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Urban Greenness and Pricing Premium on Residential Properties

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Abstract

This study examines how the urban climate affects the price, and urban greenness causes the pricing premium. To explore the greenness aspects, we construct a composite pollution index for each property traded in twin cities—Islamabad and Rawalpindi—based on the area traded properties' water, air, noise, and soil pollution. To examine the pricing efficiency of these properties, we categorize our sample into green and non-green properties using machine learning and measure the impact of environmental factors on their price. Along with other property characteristics, we observe that air pollution, noise pollution, and water pollution emerge as vital factors that define the prices of properties. Similarly, investors are willing to pay higher prices for green residential properties with a lower pollution index. The study findings are helpful for investors, housing society managers and developers, as they show that greenness pays back.

JEL Codes: R20, R30, R31

1. Introduction

Urban climate has become a global challenge for residential areas and shifted the attention of policymakers, regulatory bodies, and housing authorities to minimize pollution by developing green infrastructure, ensuring compliance with urban environmental policies and minimizing carbon emissions. Creating urban green amenities and green buildings provides a conducive living environment and further has important connections with the urban ecology (Franco and Macdonald 2018). Lambourne (2021) identified that green buildings and infrastructure bring premium and pricing advantages for investors but the lack of relevant technical skills and apparent green buildings lead to investor disinterest. Although green building infrastructure is environment-friendly and can improve consumers' social values, material costs, construction and transportation for green materials and green building features are more expensive than conventional buildings in developing countries (Tam, Hao, and Zeng 2012). One argument is to create green buildings and another is to develop green spaces and parks to mitigate the warming and environmental dynamics. We can infer that properties located in green areas face low temperature and least humidity problems, which cause the least energy consumption because more than one-third of the electricity generated in the world is being consumed in the residential sector worldwide (Umbark, Alghoul, and Dekam 2020). Another counter argument is that the development of greenbelts, parks and green spaces in residential areas is based on implementing environmental protection measures and increasing the cost of these residential properties. There is extensive empirical work on urban greenness (Franco and Macdonald 2018; Wang et al. 2013), green infrastructure and buildings (Chegut, Eichholtz, and Kok 2014; Low, Gao, and Teo 2016), and the impact of greenness and green infrastructure on the financial performance and value of stock and portfolio allocation in Real Estate Investment Trusts (Bhuyan et al. 2014; Coën and Desfleurs 2022; Ho (David), Rengarajan, and Lum 2013; Morri, Anconetani, and Benfari 2020). There is little discussion on urban climate dynamics and urban greenness on the value of residential real estate properties. Moreover, previous research on the amenity effects of open space on the real estate market has typically used to capture the distance effects of different categories of greenness and green spaces on the value of properties.

Cho et al. (2008) highlighted that having higher greenness in residential areas to higher satisfaction among inhabitants of that specific area, which further leads to higher prices and rent prices. According to the Federal Board of Revenue report, properties located in Islamabad where greenness and climate dynamics are sound are priced higher than in Rawalpindi where the urban climate is poor (Federal Board of Revenue Pakistan 2019). This is the outcome of the information cascade which states that prices are moved by the number of people who make the same decision at the same time (Bartke and Schwarze 2021; Xiao 2021); for example, buying and selling real estate properties sequentially due to successful information passing on (Salter and King 2009). Two factors inculcate the information cascade i.e. (a) most investors are ex-patriates and they invest in real estate market sequentially (Wahid, Kowalewski, and Mantell 2022). It is also evident that the Pakistanis diaspora sends huge amounts of money to Pakistan. According to the State Bank, Pakistan received a record $21.84 billion in remittances in 2019-20 and 50% of this amount is invested in the real estate (Atiq 2020). Secondly, they observe the choices made by those who invested earlier, and (b) they have some information aside from their own that helps guide their decision. The information they have been inculcated by their earlier ex-patriate investors (Yousaf and Ali 2020).

The quality of green areas and parks (38.89 and 78.08) and dissatisfaction with green areas and parks (61.11 and 21.96) in twin cities-Rawalpindi and Islamabad are reported, respectively (Numbeo 2021) which further fuel that residents of Islamabad have a higher green living standard and higher quality of greenbelts and parks than residents of Rawalpindi do (Wahid et al. 2022). As the level of greenness and availability of quality greenbelts and parks increase which causes soundness in urban climate, *ceteris paribus*, the demand for residential properties will likewise increase. To the extent that demand increases, again, *ceteris paribus*, one would expect to observe an increase in prices and premiums on residential real estate. In this study, our focal point is to measure the impact of urban climate dynamics on the prices of residential real estate properties. Secondly, to measure the role of greenness and climate indicators on the pricing premium of properties.

To identify greenness, we construct an urban climate index for each property traded in twin cities—Islamabad and Rawalpindi—based on the water, air, noise and soil pollution of the area traded properties. Furthermore, this study proposes three research questions: (a) How can one characterize the pricing of real estate property based on urban greenness? (b) What environmental factors influence the pricing of real estate properties of similar characteristics? (c) How does the greenness of a residential area affect the value of real estate resulting in pricing advantages?

The rest of the paper is structured as follows. Section 2 presents a brief overview of the relevant literature and the research questions. Section 3 discusses our data and methodology, while Section 4 presents the results. Section 5 concludes.

2. Literature Review

2.1 Climate Dynamics and the Value of Real Estate

In previous literature, various studies have been conducted on the connection between the value of real estate property and environmental aspects. Environmental factors, including the proximity of green belts and industrial zones, and the degree of air, noise and water pollution, play significant roles in defining the prices of real estate properties. For instance, Rauf & Weber (2020) found that the hedonic pricing model reflects the nominal effects of environmental factors that cause variation in the pricing of real estate properties and assets. They also found that higher greenness of real estate leads to higher prices. Similarly, Harrison et al. (2001) argued that environmental hazards have a significant role in causing price distress and causing decreases in the prices of real estate properties. Current prices of real estate properties vary because of future disaster risks in nearby areas. The same evidence was also reported in England: the higher the probability of flood and disaster risk, the higher the chances of devaluation of real estate properties. They also found that houses and residential apartments were devalued up to 40% because of the continuous flood events faced by areas nearest to a river (Lamond, Proverbs, and Hammond 2010).

Troy & Romm (2004) and Ismail et al. (2016) also reported the same occurrence in California and Malaysia, respectively: the selling price of housing units dropped by 5% because the areas were suffering from floods and the demand for properties in these areas also declined. J. Kim et al. (2017) also conducted a study on natural disasters, i.e., flooding and land sliding in Korea. The frequent disasters negatively affected residential real estate prices. The real estate properties located approximately 1 kilometer from affected areas were found to have higher prices than those within 1 kilometer. Furthermore, their findings suggest that new residential real estate societies must be developed in areas away from the disaster area. Floods and natural disasters are not the only factors that lead to a variation in real estate prices, but the risk of wildfires also leads to variation. Stetler et al. (2010) identified that in Montana, USA, the prices of and demand for real estate properties declined because of the risk of wildfires. However, many residents migrated from the affected area to non-affected areas of the country. The average selling price of housing units and apartments in the affected area declined because of the constant wildfire risk. Bin & Polasky (2004) found that in North California, millions of residents moved to other areas because of floods and other natural disasters. The demand for residential properties declined, and prices also decreased dramatically. Belanger & Bourdeau-Brien (2018) identified that the overall worth of residential properties declines because of floods and landslides in England. Therefore, English residents avoid investing in areas near the banks of rivers. Harrison et al. (2001) highlighted the same phenomenon of flooding driving real estate property prices down in Alaska, USA. They found that the average selling price of the real estate properties in flood zones was recorded as lower than in other areas away from flood zones.

2.2 Greenness of Residential Areas and the Value of Real Estate

As the distance increases from such natural sites, the average price of real estate properties decreases. On the other hand, the greenness of residential areas and the presence of green belts in nearby areas causes an increase in the prices of real estate properties with other physical attributes, such as the number of bedrooms, kitchens, and the presence of many real estate properties in China (Jim and Chen 2006). Chiarazzo et al. (2014) also reported that the overall value of real estate properties is more significant in areas situated away from industrial areas in Spain. However, due to their low proximity to industrial areas, which leads to less air and noise pollution, there is often an overvaluation of these real estate prices. Cho et al. (2008) concluded that in the United States of America, the preference for urban residences was greatly influenced by the availability of landscapes, green belts and rivers. Therefore, the pricing trend of apartments was found to be higher than the properties located near the green belt.

On the one hand, the greenness of residential areas and green buildings lower the probability of increasing global warming and natural disasters and higher construction costs due to the required environmentally friendly technology and measures. Juan et al. (2017) also highlighted that green buildings are expensive compared to traditional buildings in China. They used an artificial neutral network model and concluded that green buildings significantly positively impact the environment. Similarly, Tam et al. (2012) found that green building implementation is environmentally friendly but is expensive compared to the traditional construction of buildings in Hong Kong. The adoption of green building techniques could alleviate local industry issues. However, Ali & Al Nsairat (2009) used a green building assessment tool to determine the impact of green building on sustainability. They concluded that constructing green buildings in Jordan is too expensive to be sustainable, but that the payoff of such a scheme would have a positive impact on the environment. According to Shan & Hwang (2018), many countries use a green building rating system to analyze the overall rating of green buildings. Adopting green real estate is worthwhile for states that aim to minimize environmental hurdles. The outcome of green building development has a long-term impact on environmental stability in areas where the trend of green buildings is common.

2.3 Environmental Pollution and the Value of Real Estate

Last but not least, a crucial aspect of the real estate market that has a significant impact on the prices of real estate properties is reviewed. Cohen & Coughlin (2008) found the same pattern that was described above in Atlanta, in which housing prices decreased because of the presence of airports in nearby areas, which both cause noise pollution and disturb nearby residents; real estate properties located farther away from airports have a higher worth compared to properties nearer to airports. Fan et al. (2021) also highlighted that the noise pollution caused by bus transit in Singapore has a similar effect on residents. Furthermore, they added that the purchasing trends of Singapore citizens near the most noise-affected areas were changed, as citizens preferred to invest in properties in areas that were farther away from train and bus transit routes.

The same issues were highlighted in Taiwan by Liou et al. (2019), who found that the value of residential real estate properties declined because of the heavy flow of traffic. They further added that real estate prices were also affected by underground contaminated water. The average selling price of such real estate properties decreased by 28% compared to those in the other areas of the city. Kim et al. (2010) conducted a study using a spatial lag hedonic model to determine the impact of air pollution on real estate properties in Seoul, South Korea. They concluded that sulfur dioxide has a significant effect on the prices of residential areas. In contrast, the presence of nitrogen oxide had a negative association with the overall cost of residential real estate properties.

Likewise, Liu et al. (2017) also used a hedonic model and concluded that due to the poor water quality in Narragansett Bay, the overall prices of real estate are lower in coastal areas. They further concluded that the price of real estate properties is higher where better environmental conditions and basic utilities, such as access to water, good air quality and low pollution, are present. Schläpfer et al. (2015) found the same pattern in Switzerland: pollution hurts the price of real estate properties. Housing units located closest to the green landscape areas were recorded to be higher in price. However, Önder et al. (2004) found that the average price of real estate in Istanbul declined because of poor soil conditions in similar areas. They also found no impact of earthquakes on residential real estate prices, but misinformation and speculation contributed to a decline in housing prices.

2.4 Environmental Dynamics of the Real Estate Market of Pakistan

Pakistan spends approximately $5.2 billion on its housing market. This value constitutes approximately 2% of its GDP. The country is experiencing an average annual growth rate of roughly 9% (Wahid, Mantell, and Mumtaz 2021). Pakistan's high inflation seems to have caused housing prices to increase sharply. Nationwide housing prices, in nominal terms, rose by 5.05% to PKR 10,875 (77 USD) per square foot (sq. ft). According to the Federal Board of Revenue (FBR), industry surveys estimate that the real estate industry was valued at approximately 700 billion rupees in 2015 (The News 2015). This estimation indicates the value of the real estate market since it has become Pakistan's largest market. However, Pakistan's real estate market is fragile due to environmental and natural concerns. Table 1 shows that only the residential market of Islamabad is at an acceptable level in terms of the air, noise and water quality index, with 73, 47.2 and 51.33 indices, respectively, which are all at moderate to good levels. Residents of other small and large cities of Pakistan are suffering from severe issues and pollution due to urban sprawl without proper environmental planning or conciseness.

Table 1
Environmental Quality of Housing Markets of Pakistan

City	Air Quality Index (μg/m3)	Noise quality index (DB)	Water quality index (Mg/l)
Islamabad	73	47.2	51.33
Lahore	76.59	64.51	75.52
D.G Khan	142	78.34	73.64
Rawalpindi	74	63.54	79.35
Multan	88	59	65
Quetta	77.5	68.06	83.82
Sukhur	151	83.23	75.24
Peshawar	159	54.69	55.47
Hyderabad	155	42.31	59.09
Nawabshah	147	71.32	72.92
Sialkot	108	56	67.71
Rahim Yar Khan	147	69.65	63.98
Sargodha	97	56.25	37.5
Karachi	157	69.47	82.94

Note: This table indicates the environmental dynamics of Pakistan. μg/m3, DB and Mg/l are denoted as micrograms per cubic meter, decibels, and milligrams per letter, respectively. Source:(https://www.numbeo.com/pollution and https://www.iqair.com)

2.5 Environmental Dynamics of the Real Estate Market of the Twin Cities

Table 2 shows the environmental quality of the housing markets of Islamabad and Rawalpindi. The air pollution score for Islamabad is 32.58, while for Rawalpindi, it is 66.67, which indicates that Rawalpindi is more polluted than Islamabad. This pollution directly affects Rawalpindi's standard of living and the prices of its housing market. Islamabad is lush with greenery, which plays a role in reducing air pollution. The index of drinking water pollution and inaccessibility for Islamabad is similar to the twin cities. Moreover, the dissatisfaction index with Islamabad garbage disposal of Islamabad is higher for Rawalpindi. This finding implies that Islamabad has active garbage disposal management, which plays a significant role in the price of real estate. Proper garbage disposal management also encourages people to buy houses. The index of dirtiness and untidiness for Islamabad is lower than that of Rawalpindi, which is one of the reasons that people are more likely to choose Islamabad as their place of living.

Table 2
Environmental Quality of the Housing Markets of Islamabad Rawalpindi

Indicators	Islamabad		Rawalpindi	
	Index	Remarks	Index	Remarks
Air Pollution	32.58	Low	66.67	High
Drinking Water Pollution and Inaccessibility	41.95	Moderate	54.63	Moderate
Dissatisfaction with Garbage Disposal	36.16	Low	68.52	High
Dirty and Untidy	28.85	Low	65.74	High
Noise and Light Pollution	47.2	Moderate	63.54	High
Water Pollution	51.33	Moderate	79.35	High
Dissatisfaction to Spend Time in the City	29.06	Low	61.21	High
Dissatisfaction with Green and Parks in City	21.96	Low	61.11	High
Air quality	67.42	High	33.33	Low
Drinking Water Quality and Accessibility	58.05	Moderate	45.37	Moderate
Garbage Disposal Satisfaction	63.84	High	31.48	Low
Clean and Tidy	71.15	High	34.26	Low
Quiet and No Problem with Night Lights	52.8	Moderate	36.46	Low
Water Quality	48.67	Moderate	20.65	Low
Comfortable to Spend Time in the City	70.94	High	38.79	Low
Quality of Green and Parks	78.08	High	38.89	Low

Note: Table indicates the environmental dynamics of twin cities including air, noise, soil pollution index which further fuel dissatisfaction in residents of twin cities. Sam is reported in above table. Source: (https://www.numbeo.com/pollution)

Similarly, Table 2 shows that Islamabad's noise and light pollution index is lower than that for Rawalpindi. The water pollution index for Islamabad is 51.33, while for Rawalpindi, it is 79.35, which is alarming for both twin cities because water pollution can lead to a vast variety of diseases. Generally, Pakistan remains exceptionally vulnerable to the impacts of climate change. According to the Global Climate Risk Index 2020, Pakistan is ranked fifth among the countries most vulnerable to climate change. Between 1999 and 2018, the country witnessed 152 extreme weather events and suffered huge losses equaling $3.8 billion (UNDP 2020).

Furthermore, the dissatisfaction with time spent in the city of Islamabad is lower than in Rawalpindi, which indicates that people in Rawalpindi do not enjoy living in it. Life in Islamabad is far better than that in Rawalpindi, which is why more people like to live in the city of Islamabad. Because of dissatisfaction with greenery and parks, air quality, drinking water quality, and garbage disposal, satisfaction is higher among people in Islamabad, as shown in Table 2. People in Islamabad are more satisfied with the city's garbage disposal than in Rawalpindi, and this satisfaction also leads to a higher value of properties in Islamabad.

In addition, citizens' satisfaction with other elements, such as cleanliness and tidiness, low noise pollution,, good water quality, comfort with spending time in the city, and the quality of greenery and parks, Islamabad is much higher than in Rawalpindi, as shown in Table 2. The Capital Development Authority (CDA) in Islamabad has been actively involved in establishing new parks and maintaining existing parks. All of these values directly affect citizens' choices and the prices of properties. Islamabad has more facilities, which is one of the reasons that the real estate market value of Islamabad is higher than that of Rawalpindi. A survey conducted by the CDA revealed that 60% of respondents were happy with the elements mentioned in the questionnaire concerning the upkeep of green areas and plant care in Islamabad, and a total of 60% of individuals were pleased with the CDA's efforts to halt the occupancy and encroachment on government property. Similarly, 60% were pleased with repairing sidewalks and lane markings, and 45% said they were satisfied with the timely collection and disposal of waste (Capital Development Authority 2021). These positive sentiments toward Islamabad's real estate market lead to an increase in the value of properties.

2.6 Pollution and Climate Dynamics in the Twin Cities

Table 3 compares air and noise pollution between the twin cities, i.e., Islamabad and Rawalpindi. The traffic conditions in Islamabad are better than those in Rawalpindi. Due to the highly populated area, there is an increase in traffic flow in Rawalpindi, and it has become more difficult to travel within the city. According to a comparative review of the 2017 and 2021 surveys, traffic on the major roads of Rawalpindi has increased threefold. According to the 2017 survey, 75,000 and 275,000 vehicles passed through Ammar Chowk and Muree Road daily, respectively, while 300,000 and 600,000 vehicles passed through Ammar Chowk and Muree Road daily in 2021 (tribune 2021). As a result, the time index, Exp. Index and inefficiency index for Islamabad are better than those for Rawalpindi, as shown in Table 3.

Table 3

Air and Nosie Pollution in Islamabad Rawalpindi

Indicator	Rawalpindi	Islamabad
Traffic Index:	199.77	157.75
Time Index (in minutes):	46.05	35.05
Time Exp. Index:	3997.14	565.11
Inefficiency Index:	196.2	209.93
CO_2 Emission Index:	5851.09	7129.33
Pollution Index:	76.96	41.86
Pollution Exp Scale:	135.6	70.55
PM_{10}	448	217
$PM_{2.5}$	107	66
PM_{10} Pollution Level:	Extremely High	Extremely High

Note: Table indicates the magnitude of noise pollution due to traffic and air pollution due to carbon emission produced by traffic. PM_{10} indicates PM10 describes inhalable particles with diameters generally 10 micrometers and smaller. PM 2. 5 refers to the atmospheric particulate matter with a diameter of less than 2.5 micrometers, which is about 3% of the diameter of human hair. Source: (https://www.numbeo.com)

Furthermore, the pollution index, the index of pollution exp. scale and other indices such as PM 10, PM 2.5 and the index of PM10 pollution level in Islamabad are environmentally sound and lower than those in Rawalpindi. These indices show that pollution in Islamabad is lower, therefore, more people want a house and to live in Islamabad which results in higher prices of real estate property. The greater the demand is, the higher the price will be. The values of these indices have a significant impact on the real estate market prices. Comparatively, the indices of Islamabad are better, which directly affects the price of property. Owing to these values, the price of a house in Islamabad is almost double that of a house in Rawalpindi. The demand and price are both higher in Islamabad than in Rawalpindi. Demand drives sales, and demand continues to climb. The population of Islamabad has not decreased, which explains why the housing demand continues to rise year after year. Aside from the bleak and tragic views of recent years, there is reason to believe that the real estate market in Islamabad will have a lot to look forward to in 2021. This lovely and rich city is known for its pleasant weather (dawn 2021).

Table 3

Regarding environmental factors, all indicators, such as proximity to industrial zones, proximity to green belts, air pollution, noise pollution, and probability of disaster, significantly impact pricing. Generally, Pakistan's environmental conditions have been gradually worsening. Lahore has become the 2nd highest polluted city in the world. Rawalpindi had a PM2.5 average of 40.8 μg/m³, placing it into the 'unhealthy for sensitive groups' bracket, which requires a PM2.5 reading of anywhere between 35.5 to 55.4 μg/m³ for classification. This reading places Rawalpindi at 8th place out of all cities registered in Pakistan and 224th place in all cities ranked worldwide in terms of their pollution levels. The climate dynamics of Rawalpindi are very sound, as shown in Fig. 1.

Figure 1

Islamabad is making gradual improvements to its air quality. In 2017, Islamabad had a PM2.5 yearly average of 39.2 μg/m³, placing it into the 'unhealthy for sensitive groups' bracket (35.5 to 55.4 μg/m³). The climate dynamics of Islamabad are very sound, as shown in Fig. 2.

Figure 2

3. Methodology

3.1 Data and Sources

We collected data on 1580 properties located in Islamabad and Rawalpindi. After removing the outliers and missing values, our sample was reduced to 1500 properties. Of this, 48% of the data came from Islamabad and 52% related to Rawalpindi. The market value of properties was obtained from Zameen.com, OLX, property dealers, local housing authorities, and other property recording systems in Islamabad and Rawalpindi. The data include 10% of the overall traded properties in Islamabad and Rawalpindi from 2017 to 2019 before covid-19 pandemic. To match the prices and characteristics of the properties, we identified the location and local housing authority of the property from its sale agreement. To measure the property's proximity to essential utilities such as schools, hospitals, railway stations, airports, consumer markets, and megaprojects, we used Google Maps. The market sentiment at the date of sale of a specific property was calculated using data provided in the economic survey of Pakistan in the construction and real estate sectors.

3.2 Hedonic Model with Greenness

To examine the determinants of the pricing of real estate properties in Pakistan, we applied the hedonic regression method along with environmental factors to capture the impact of the greenness of residential areas on the value of real estate properties.

Price = f (location, structure, neighborhood, and environmental factors) (1)

Equation (1) explains that the price of real estate depends on its characteristics (e.g., location, structure, neighborhood, environmental, and administrative factors). Consequently, we develop the following model:

$$Price_i = \alpha_i + \delta_i\left(Prox_{Rail}\right) + \left(Prox_{airp}\right) + \delta_i\left(Prox_{CCen}\right) + \gamma_i\left(No_{Bedr}\right) + \gamma_i\left(No_{Batr}\right) + \gamma_i\left(Size_{Bedr}\right) + \gamma_i\left(Avai_{Gar}\right) + \gamma_i\left(Avail_{Garg}\right) + \gamma$$

2

where prices indicate the total price of the house. The first three indicators of proximity to railway stations, airports, and city centers depict the role of location in the pricing of real estate property in Pakistan. These are further elaborated on: Prox-Bus represents the geographic proximity of each specific property to a metro bus station, Prox-Rail indicates the geographic proximity of each specific property to a railway station, Prox-air exhibits the geographic proximity of each specific property to an airport, and Prox-ccen indicates the geographic proximity of each specific property to the city centers of both cities—the Blue Area in Islamabad and Saddar Bazar in Rawalpindi.

Furthermore, five features, such as the number of bedrooms, bathrooms, size of the rooms, presence of gardens, and garages, depict the structure of houses. $\mathrm{No}_{\mathrm{Bedr}} and \mathrm{No}_{\mathrm{Batr}}$ depict the total number of bedrooms and bathrooms, respectively. Similarly, $\mathrm{Size}_{\mathrm{Bedr}}$ indicates the size of each room, and $\mathrm{Avai}_{\mathrm{Gar}}$ and $\mathrm{Avail}_{\mathrm{Garg}}$ indicate the availability of a garden and garage, respectively. Additionally, the role of the property's neighborhood is also considered in this study; for example, $\mathrm{Prox}_{\mathrm{Mkt}}$, $\mathrm{Prox}_{\mathrm{Sch}}$, and $\mathrm{Prox}_{\mathrm{Job}}$ indicate the geographic proximity of each specific property to market, school, and job centers, respectively, and $\mathrm{Crime}_{\mathrm{rate}}$ depicts the total number of criminal cases reported at the nearest police station.

Pollu-water indicates underground water quality, and Prox-indus reflects the proximity of selected residential areas from industrial zones. Similarly, prox-greenbelt indicates the geographical distance from green belts, and air pollut and noise pollution reflect selected sample areas' air pollution and noise pollution index. Disrisk indicates the proximity of real estate residential areas from disaster or flood zones, e.g., Nala Lai in Rawalpindi and the probability of earth quickly.

Furthermore, to clarify the model's specification and robustness of the variables, we use LASSO regression, which is widely used to select variables and measure the model's accuracy. This technique was first introduced by Santosa and Symes (1986) and used by Tibshirani (1996). The specifications of the LASSO regression are as follows:

$$Price_i = \frac{1}{2m}\sum_{i=1}^{m}\left(y_i - \beta_0 + \sum_{j=1}^{p} x_i\beta_j\right)^2 + \lambda\sum_{j=1}^{p}\left|\beta_j\right|$$

(3)

To estimate the boundary of the fair price, we use stochastic frontier analysis (SFA) by using the following equation:

{Price}_{i}=f\left({x}_{i}, \beta \right)+{ϵ}_{i}

(4)

{ϵ}_{i}={v}_{i}-{u}_{i}
5

where the subscript *i* indicates the number of cross-sections or observations—1500 in our case. {Price}_{i} indicates the fair offer price, and {x}_{i} denotes the jx1 vector of determinants identified in Eq. (1) after removing the fragile characteristics. {u}_{i} is the log difference between the fair price and actual offer price ({u}_{i}={ln fair price}_{i}-{ln actual price}_{i}). By rearranging the equation, we obtain \text{exp}\left(-{u}_{i}\right)=\frac{actual price}{Fair price}. We apply the SFA to measure the pricing inefficiency of real estate properties of different housing societies in Islamabad and Rawalpindi using cross-sectional data. This measure is based on observations across low- and high-prestige societies. We used an output-oriented model that estimates the output technical efficiency using input or factors determining the price, for example, in our case, the different features of houses (e.g., structure, location, and neighborhood) to calculate the maximum level of price denoted as the "fair price" in our study.

3.3 Artificial Intelligence (AI)

We applied machine learning on 1500 observations, including 1046 (69.7%) observations and 454 (30.3%) were holdout and test with trained data. All characteristics of hedonic model were taken as control variables and water, air, noise and soil pollution were tested. The train set was used to train AI/machine learning (ML) techniques, and the test set evaluated the AI/ML techniques. We applied Support Vector Machine (SVM), Stochastic Frontier Analysis (SFA), OLS, LASSO, Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and Artificial Neural Networks (ANNs) using the AI/ML libraries of Python. SVM was applied to classify the binary decision, which constructs a hyperplane(s) in a high-dimensional space that maximizes the margin. The large margin means a lower generalization error and better performance; it usually performs well on a complex and nonlinear but medium-sized dataset (Cortes and Vanik 1995).

4. Findings And Discussion

4.1 Determinants of Prices of Real Estate

To test the hedonic model's impact and sensitivity on residential properties' prices along with environmental factors, we used Model 1, which shows the impact of the hedonic model on the price of residential properties in Islamabad and Rawalpindi. Table 4 shows that the house size, number of bedrooms, and presence of gardens (\beta=2.254, 0.465 & 2.838, $p < 0.05$) have significant positive impacts on the prices of residential real estate properties, which shows that the design of real estate property has a strong and positive impact on the prices of residential properties. Similarly, the proximity to the nearest markets, proximity to city centers and crime rate (\beta= -0.582, -0.009 and − 0.057 $p < 0.05$, respectively) have a significant positive impact on the prices of residential real estate properties. In this model, house size and crime rate are very prominent factors explaining the variation in the prices of real estate properties in Pakistan. The crime rate is an external factor that affects the overall region and sector prices if the crime rate is higher than the average crime reported in any city or country. According to the latest stats released by the World Crime Index issued in a report by the international organization Numbeo, Islamabad’s current safety index stands at 71.37, which is remarkable if we compare it with Rawalpindi, which stands at 67.12. Because of Islamabad’s low crime rates, the United Nations (UN) also restored Islamabad’s status as a family station. This status means that the UN's International Civil Service Commission (ICSC) considers Islamabad a safe city for UN personnel to visit with their families. As a result, the prices of residential properties in Islamabad are higher than those in Rawalpindi.

Table 4
Determinants of Prices of Real Estate Properties

	Model-I	Model-II	Model-III	Model-IV	Model-V	Model-VI	Model-VII	LASSO
House Size	2.254	2.256	2.258	2.259	2.255	2.247	2.240	2.008
	(20.33)**	(20.37)**	(20.39)**	(20.38)**	(20.36)**	(20.30)**	(20.15)**	(37.82)**
No. Bedrooms	0.465	0.462	0.465	0.466	0.472	0.468	0.464	0.004
	(2.42)*	(2.41)*	(2.42)*	(2.43)*	(2.46)*	(2.45)*	(2.42)*	(2.46)**
Room Size	0.002							
	(0.62)							
No. Bathrooms	0.162							
	(0.72)							
Presence of Garden	2.838	2.821	2.803	2.809	2.743	2.747	2.757	3.153
	(2.34)*	(2.33)*	(2.31)*	(2.31)*	(2.26)*	(2.27)*	(2.28)*	(3.24)**
Presence of Garage	0.047							
	(0.04)							
Prox Railway Station	0.008							
	(0.23)							
Prox Market	-0.582	-0.568	-0.570	-0.571	-0.596	-0.588	-0.581	-0.639
	(3.53)**	(3.45)**	(3.47)**	(3.47)**	(3.62)**	(3.57)**	(3.52)**	(4.01)**
Prox City center	-0.009							
	(2.18)*							
Prox Airport	-0.055							
	(1.85)							
Prox School	-0.152							
	(0.99)							
Prox Job Places	-0.129	-0.126	-0.130	-0.134	-0.106	-0.123	-0.115	-0.193
	(2.83)**	(2.77)**	(2.85)**	(2.84)**	(2.19)*	(2.50)*	(2.26)*	(2.00)*
Crime rate	-0.057	-0.053	-0.052	-0.048	-0.040	-0.033	-0.037	-0.040
	(3.48)**	(3.23)**	(3.16)**	(2.52)*	(2.06)*	(1.67)	(1.80)	(2.35)*
Water Pollution		-2.202	-1.823	-1.894	-1.502	-1.230	-0.324	
		(2.03)*	(3.49)**	(4.53)**	(4.30)**	(4.14)**	(0.19)	
Green Index			-2.309	-2.202	-2.455	-2.618	-2.516	-1.948
			(4.09)**	(5.03)**	(5.15)**	(5.22)**	(5.17)**	(3.80)**
Prox Greenbelt				0.013	0.012	0.017	0.013	0.022
				(5.33)**	(5.05)**	(5.19)**	(4.08)**	(5.05)**

Note: The study sample comprises 1500 property situations in Rawalpindi and Islamabad. Akaike's Information Criterion (AIC), Bayesian Information Criterior (BIC). ***; ** represent significance at the 1% and 5% levels, respectively.

	Model-I	Model-II	Model-III	Model-IV	Model-V	Model-VI	Model-VII	LASSO
Air Pollution					-0.069	-0.042	-0.036	-0.070
					(4.20)**	(5.26)**	(3.04)**	(2.35)*
Noise Pollution						-0.066	-0.066	-1.891
						(4.13)**	(2.10)*	(4.22)**
Soil Pollution							-0.030	-0.121
							(3.67)**	(5.12)**
Cons	0.522	1.464	2.638	2.695	0.282	1.604	1.416	1.244
	(0.22)	(0.57)	(0.94)	(0.96)	(0.09)	(0.51)	(0.44)	(0.54)
R^2	0.60	0.64	0.65	0.67	0.71	0.72	0.77	0.78
Df	13	14	15	16	17	18	19	
AIC	5212.47	4820.41 4871.21	4615.06 4672.08	4517.11	4399.31 4367.59	4298.88 4272.84	4239.01	
BIC	5309.99			4579.32			4218.03	

Note: The study sample comprises 1500 property situations in Rawalpindi and Islamabad. Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC). ***; ** represent significance at the 1% and 5% levels, respectively.

Similarly, environmental factors have been tested to measure the impact of each variable on the prices of residential properties using a hedonic model. Environmental variables are added to the specification incrementally from Model II to Model VIII. To test the robustness of the environmental control variables, we apply three criteria: Akaike's information criterion (AIC), Bayesian information criterion (BIC) and {R}^{2}. In Model II, we added our variable representing water pollution. The test statistics are AIC = 4820.41, BIC = 4871.21, and R^2 = 0.64. The value of \beta = -2.202 for this variable is significant at the 95% confidence interval ($p < 0.05$). Thus, the explanatory power of this model is superior to that of Model-I, as signified by a lower AIC and BIC and a higher R^2. These findings indicate that groundwater availability is a crucial factor when explaining the prices of residential areas in Islamabad and Rawalpindi. According to the Water and Sanitation Agency (WASA), due to the high demand for water and low rainfall, the ground water level of the twin cities has dropped to 600 feet, which is worsened by the water level continuing to fall approximately 6 feet annually. However, according to some independent analysts, the annual groundwater level falls by seven to nine feet (Shirazi 2021). As a result, residents of the twin cities pay approximately Rs15000 to Rs17000 (100–110 USD) for a tanker that contains 1000 to 1200 liters of water.

In Model III, we added a variable representing the proximity to industrial areas. The test statistics are AIC = 4615.06, BIC = 4672.08, and R^2 = 0.65. The value of \beta =-2.309for this variable is significant at the 99% confidence interval ($p < 0.01$). The explanatory power of this model is superior to that of Model-I, as signified by a lower AIC and BIC and a higher R^2. In prior literature, researchers have also explored whether proximity to industrial areas causes various environmental issues that further fuel the low prices of residential areas near these industrial zones (Perlin, Wong, and Sexton 2001). Similarly, we included proximity to green belts and obtained AIC = 4517.11, BIC = 4579.32, R^2 = 0.67. The value of \beta =0.013for that variable is significant at the 99% confidence interval ($p < 0.01$) as shown in Table (4). Cho et al. (2008) identified that investors prefer urban residences near landscapes, green belts and rivers. It is generally presumed that as proximity to greenbelts decreases, *ceteris paribus*, the demand for residential properties near greenbelts will likewise increase. To the extent that demand increases, again, *ceteris paribus*, one would expect to observe an increase in the prices of residential properties near green belts.

In Model V, we included air pollution as an environmental factor to measure the effects of air pollution on the prices of residential properties in Pakistan. The results show that due to the inclusion of air pollution, AIC = 4399.31, BIC = 4367.59, and R^2 = 0.71. The value of \beta =-0.069for this variable is significant at the 99% confidence interval ($p < 0.01$) as shown in Table 4. This value indicates that air pollution has a significant role in defining the prices of real estate properties in Pakistan. The air quality index of both Rawalpindi and Islamabad is declining annually, which poses a heavy threat to both the environment and human health. The trickle-down effects of air quality can be seen in Pakistan's residential properties' prices. Industrialization, unplanned urbanization, and huge traffic volumes contribute to air pollution. Looking at the statistics from 2019, Rawalpindi had a PM2.5 average of 40.8 μg/m³, placing it into the 'unhealthy for sensitive groups' bracket, which requires a PM2.5 reading between 35.5 and 55.4 μg/m³ for classification. This reading places Rawalpindi as 8th out of all cities registered in Pakistan and 224th place in all cities ranked worldwide in terms of their pollution levels. On the flip side, regarding the air pollution levels, Islamabad had PM2.5 readings of 35.2 μg/m³ as a yearly average in 2019. This average ranks it as the cleanest city in the country, at 10th place out of all cities currently ranked in Pakistan.

Similarly, we test the potential impacts of noise pollution on the prices of residential properties in the twin cities. In this regard, we included noise pollution as an explanatory variable in the model, and the findings show that model VI, in which noise pollution is included, performed better in terms of AIC = 4298.88, BIC = 4272.84, and R^2 = 0.72. The value of \beta = -0.066 for this variable is significant at the 99% confidence interval ($p < 0.01$). This value shows that noise pollution significantly impacts the prices of residential properties in the twin cities. Similarly, disaster risk shows that the higher the risk of disaster is, the lower the prices of residential properties in the twin cities.

4.2 Pricing Premium Based on Greenness

To test the greenness of real residential properties, we constructed an urban climate index for each selected property of our sample. This index included air pollution, noise pollution, water pollution, and soil pollution in the specific area where the traded property is located. The index is based on accuracy and precision obtained using machine learning of air pollution, noise pollution, water pollution, and soil pollution, as shown below: -

$$\text{Evirenmenal Score}_{i}=\text{Accuracy Level* water pollution index}_{i}+\text{ccuracy Level*air pollution index}_{i}+\text{ccuracy Level*Noise pollution index}_{i}+\text{ccuracy Level*}\text{Soil pollution index}_{i} \left(6\right)$$

We calculated the environmental score of each specific property based on air pollution, noise pollution, water pollution and the soil pollution index. Based on environmental score, we calculate the greenness index of each property as follows: -

$$\text{Urban Climate Index}_{i}= \frac{(\text{Evirenmenal Score}_{i}-\text{Min.}\text{Evirenmenal Score}_{j})}{(\text{Max.}\text{Evirenmenal Score}_{j}-\text{Min.}\text{Evirenmenal Score}_{j})} \quad 7$$

$\text{Evirenmenal Score}_{i}$ indicates the environmental score of each property, $\text{Min.}\text{Evirenmenal Score}_{j}$ & $\text{Max.}\text{Evirenmenal Score}_{j}$ indicate the minimum and maximum score of the entire sample.

Furthermore, we also calculated the median index. If the score of a specific property is equal to or higher than the median of urban climate index, it was categorized as non-green; otherwise, it was categorized as a green residential property. Further, to validate our calculation of the dummy based on the environmental score, we use ML in Python. The result of the ML model as shown in Table 5 indicates accuracy above 80% and that the SVM, LR, DT, RF, and ANN models were deployed correctly. The comparison of the different ANN architectures is also shown Fig. 3. Therefore, we can assume that these environmental indicators accurately measure the greenness of residential areas.

Table 5
Accuracy and Confirmatory Diagnostics for Greenness Using ML

Method	Accuracy	Precision	Recall	F1 score
SVM (Linear)	0.771	0.825	0.833	0.761
SVM (RBF)	0.791	0.776	0.847	0.794
Logistic Regression	0.757	0.824	0.798	0.795
Decision Tree	0.766	0.805	0.802	0.771
Random Forest (Estimators = 3)	0.819	0.797	0.779	0.825
Random Forest (Estimators = 5)	0.823	0.765	0.813	0.767
Random Forest (Estimators = 8)	0.820	0.782	0.84	0.822
Random Forest (Estimators = 10)	0.844	0.852	0.791	0.782
Random Forest (Estimators = 15)	0.763	0.788	0.761	0.853
ANN (Layers = 2, Neurons = 64)	0.831	0.805	0.775	0.787

Note: The table indicates the accuracy of the measure for the segregation of housing societies into high prestige = 1 and low prestige = 0 based on socio-economic and environmental preferences, using Python and 1500 observations. SVM: support vector machine, LR: logistic regression, DT: decision tree, RF: random forest, ANN: artificial neural networks.

We used stochastic frontier analysis (SFA) to test the pricing efficiency. Table 6 shows that green residential properties are overpriced by an average of 3.676 million rupees (an average actual price = 30.3454, an average estimated fair price = 26.668), as shown in Fig. 4, and similarly, non-green residential real estate is underpriced by an average of -0.222 (an average actual price = 28.222, an average estimated fair price = 28.445), as shown in Fig. 5.

Table 6
Estimation of Fair Prices of Real Estate Properties

	Green Residential Area		Non-Green Residential Area	
	OLS	**SFA**	**OLS**	**SFA**
House Size	2.145	2.162	3.180	3.180
	(14.60)**	(15.16)**	(12.34)**	(12.47)**
No. Bedrooms	0.345	0.340	2.509	2.509
	(3.58)**	(4.63)**	(4.73)**	(4.78)**
Room Size	0.001	0.001	0.028	0.028
	(0.20)	(0.24)	(3.68)**	(3.71)**
No. Bathrooms	0.321	0.241	0.185	0.185
	(0.93)	(0.70)	(0.66)	(0.66)
Presence of Garden	3.497	3.376	0.540	0.540
	(2.28)*	(2.27)*	(0.21)	(0.22)
Presence of Garage	1.406	1.464	0.985	0.984
	(0.93)	(1.00)	(0.37)	(0.38)
Prox Railway Station	-0.183	-0.196	-0.193	-0.193
	(1.20)	(1.32)	(4.89)**	(4.94)**
Prox Market	-0.909	-0.945	-0.246	-0.246
	(3.41)**	(3.61)**	(1.26)	(1.27)
Prox City center	-0.050	-0.047	-0.114	-0.114
	(3.60)**	(5.57)**	(1.70)	(1.72)
Prox Airport	-0.328	-0.332	-0.017	-0.017
	(5.08)**	(5.23)**	(0.50)	(0.51)
Prox School	-0.496	-0.487	-0.443	-0.443
	(2.23)*	(2.23)*	(2.15)*	(2.17)*
Prox Job Places	-0.039	-0.047	-0.258	-0.258
	(0.60)	(0.72)	(3.99)**	(4.03)**
Crime rate	-0.189	-0.191	-0.141	-0.120
	(4.04)**	(4.01)**	(5.01)**	(5.01)**
Cons	6.446	4.420	4.303	4.209
	(1.29)	(1.39)	(1.98)	(1.97)*
R^2	0.66		0.80	
N	710	710	790	790
Actual Price	30.3454		28.222	
Fair Price		(26.668)		(28.445)
Mean Difference		3.676**		-0.222**

Note: This table displays the determinants of fair prices of a sample of 1500 real estate properties using SFA. Price of the properties are presented in PKRs (million). To test the significant difference in the mean, a t-test was applied. ***; ** represent significance at the 1% and 5% levels, respectively.

Rawalpindi and Islamabad are more than just the inseparable twins of Pakistan – one is the capital and home to highly esteemed bureaucrats, diplomats, and famous personalities of Pakistan, while the other hosts the headquarters of the armed forces of the country. The debate over the superior twin – Rawalpindi vs. Islamabad – has existed for a long time. The cost of living in both cities differs for several reasons. This trend shows that investors are willing to pay higher prices for increased greenness and purification. The most crucial factor in Islamabad’s favor is that it is famous for featuring lavish lifestyles with a high cost of living. Rawalpindi is relatively economical, and it is cherished by anyone who is looking to make the most of a limited budget.

4.3 Urban Greenness and Pricing Advantages

In order to test the effects of the urban greenness index and the individual environmental factors on the pricing dynamics of residential properties. We divide our sample into four quartiles and applied SFA on these four the models separately i.e. Model-I = urban pollution index < 25%, (b) Model-II = urban pollution index > 25% < 50%, (c) Model-III = urban pollution index > 50% % < 75% and (d) Model-IV = urban pollution index > 75%. The result in Table (7) Model-I to Model-IV shows that green residential properties to non-green properties are overpriced and underpriced by an average of (mean difference = 4.97**, 2.31**, -0.24** and − 3.76**) which teaches that the higher the level of urban greenness cause lower urban pollution index which further lead to pricing advantages for residents of these areas. The interrelationship between urban pollution and pricing performance is also shown in Fig. 6. One of the reasons for the difference in prices of residential properties in Islamabad and Rawalpindi is the increased presence of greenbelts, parks and natural water resorts in Islamabad. Islamabad, situated at the foothills of Margalla, is known across the globe for its exceptional natural beauty, lush green landscapes and hiking trails, which further fuel increases in the prices of real estate in the city.

Similarly, water pollution in the real estate market has significant importance in determining the prices of residential properties. Lamond, Proverbs, and Hammond (2010) found that houses and residential apartments were devalued by up to 40% because of water pollution. We include the water pollution index in Model-V and find that properties are underpriced by -1.47** million due to water pollution as shown in Table (7), which shows that water pollution plays a significant role in defining the pricing of residential properties in twin cities.

Kim et al. (2010) identified that sulfur dioxide and nitrogen oxide significantly impact residential areas. Although residential areas of Islamabad show better performance in air quality index compared to rest of the cities of Pakistan, Pakistan as a whole is generally suffering from air pollution, as Pakistan is ranked as the country with the 2nd highest air pollution on average, with a US Air Quality Index (AQI) score of 152 (Iqair.com 2021). To test the impact of air pollution on real estate property prices, we included the air pollution as explanatory in Model-VI by controlling hedonic characteristics and we find that air pollution cause underpricing by -2.19** million as shown in Table 7. This shows that higher the air pollution, the higher the pricing disadvantage.

Table 7
Estimation of Fair Prices of Real Estate Properties

	Model-I	Model-II	Model-III	Model-IV	Model-V	Model-VI	Model-VII	Model-VIII
House Size	1.955	1.722	1.264	1.736	1.058	1.853	1.872	1.885
	(7.10)**	(4.50)**	(2.63)**	(6.33)**	(19.94)**	(19.16)**	(18.99)**	(19.02)**
No. Bedrooms	3.563	2.977			0.582	0.496	0.562	0.537
	(4.01)**	(2.43)*			(3.28)**	(3.01)**	(3.35)**	(3.18)**
Room Size	0.055	0.047				0.038	0.024	0.067
	(3.51)**	(2.26)*				(2.23)*	(2.23)*	(2.05)*
No. Bathrooms	1.263	1.688						
	(2.35)*	(2.26)*						
Presence of Garden	3.241			3.101				
	(3.75)**			(3.00)**				
Presence of Garage	1.101	1.585				1.454		
	(4.25)**	(4.34)**				(3.15)**		
Prox Railway Station	-0.039		-0.129		-0.014			
	(1.11)		(2.21)*		(3.58)**			
Prox Market	-0.353		-0.166	-0.193	-0.456			
	(3.40)**		(2.22)*	(2.11)*	(3.00)**			
Prox City center	-0.014							-0.011
	(1.13)							(2.24)*
Prox Airport	-1.241			-2.101			-1.241	
	(3.75)**			(3.12)**			(3.75)**	
Prox School	-1.561	-1.585				-1.098	-1.089	-1.651
	(3.25)**	(6.34)**				(3.15)**	(4.25)**	(4.34)**
Prox Job Places	-0.039		-0.129		-0.014		-0.039	
	(1.11)		(2.21)*		(3.58)**		(1.11)	
Crime rate	-0.353		-0.166	-0.193	-0.456		-0.353	
	(3.40)**		(2.22)*	(2.11)*	(3.00)**		(3.40)**	
Usigma	-3.241	-0.183	-0.196	-0.193	-0.193	-0.196	-1.321	-3.110
	(4.75)**	(2.75)**	(4.11)**	(1.23)	(1.56)	(4.11)**	(3.75)**	(3.75)**
Water Pollution					-0.481			
					(15.50)**			
Air Pollution						-0.349		
						(22.80)**		
Noise Pollution							-0.637	
							(21.13)**	
Soil Pollution								-0.743
								(20.54)**
Avg. Actual Price	30.43	29.43	26.43	27.43	26.43	26.01	25.21	25.34
Avg. Fair Price	25.46	27.12	26.67	31.19	27.90	28.20	28.12	26.02
Mean Difference	4.97**	2.31**	-0.24**	-3.76**	-1.47**	-2.19**	-2.91**	-0.68

Note: Model-I = urban pollution index < 25%, (b) Model-II = urban pollution index > 25% < 50%, (c) Model-III = urban pollution index > 50% % < 75% and (d) Model-IV = urban pollution index > 75%. In Model V-VIII, water, air, noise and soil pollution are included as explanatory variables.

	Model-I	Model-II	Model-III	Model-IV	Model-V	Model-VI	Model-VII	Model-VIII
Vsigma	-1.123 (1.75)	-0.103 (1.02)	-0.121 (1.11)	-0.193 (1.23)	-0.211 (1.56)	-0.312 (1.11)	-1.810 (1.15)	-1.212 (1.21)
N	330	206	456	508	1,500	1,500	1,500	1,500

Note: Model-I = urban pollution index < 25%, (b) Model-II = urban pollution index > 25% < 50%, (c) Model-III = urban pollution index > 50% % < 75% and (d) Model-IV = urban pollution index > 75%. In Model V-VIII, water, air, noise and soil pollution are included as explanatory variables.

Fan et al. (2021) highlighted that noise pollution strongly influences on the prices of residential real estate. This pollution is an invisible danger that cannot be easily observed but is present nonetheless. Noise pollution is considered to be any unwanted or disturbing sound that affects the health and well-being of humans and other organisms. There are various sources that cause noise pollution, including street traffic, air traffic, construction sites, catering and night life, and animals. To test the impact of air pollution on real estate property prices, we included noise pollution as an explanatory variable Model-VII by controlling hedonic characteristics and we find that noise pollution cause underpricing by -2.91** million. This shows that the higher the air pollution, the higher the pricing disadvantage. We find that soil pollution has no significant impact on prices of residential real estate properties.

We also use the Machine Learning (ML) mechanism to measure the role of water, air, noise and soil pollution on overall sample. The out of 1500 observations, 1046 (69.7%) observations were trained and 454 (30.3%) were holdout and test with trained data. The result of SVM: support vector machine, LR: logistic regression, DT: decision tree, RF: random forest, ANN: artificial neural networks showed 80–85% accuracy and precision. The result shown in Figure (7) shows that having similar characteristics of properties, water, air and noise pollution play a significant role in defining prices. The population of Islamabad is increasing very quickly due to migrants from Afghanistan and other cities in Pakistan because of capital territory and employment opportunities. This also increases various types of pollution, such as air, noise, and soil pollution. However, Islamabad has fared very well compared to its neighboring cities, free of the catastrophic spikes of pollution that some of them display. The Capital Development Authority (CDA) has implemented various initiatives to improve the environmental conditions in Islamabad, with a yearly average of 38.6 μg/m³. Due to these initiatives and the greenness of the residential areas of Islamabad, the prices of properties in Islamabad are higher than those in Rawalpindi.

5. Conclusion

The main goal of this paper is to measure the impact of the greenness of residential properties on their prices and determine how much more investors are willing to pay for properties in green residential areas than those in non-green residential areas and greenness causes pricing advantages. We find that the higher the level of greenness and the lower the pollution index, the more investors are willing to pay. Second, air pollution, noise pollution, water and soil pollution emerged as vital factors defining the prices of properties in the hedonic model. This result indicates that urban greenness as an output of urban climate has a significant role in determining the pricing advantages.

The study's findings are different from previous literature that investors are willing to pay higher prices for the properties even those located very far from the city center and job places due to greenness and low pollution index. There are two reasons for it, (a) most cities of Pakistan are highly polluted due to the higher level of urban climate which in result causes various diseases, especially for children and old age family members and (b) after the Paris agreement, regulatory bodies are trying to encourage and ensure compliance with environmentally friendly initiatives which further leads to the development of new societies outside the cities with least urban climate risks and higher greenness. In addition, financial institutions are directed to pay mortgages to green housing societies and residential areas.

The findings of this study may be of interest for regulatory bodies and investors as it contributes to strategies for enhancing the value of their properties by focusing on the environment. This study used only the different external characteristics of real estate properties. To build on these findings, future research should be conducted on how the greenness of residential areas and societies encourages expatriates to invest, which can further lead to higher FDI inflows of green properties and remittances, and how much an investor can earn from green properties in the long run by comparing the prices of green and non-green properties by holding for the short- and long-run.

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The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Abdul Wahid and Muhammad Zubair Mumtaz contributed to the study conception and design. Material preparation, data collection and analysis were performed by Abdul Wahid and Zubair Mumtaz. The first draft of the manuscript was written by Abdul Wahid and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Figures

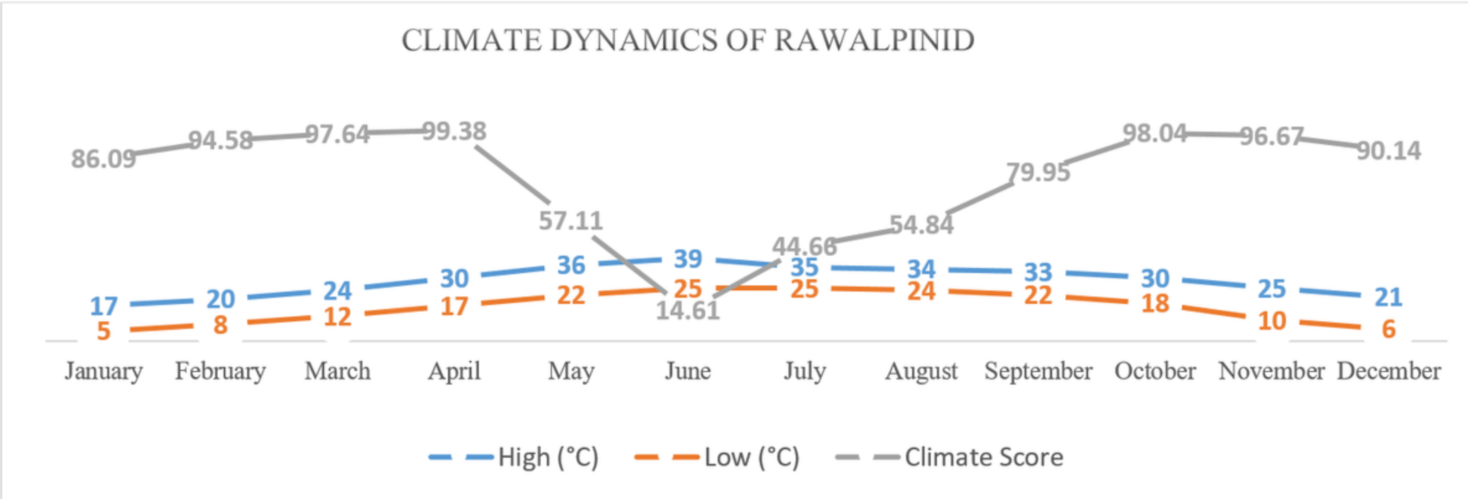

Figure 1

Climate Dynamics of Rawalpindi

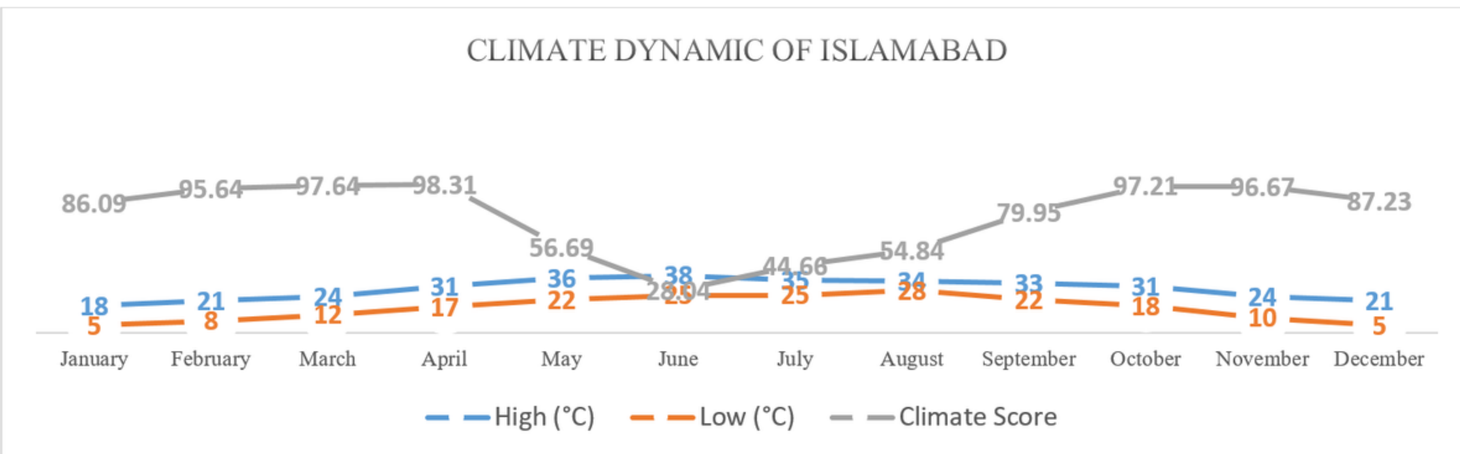

Figure 2

Climate Dynamics of Islamabad

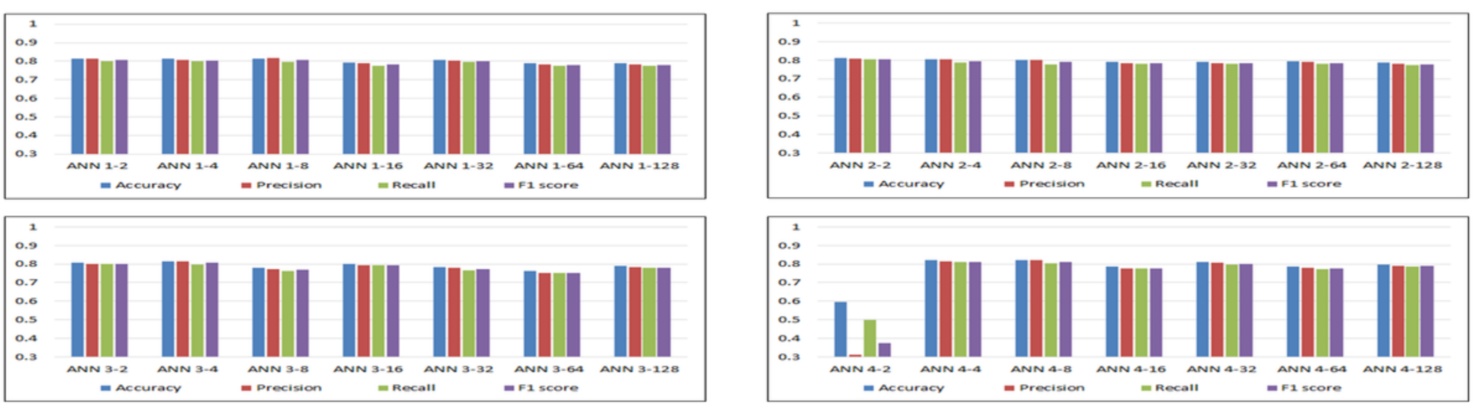

Figure 3

Accuracy and Precision Level

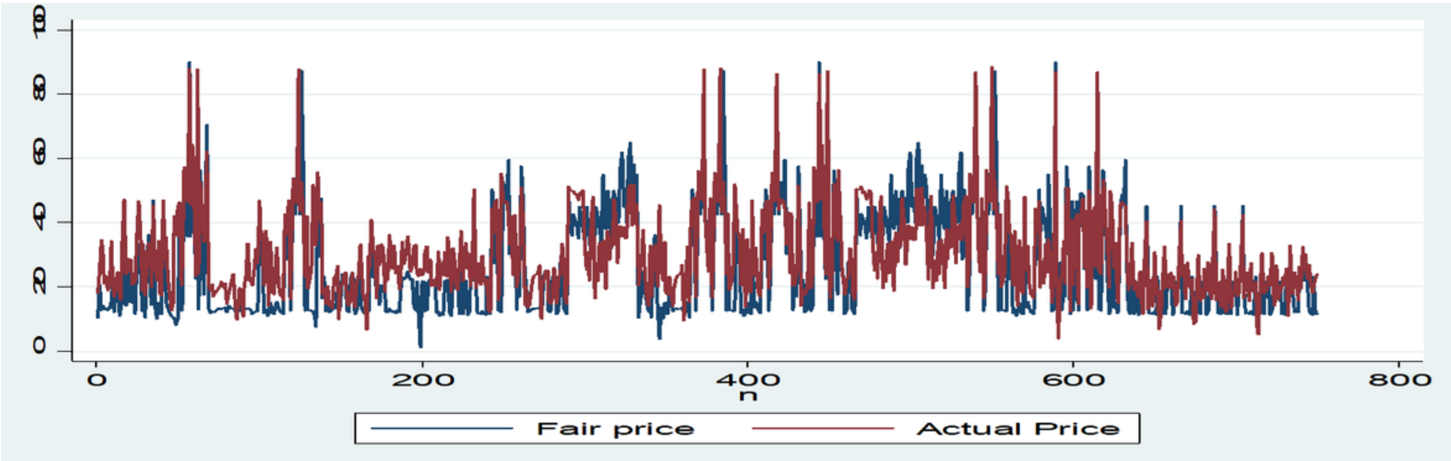

Figure 4

Actual and Fair Price of Green Real Estate Properties (in Million PKRs)

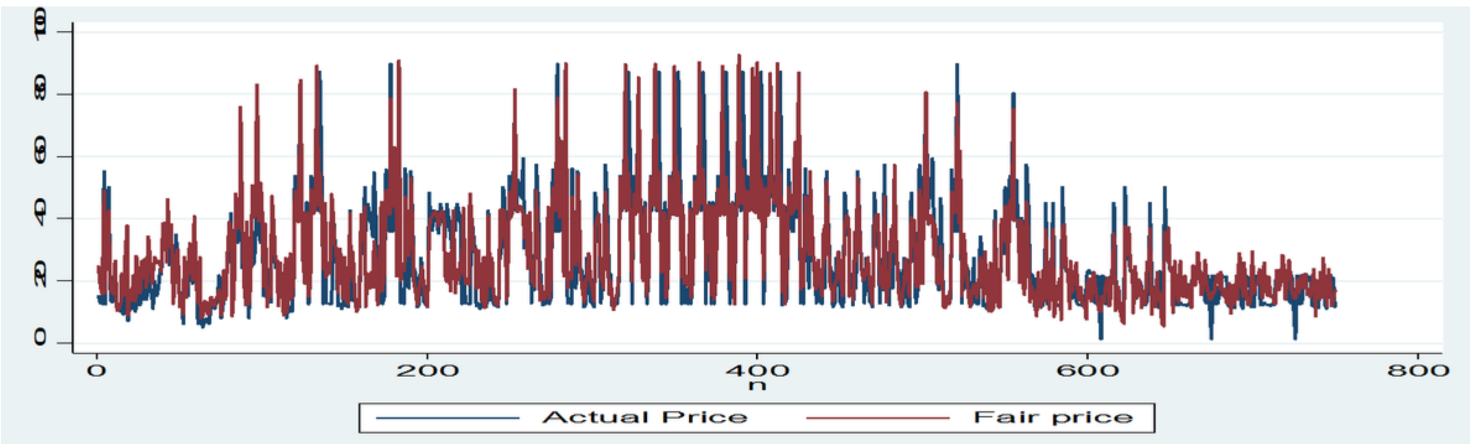

Figure 5

Actual and Fair Price of Non-Green Real Estate Properties (in Million PKRs)

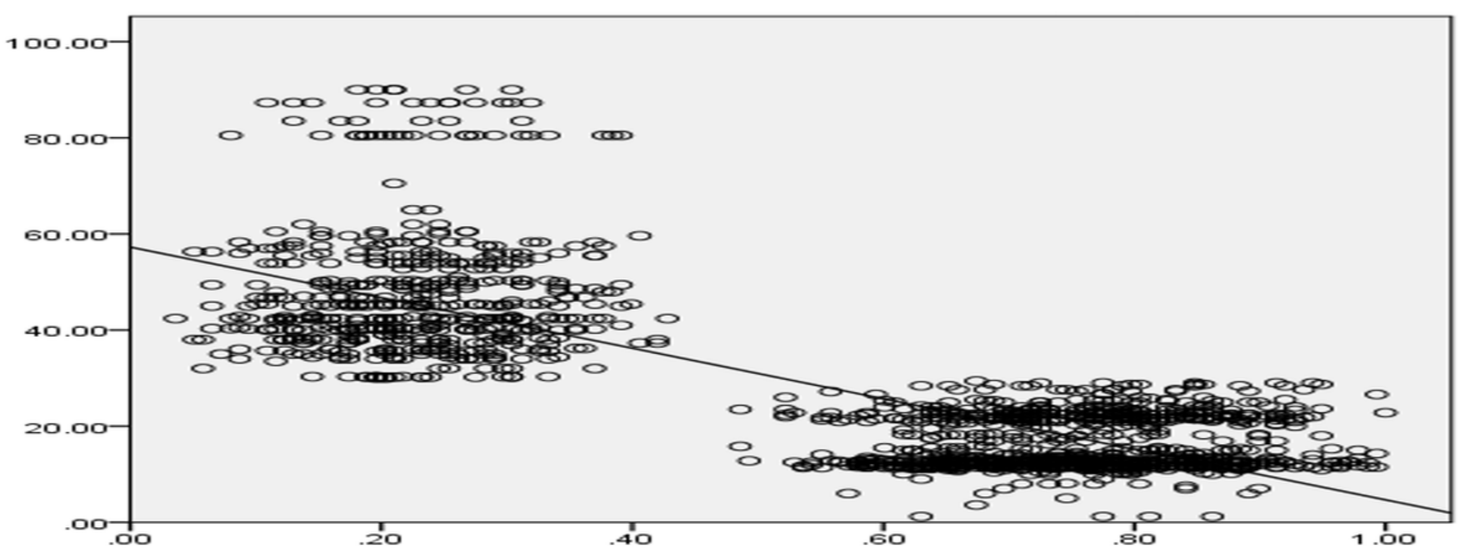

Figure 6

Dynamics of Urban Pollution and Pricing of Residential Real Estate Properties

Note: The liner curve is constructed on overall sample i.e. 1500 observations using machine learning. On the x-axis, a composite urban pollution index of specific properties location is placed and on the y-axis, prices of the same properties are stated.

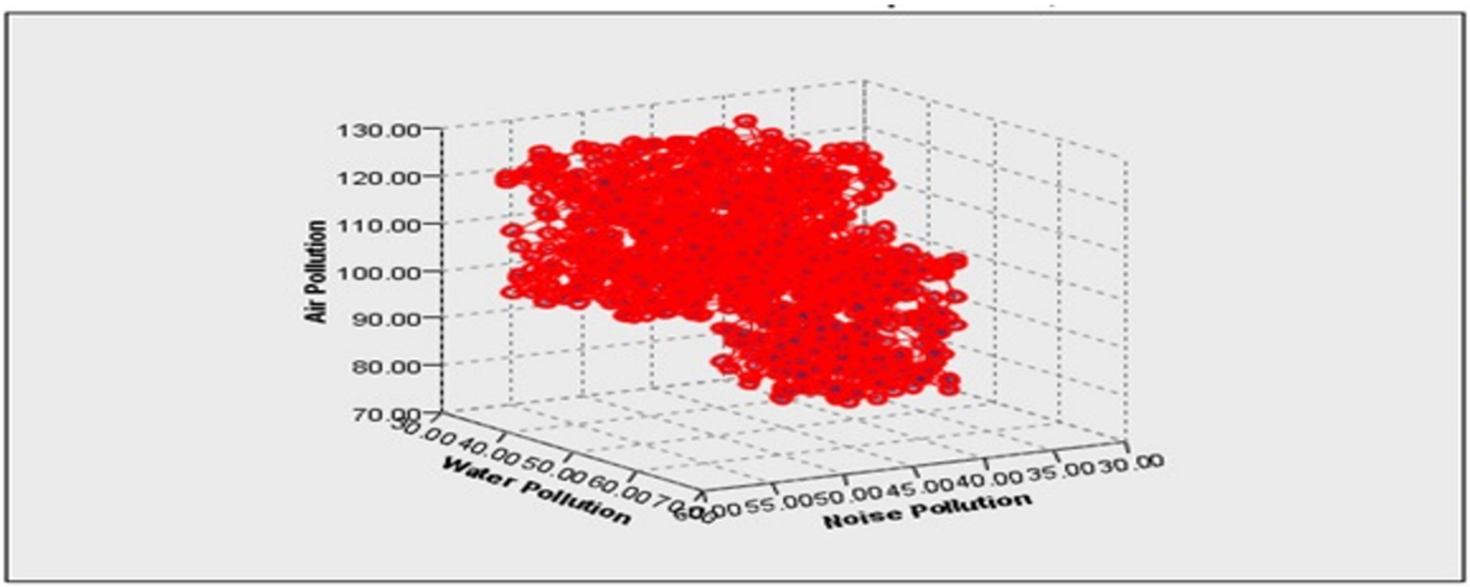

Figure 7

Pricing Dynamics and Pollution Level Using Machine Learning

Note: The neuro-network was applied to 1500 observations using machine learning, including 1046 (69.7%) observations and 454 (30.3%) were holdout and tested with trained data. The result of SVM: support vector machine, LR: logistic regression, DT: decision tree, RF: random forest, ANN: artificial neural networks showed 80-85% accuracy and precision. All characteristics of the hedonic model were taken as control variables and water, air, noise and soil pollution were tested. Three indicators such as noise, air and water pollution emerged as robust in defining volatility in pricing of residential properties.