA, 2019.

Gabrielli, L., & French, N. (2020). Pricing to market: property valuation methods – a practical review. *Journal of Property Investment and Finance*. https://doi.org/10.1108/JPIF-09-2020-0101

Gaffney, M. (2009). The role of land markets in economic crises. *American Journal of Economics and Sociology*, *68*(4), 855–888. https://doi.org/10.1111/j.1536-7150.2009.00657.x

Gao, S., Li, L., Li, W., Janowicz, K., & Zhang, Y. (2017). Constructing gazetteers from volunteered Big Geo-Data based on Hadoop. *Computers, Environment and Urban Systems*, *61*, 172–186. https://doi.org/10.1016/j.compenvurbsys.2014.02.004

Getis, A. (2008). A history of the concept of spatial autocorrelation: A geographer's perspective. *Geographical Analysis*, *40*(3), 297–309. https://doi.org/10.1111/j.1538-4632.2008.00727.x

Getis, A., & Ord, J. K. (2010). The analysis of spatial association by use of distance statistics. In *Perspectives on spatial data analysis* (pp. 127–145). Springer.

Gilderbloom, J. I., Riggs, W. W., & Meares, W. L. (2015). Does walkability matter? An examination of walkability's impact on housing values, foreclosures and crime. *Cities*, *42*(PA), 13–24. https://doi.org/10.1016/j.cities.2014.08.001

Gluszak, M., & Zygmunt, R. (2018). Development density, administrative decisions, and land values: An empirical investigation. *Land Use Policy*, *70*, 153–161. https://doi.org/10.1016/j.landusepol.2017.10.036

Goix, R. Le, Giraud, T., Cura, R., Le Corre, T., & Migozzi, J. (2019). Who sells to whom in the suburbs? Home price inflation and the dynamics of sellers and buyers in the metropolitan region of Paris, 1996–2012. *PLoS ONE*, *14*(3), e0213169. https://doi.org/10.1371/journal.pone.0213169

Goodchild, M. F. (2013). The quality of big (geo)data. *Dialogues in Human Geography*, *3*(3), 280–284. https://doi.org/10.1177/2043820613513392

Goodman, A. C. (1978). Hedonic prices, price indices and housing markets. *Journal of Urban Economics*, *5*(4), 471–484. https://doi.org/10.1016/0094-1190(78)90004-9

Griffith, D. A. (2004). Spatial Autocorrelation. In *Encyclopedia of Social Measurement* (pp. 581–590). Elsevier. https://doi.org/10.1016/B0-12-369398-5/00334-0

Grislain-Letrémy, C., & Katossky, A. (2014). The impact of hazardous industrial facilities on housing prices: A comparison of parametric and semiparametric hedonic price models. *Regional Science and Urban Economics*, *49*, 93–107. https://doi.org/10.1016/j.regsciurbeco.2014.09.002

Gul, A., Nawaz, M., Basheer, M. A., Tariq, F., & Raheel Shah, S. A. (2018). Built houses as a tool to control residential land speculation - A case study of Bahria Town, Lahore. *Habitat International*, *71*, 81–87. https://doi.org/10.1016/j.habitatint.2017.11.007

Guo, H., Wang, L., Chen, F., & Liang, D. (2014). Scientific big data and Digital Earth. *Chinese Science Bulletin*, *59*(35), 5066–5073. https://doi.org/10.1007/s11434-014-0645-3

Haque, N. U. (2015). Flawed urban development policies in Pakistan. *PIDE Working Papers*, *1*(119), 1–20. https://www.researchgate.net/profile/Nadeem-Haque-2/publication/286946488_Flawed_urban_development_policies_in_Pakistan/links/58ae726392851cf7ae85bacc/Flawed-urban-development-policies-in-Pakistan.pdf

Harris, R., Singleton, A., Grose, D., Brunsdon, C., & Longley, P. (2010). Grid-enabling geographically weighted regression: A case study of participation in higher education in England. *Transactions in GIS*, *14*(1), 43–61. https://doi.org/10.1111/j.1467-9671.2009.01181.x

Hassan, M. M., Ahmad, N., & Hashim, A. H. (2021). Homebuyers Superstitious Belief: Feng Shui and Housing Property. *International Journal of Academic Research in Business and Social Sciences*, *11*(7). https://doi.org/10.6007/ijarbss/v11-i7/10297

Helbich, M., Jochem, A., Mücke, W., & Höfle, B. (2013). Boosting the predictive accuracy of urban hedonic house price models through airborne laser scanning. *Computers, Environment and Urban Systems*, *39*, 81–92. https://doi.org/10.1016/j.compenvurbsys.2013.01.001

Hu, S., Cheng, Q., Wang, L., & Xu, D. (2013). Modeling land price distribution using multifractal IDW interpolation and fractal filtering method. *Landscape and Urban Planning*, *110*, 25–35. https://doi.org/10.1016/j.landurbplan.2012.09.008

Hubert, L. J., Golledge, R. G., & Costanzo, C. M. (1981). Generalised Procedures for Evaluating Spatial Autocorrelation. *Geographical Analysis*, *13*(3), 224–233. https://doi.org/10.1111/j.1538-4632.1981.tb00731.x

Ibeas, ángel, Cordera, R., Dell'Olio, L., Coppola, P., & Dominguez, A. (2012). Modelling transport and real-estate values interactions in urban systems. *Journal of Transport Geography*, *24*, 370–382. https://doi.org/10.1016/j.jtrangeo.2012.04.012

Jiang, B. (2018). Spatial heterogeneity, scale, data character and sustainable transport in the big data era. In *ISPRS International Journal of Geo-Information* (Vol. 7, Issue 5, p. 167). Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/ijgi7050167

Kauko, T. (2003). On current nueral network applications involving spatial modelling of property prices. *Journal of Housing and the Built Environment*, *18*(2), 159–181. https://doi.org/10.1023/A:1023977111302

Kim, C. W., Phipps, T. T., & Anselin, L. (2003). Measuring the benefits of air quality improvement: A spatial hedonic approach. *Journal of Environmental Economics and Management*, *45*(1), 24–39. https://doi.org/10.1016/S0095-0696(02)00013-X

Knight, J. R. (2008). Hedonic Modeling of the Home Selling Process. In P. T. Andrea Baranzini, José Ramirez, Caroline Schaerer (Ed.), *Hedonic Methods in Housing Markets; Pricing Environmental Amenities and Segregation* (pp. 39–54). Springer Science+Business Media, LLC, 233 Spring Street, New York, NY 10013, USA. https://doi.org/10.1007/978-0-387-76815-1_2

Koschinsky, J., Lozano-Gracia, N., & Piras, G. (2012). The welfare benefit of a home's location: An empirical comparison of spatial and non-spatial model estimates. *Journal of Geographical Systems*, *14*(3), 319–356. https://doi.org/10.1007/s10109-011-0148-6

Krause, A. L., & Bitter, C. (2012). Spatial econometrics, land values and sustainability: Trends in real estate valuation research. *Cities*, *29*(SUPPL.2). https://doi.org/10.1016/j.cities.2012.06.006

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, *74*(2), 132–157. https://doi.org/10.1086/259131

Larson, W., & Shui, J. (2020). *Land Valuation using Public Records and Kriging: Implications for Land versus Property Taxation in Cities*. https://www.fhfa.gov/PolicyProgramsResearch/Research/PaperDocuments/wp2001.pdf

LeSage, J. P. (2008). An introduction to spatial econometrics. In *Revue d'Economie Industrielle* (Vol. 123, Issue 3, pp. 19–44). https://doi.org/10.4000/rei.3887

Li, L., & Revesz, P. (2004). Interpolation methods for spatio-temporal geographic data. *Computers, Environment and Urban Systems*, *28*(3), 201–227.

Li, S., Ye, X., Lee, J., Gong, J., & Qin, C. (2017). Spatiotemporal Analysis of Housing Prices in China: A Big Data Perspective. *Applied Spatial Analysis and Policy*, *10*(3), 421–433. https://doi.org/10.1007/s12061-016-9185-3

Li, Z., & Fotheringham, A. S. (2020). Computational improvements to multi-scale geographically weighted regression. *International Journal of Geographical Information Science*, *34*(7), 1378–1397. https://doi.org/10.1080/13658816.2020.1720692

Li, Z., Fotheringham, A. S., Li, W., & Oshan, T. (2019). Fast Geographically Weighted Regression (FastGWR): a scalable algorithm to investigate spatial process heterogeneity in millions of observations. *International Journal of Geographical Information Science*, *33*(1), 155–175. https://doi.org/10.1080/13658816.2018.1521523

Liang, X., Liu, Y., Qiu, T., Jing, Y., & Fang, F. (2018). The effects of locational factors on the housing prices of residential communities: The case of Ningbo, China. *Habitat International*, *81*, 1–11. https://doi.org/10.1016/j.habitatint.2018.09.004

Liao, W. C., & Wang, X. (2012). Hedonic house prices and spatial quantile regression. *Journal of Housing Economics*, *21*(1), 16–27. https://doi.org/10.1016/j.jhe.2011.11.001

Lovett, A. A. (2019). *Economic Valuation of Services* (C. von H. et al. (eds.) (ed.); Landscape, pp. 315–326). Springer, Dordrecht. https://doi.org/10.1007/978-94-024-1681-7_20

Lumley, T., Diehr, P., Emerson, S., & Chen, L. (2002). The importance of the normality assumption in large public health data sets. In *Annual Review of Public Health* (Vol. 23, pp. 151–169). https://doi.org/10.1146/annurev.publhealth.23.100901.140546

Ma, J., Cheng, J. C. P., Jiang, F., Chen, W., & Zhang, J. (2020). Analysing driving factors of land values in urban scale based on big data and non-linear machine learning techniques. *Land Use Policy*, *94*, 104537. https://doi.org/10.1016/j.landusepol.2020.104537

Machin, S. (2011). Houses and schools: Valuation of school quality through the housing market. *Labour Economics*, *18*(6), 723–729. https://doi.org/10.1016/j.labeco.2011.05.005

Malaitham, S., Fukuda, A., Vichiensan, V., & Wasuntarasook, V. (2020). Hedonic pricing model of assessed and market land values: A case study in Bangkok metropolitan area, Thailand. In *Case Studies on Transport Policy* (Vol. 8, Issue 1, pp. 153–162). Elsevier. https://doi.org/10.1016/j.cstp.2018.09.008

Malik, S., Roosli, R., & Tariq, F. (2020). Investigation of informal housing challenges and issues: experiences from slum and squatter of Lahore. *Journal of Housing and the Built Environment*, *35*(1), 143–170. https://doi.org/10.1007/s10901-019-09669-9

Mankad, M. D. (2021). Comparing OLS based hedonic model and ANN in house price estimation using relative location. *Spatial Information Research*, 1–10. https://doi.org/10.1007/s41324-021-00416-3

Mitchell, A. (2005). *The ESRI guide to GIS analysis. Volume 2, Spatial measurements and statistics* (First Edit). Esri Press.

Munshi, T. (2020). Accessibility, infrastructure provision and residential land value: Modelling the relation using geographic weighted regression in the city of Rajkot, India. *Sustainability (Switzerland)*, *12*(20), 1–16. https://doi.org/10.3390/su12208615

Ord, J. K., & Getis, A. (1995). Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis*, *27*(4), 286–306. https://doi.org/10.1111/j.1538-4632.1995.tb00912.x

Ord, J. K., & Getis, A. (2001). Testing for local spatial autocorrelation in the presence of global autocorrelation. *Journal of Regional Science*, *41*(3), 411–432. https://doi.org/10.1111/0022-4146.00224

Oshan, T. M., Li, Z., Kang, W., Wolf, L. J., & Stewart Fotheringham, A. (2019). MGWR: A python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. *ISPRS International Journal of Geo-Information*, *8*(6), 269. https://doi.org/10.3390/ijgi8060269

Ouattara, K., Kim, Y., Raza, H., Hadi, Q. ul A., Rostom, A. M. T., Milyutin, A., Rashid, A. A., Khan, B. N., Haq, E., Grigoryeva, E., Funahashi, J., Chiquier, L., Zaheer, N., Dione, N. T., Hassler, O., Shaikh, S. A., Ahmad, S., Athar, S., & Conde, V. M. O. (2018). *PAKISTAN HOUSING FINANCE PROJECT (P162095)Report No: PAD2385*.

Pace, R. K., & Gilley, O. W. (1998). Generalising the OLS and grid estimators. *Real Estate Economics*, *26*(2), 331–347. https://doi.org/10.1111/1540-6229.00748

Pagourtzi, E., Assimakopoulos, V., Hatzichristos, T., & French, N. (2003). Real estate appraisal: A review of valuation methods. In *Journal of Property Investment & Finance* (Vol. 21, Issue 4, pp. 383–401). MCB UP Ltd. https://doi.org/10.1108/14635780310483656

Pakistan Bureau of Statistics. (2019). *Population Census*. https://www.pbs.gov.pk/content/population-census

Peeters, A., Zude, M., Käthner, J., Ünlü, M., Kanber, R., Hetzroni, A., Gebbers, R., & Ben-Gal, A. (2015). Getis-Ord's hot- and cold-spot statistics as a basis for multivariate spatial clustering of orchard tree data. *Computers and Electronics in Agriculture*, *111*, 140–150. https://doi.org/10.1016/j.compag.2014.12.011

Redfearn, C. L. (2009). How informative are average effects? Hedonic regression and amenity capitalisation in complex urban housing markets. *Regional Science and Urban Economics*, *39*(3), 297–306. https://doi.org/10.1016/j.regsciurbeco.2008.11.001

Rizvi, Z. M. (2018). *National Affordable Housing Policy* (pp. 1–22).

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34–55.

Sabir, M., Torre, A., & Magsi, H. (2017). Land-use conflict and socio-economic impacts of infrastructure projects: the case of Diamer Bhasha Dam in Pakistan. *Area Development and Policy*, *2*(1), 40–54. https://doi.org/10.1080/23792949.2016.1271723

Sah, V., Conroy, S. J., & Narwold, A. (2016). Estimating School Proximity Effects on Housing Prices: the Importance of Robust Spatial Controls in Hedonic Estimations. *Journal of Real Estate Finance and Economics*, *53*(1), 50–76. https://doi.org/10.1007/s11146-015-9520-5

Salon, D., Wu, J., & Shewmake, S. (2014). Impact of bus rapid transit and metro rail on property values in Guangzhou, China. In *Transportation Research Record* (Vol. 2452, pp. 36–45). National Research Council. https://doi.org/10.3141/2452-05

Scott, L. M., & Janikas, M. V. (2010). Spatial Statistics in ArcGIS. In M. M. F. A. Getis (Ed.), *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications* (pp. 27–41). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-03647-7_2

Seo, K., Golub, A., & Kuby, M. (2014). Combined impacts of highways and light rail transit on residential property values: A spatial hedonic price model for Phoenix, Arizona. *Journal of Transport Geography*, *41*, 53–62. https://doi.org/10.1016/j.jtrangeo.2014.08.003

Shabana, Ali, G., Bashir, M. K., & Ali, H. (2015). Housing valuation of different towns using the hedonic model: A case of Faisalabad city, Pakistan. *Habitat International*, *50*, 240–249. https://doi.org/10.1016/j.habitatint.2015.08.036

Singh, A., Sharma, A., & Dubey, G. (2020). Big data analytics predicting real estate prices. *International Journal of Systems Assurance Engineering and Management*, *11*(2), 208–219. https://doi.org/10.1007/s13198-020-00946-3

Taylor, L. O. (2008). Theoretical Foundations and Empirical Developments in Hedonic Modeling. In P. T. Andrea Baranzini, José Ramirez, Caroline Schaerer (Ed.), *Hedonic Methods in Housing Markets; Pricing Environmental Amenities and Segregation* (pp. 15–37). Springer Science + Business Media, LLC, 233 Spring Street, New York, NY 10013, USA. https://doi.org/10.1007/978-0-387-76815-1_1

Thompson, E., Butters, R. B., & Schmitz, B. T. (2012). The property value premium of a place of worship. *Contemporary Economic Policy*, *30*(2), 215–222. https://doi.org/10.1111/j.1465-7287.2011.00255.x

Tian, G., Wei, Y. D., & Li, H. (2017). Effects of accessibility and environmental health risk on housing prices: a case of Salt Lake County, Utah. *Applied Geography*, *89*, 12–21. https://doi.org/10.1016/j.apgeog.2017.09.010

Wahid, A., Mantell, E. H., & Mumtaz, M. Z. (2021). Under invoicing in the residential real estate market in Pakistan. *International Journal of Strategic Property Management*, *25*(3), 190–203. https://doi.org/10.3846/ijspm.2021.14337

Wajahat, F. (2012). Perceptions of tenure security in a squatter settlement in Lahore, Pakistan. In *Transforming Asian Cities: Intellectual Impasse, Asianising Space, and Emerging Translocalities* (pp. 137–147). https://doi.org/10.4324/9780203093894

Wang, W., van Noorloos, F., & Spit, T. (2020). Stakeholder power relations in Land Value Capture: comparing public (China) and private (U.S.) dominant regimes. *Land Use Policy*, *91*, 104357. https://doi.org/10.1016/j.landusepol.2019.104357

Wani, S., Shaikh, H., & Harman, O. (2020). Urban property taxes in Pakistan's Punjab. *International Growth Centre (IGC)*. http://eprints.lse.ac.uk/108451/1/Wani_urban_property_taxes_published.pdf

Wen, H., Jin, Y., & Zhang, L. (2017). Spatial heterogeneity in implicit housing prices: evidence from Hangzhou, China. *International Journal of Strategic Property Management*, *21*(1), 15–28. https://doi.org/10.3846/1648715X.2016.1247021

Wen, H., Xiao, Y., & Zhang, L. (2017). School district, education quality, and housing price: Evidence from a natural experiment in Hangzhou, China. *Cities*, *66*, 72–80. https://doi.org/10.1016/j.cities.2017.03.008

Wooldridge, J. M. (2016). *Introductory econometrics: A modern approach* (Fifth Edit). Nelson Education, Ltd.

Wu, C., Ye, X., Ren, F., Wan, Y., Ning, P., & Du, Q. (2016). Spatial and social media data analytics of housing prices in Shenzhen, China. *PLoS ONE*, *11*(10), e0164553. https://doi.org/10.1371/journal.pone.0164553

Wu, Y., Wei, Y. D., & Li, H. (2020). Analysing Spatial Heterogeneity of Housing Prices Using Large Datasets. *Applied Spatial Analysis and Policy*, *13*(1), 223–256. https://doi.org/10.1007/s12061-019-09301-x

Xiao, Y., Chen, X., Li, Q., Yu, X., Chen, J., & Guo, J. (2017). Exploring determinants of housing prices in Beijing: An enhanced hedonic regression with open access POI data. *ISPRS International Journal of Geo-Information*, *6*(11), 358. https://doi.org/10.3390/ijgi6110358

Yang, L., Chau, K. W., Szeto, W. Y., Cui, X., & Wang, X. (2020). Accessibility to transit, by transit, and property prices: Spatially varying relationships. *Transportation Research Part D: Transport and Environment*, *85*, 102387. https://doi.org/10.1016/j.trd.2020.102387

Yang, L., Chu, X., Gou, Z., Yang, H., Lu, Y., & Huang, W. (2020). Accessibility and proximity effects of bus rapid transit on housing prices: Heterogeneity across price quantiles and space. *Journal of Transport Geography*, *88*, 102850. https://doi.org/10.1016/j.jtrangeo.2020.102850

Yang, L., Wang, B., Zhang, Y., Ye, Z., Wang, Y., & Li, P. (2018). Willing to pay more for high-quality schools? A hedonic pricing and propensity score matching approach. *International Review for Spatial Planning and Sustainable Development*, *6*(1), 45–62. https://doi.org/10.14246/irspsd.6.1_45

Yuan, F., Wei, Y. D., & Wu, J. (2020). Amenity effects of urban facilities on housing prices in China: Accessibility, scarcity, and urban spaces. *Cities*, *96*, 102433. https://doi.org/10.1016/j.cities.2019.102433

Yuen, B., & Choi, S. (2012). *Making Spatial Change in Pakistan Cities Growth Enhancing* (PK 11/12; World Bank Policy Paper Series on Pakistan).

Zaman, K. U., & Baloch, A. A. (2011). Urbanisation of Arable Land in Lahore City in Pakistan: A Case-Study. *Canadian Social Science*, *7*(4), 58–66. http://ojs.ecsdev.org/index.php/ejsd/article/view/6

Zhang, L., Chen, J., Hao, Q., & Li, C.-Z. Z. Measuring the NIMBY effect in urban China: the case of waste transfer stations in metropolis Shanghai. *Journal of Housing and the Built Environment*, *33*(1), 1–18. https://doi.org/10.1007/s10901-017-9565-2