Valuing the Impact of Air Pollution in Urban Residence Using Hedonic Pricing and Geospatial Analysis, Evidence From Quito, Ecuador

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ABSTRACT: Air pollution is one of the hazardous effects of urbanization. Hereby, one the most polluted cities in Ecuador is the Metropolitan District of Quito (DMQ). This study attempts to determine the marginal willingness to pay for a cleaner air in the DMQ using the impact of air pollutants on price properties. Spatial interpolation techniques visualized pollutant concentrations in the DMQ. Additionally, a hedonic price model estimated air pollution impact on properties. Results demonstrated hazard levels for at least three pollutants, being Particulate Matter $PM_{2.5}$, Nitrogen Dioxide NO_2, and Sulfur Dioxide SO_2. Subsequently, the economic impact on the house market was statistically significant with a decrease in property value between 1.1% and 2.8%. These drop of value between 1,846.20 up to 4,984.74 US$ (United States Dollars) represents a substantial loss in property value for the DMQ and loss of revenues for the city.

KEYWORDS: Air pollution, GIS interpolation, hedonic model, residence value

Introduction

Air pollution is one of the most serious health problems for the public in the world, while its impact is determined through human health negative effects as well as prices of urban residences (Kumar et al., 2016; Liu et al., 2018; Perera, 2017; Riojas-Rodríguez et al., 2016; Romero-Placeres et al., 2006; Vallejo et al., 2003). The World Health Organization (WHO, 2018) released a study on environmental air pollution and estimated that, in both urban and rural areas, 4.2 million premature deaths yearly around the world. In addition, the WHO asserts that people from low- and middle-income countries are enormously more affected by air pollution (Abbas et al., 2019; Edelman Saul et al., 2020; Siddharthan et al., 2018; Thondoo et al., 2019). According to the Pan American Health Organization (PAHO, 2018) a total of 249,000 premature deaths were imputable to outdoor air pollution, from which some 83,000 were directly related to solid fuels as source of household energy use. The PAHO document also indicated that at the area of the Americas around 93,000 deaths occur annually in low- and middle-income countries, while correspondingly some 44,000 fatalities occur in high-income countries.

Additionally, air pollution is one of the associated effects of urbanization and population growth (Duh et al., 2008; Hussain et al., 2019; Kumar et al., 2016; Liu et al., 2018). This global reality is nothing different to Ecuador, a small developing Andean country in northwestern South America, as especially the high levels of air pollution occur in the country's biggest cities, due to their number of inhabitants, automotive fleet, and industries. Such conditions match those of one of the most polluted cities in the country, being the Metropolitan District of Quito (DMQ) (Estrella et al., 2019).

The decline of the air quality in the city of Quito is mainly caused by the accelerated growth of the population, the increase in the number of automobiles, and the progressive development of industries Ministry of Environment of Ecuador (MAE, 2019). These industries include a textile, plastics, automobile assembly plants, and metal melting clustering both at the northern and southern side of the city (Chiriboga, 2009; Distrito Metropolitano de Quito, 2014). However, Estrella et al. (2019) argues that it has been a reduction of air contamination due to restrictions of car traffic circulation. Furthermore, a study by the country's census National Institute of Census and Statistics (INEC) indicated that in 2010 the motorized vehicles amounted to up to 1,226,349 automobiles, while in 2015 the figure reached a total of 1,925,368 automobiles, leading to some 57% of growth of its automotive park in only 5 years (INEC, 2019). The INEC report mentions only official registered vehicles, while DMQ has 22.5% of all registered vehicles. An estimate of some 118,000 vehicles were not registered in 2018. Additionally, the DMQ population is of about 2.7 million people for 2020 (INEC, 2017). Consequently, the DMQ became the most densely populated city in Ecuador.

From an economic point of view, air quality is a public good that embodies both positive and negative externalities. As Baumol and Oates (1988), Goulder and Parry (2008), Baker and Ruting (2014), and Cahoon et al. (2020) have pointed out, air pollution is a negative externality because the lack of prices of air quality allows allocating them inefficiently. Moreover, incomplete information, uncertainty, irreversibility, transfrontier impacts, and the possibility of catastrophic environmental changes, among others, complicate the decision process for policymakers (Armeni, 2016; Collins et al., 2019; Dermont, 2019; Francis et al., 2005; Kørnøv & Thissen, 2000; Likens, 2010; Mubeen et al., 2020; Simms, 2012; von Winterfeldt, 2013). Nonetheless, recent studies regarding environmental economic values are likely to provide guidelines to policymakers (Butler & Oluoch-Kosura, 2006; Costanza

et al., 1997; Gowdy, 2004; Guerry et al., 2015; Sagoff, 2008). Resources that once were considered as non-valuable or of little importance, such as landscape or air quality, are currently considered as a significant source of value and are able to be monetarily quantified (Costanza et al., 1998; Grêt-Regamey et al., 2008; Khanna & Plassmann, 2004; Pearce, 1994).

In addition, air quality demonstrates very high temporal and quality variations (Bajari et al., 2012; Gerdol et al., 2014; Nourse, 1967). This imposes difficulties to monitor pollutants, even though many of the cities around the world, including the DMQ, have installed air quality monitoring networks. Subsequently, spatial interpolations methods are being used in order to create a surface grid for broaden areas. These interpolation techniques allow to estimate concentrations of pollutants using only several monitor stations. In addition, other Geographic Information Systems (GIS) tools are also used in order to visualize air pollution problem of the DMQ and establish the major areas of concentration and risk. The GIS techniques have been applied in order to analyze spatial and temporal distribution of air pollutants (Chiarazzo, Coppola et al., 2014; Deng et al., 2011; Fuertes et al., 2019; Henshaw et al., 2004; Jensen et al., 2001; Kumar et al., 2016; Liu & Ichinose, 2017; Liu et al., 2018; Maantay, 2007; Marquez & Smith, 1999; Sohrabinia & Khorshiddoust, 2007; Streets et al., 2013; van Westen, 2004). Interpolation applications have been generated by several studies (Kim et al., 2014; Whitworth et al., 2011; Wong et al., 2004), as well as those of applications of GIS and hedonic prices (Azmi et al., 2012; Bucsela et al., 2010; Cebula, 2009; Chen & Jin, 2019; Chiarazzo, Dell'Olio et al., 2014; Krotkov et al., 2016; Liu & Ichinose, 2017; Richter et al., 2004). Studies about negative effects of contamination or other environmental hazards on housing attributes have been also widely presented (Abbas et al., 2021; Bajari et al., 2012; Bin & Polasky, 2004; Bin et al., 2008; Brookshire et al., 1985; de Koning et al., 2018; Echegaray-Aveiga et al., 2020; Egbenta et al., 2015; Jurado & Southgate, 1999; MacDonald et al., 1987, 1990; NeJhaddadgar et al., 2020; Raza Abbasi et al., 2021; Rodriguez et al., 2017; Samarasinghe & Sharp, 2010).

The impact of air pollution on house market prices varied depending on each region analyzed as well as on the pollutant. Nourse (1967) encountered a decrease on house value 245.00 US\$ (United States Dollars) for 0.5 mg of SO_2. He was one of the first to estimate the impact of air pollution on residence value. In the same year, Ridker and Henning (1967) found a drop of 0.25 mg/m²/day of SO_2 would increase property value between 83.00 and 245.00 US\$ for the Saint Louis metropolitan area. They added, that such reduction on SO_2 and other sulfates would represent an increase in property value of as much as 82 US\$ million for the city of Saint Louis, which it was reasonably to think that householders would be willing to pay, at least that given amount. Using information from Boston metropolitan area, Harrison and Rubinfeld (1978) estimated the willingness to pay for air quality improvements for reductions in concentrations of NO_2 from 2.0 to 1.0 ppm and found average

annual benefits per household range from 59.17 to 118.00 US\$. Nelson (1978) estimated for residential property values for the Washington, D. C. area using prices and clean air as endogenous variables in a simultaneous equation model, and found an increase of property value of 57.61 US\$ when NO_x reduces by 1 µg/m³ and 14.11 US\$ for a reduction of 0.001 ppm. Using a Random Utility Model, Palmquist and Israngkura (1999) estimated the impact of total suspended particular matter (TSP), NO_2, SO_2, and O_3. They also found that a reduction of 20% of TSP will increase of US\$ 1,548.76 in property value, being a higher value than a hedonic price estimate.

Most recent studies, Bayer et al. (2009) based on EPA air pollution standards for PM_{10}, yielded that household willingness to pay for a reduction in one unit of average concentrations of PM_{10}, was between 149.00 and 185.00 US\$. Their multitemporal study focused on the temporal variation and used 1982 to 1984 constant dollars. Similar to Bayer et al. (2009) findings, Carriazo and Gomez-Mahecha (2018) estimated a reduction of PM_{10} to EPA standards (50 µg/m³) level in the city of Bogota, Colombia will increase house value in 145.92 US\$ per household and a reduction to WHO standards (20 µg/m³) level will benefit house value in 2,275.68 US\$. In the same study, they sought to establish the impact in household welfare adding a second state (SS) model, which allows to identify the demand function and the value of non-marginal changes in air quality. Bajari et al. (2012) encountered price elasticities for three pollutants to be statistically significant with values of –0.07 for PM_{10}, –0.16 for SO_2, and –0.60 for O_3. Individual willingness to pay was 94.00 to 104.00 US\$ for PM_{10}, 54.00 to 141.00 USD\$ for SO_2, and 170.00 to 180 US\$ for O_3 for median house price of \$417,000. Chen and Jin (2019) discovered that an increase of 10% on $PM_{2.5}$ concentration reduces local housing price in 2.4% for an average house size of 101 m², a decrease in value of 17.33/m². Carriazo et al. (2013), for example, notice that there are unobserved variables that most hedonic pricing studies are not taken in account and that results in an overestimation of environmental quality variables using OLS models. Alternatively, Lavín et al. (2011) use wage and rent to estimate implicit prices of crime rate and air pollution using spatially compensating price differentials in the housing and labor markets. These studies helped to reduce the information gap between environmental amenities and house market prices.

Therefore, the current study attempts to determine the marginal willingness to pay for a cleaner air among housing owners in the DMQ, Ecuador. Generating such task, the air pollution impacts on housing values are estimated. Finally, a characterization of the property stock is conducted by using GIS tools, while $PM_{2.5}$, CO, NO_x, O_3, and SO_2 are taken as variables in order to estimate the air pollution impacts on property values.

Methodology

Hedonic pricing model

The hedonic property value model states that individuals can perceived the differences in housing unit characteristics and obtain

different levels of utility from these characteristics. Once the transactions are made, individuals perform trade-offs between money and attributes that reveal the marginal value of these attributes. Assuming that individuals are fully aware of each house unit characteristics (Alberini, 2019; Bishop et al., 2020; Longo & Alberini, 2006). We used the hedonic traditional model developed by Lancaster (1966), Kain and Quigley (1970), and Rosen (1974), which is a function of a combination of structural, neighborhood as well as environmental characteristics. The econometric model relates housing sales prices from three different areas of the DMQ. The model may be expressed as:

$$P_h = f_h(S_h, N_h, \ldots, X_h) \tag{1}$$

Where P_h is housing sale price, S_h refers to structural attributes, N_h refers to social attributes, and X_h other attributes including environmental attributes. The P_h is a vector representing house prices, while the $S_h = S_{h1}, \ldots, S_{hn}$ is a vector representing house structural attributes, such as house construction area in square meters, number of bedrooms, number bathrooms, number of floors area, and so forth. The $N_h = N_{h1}, \ldots, N_{hn}$ is a vector representing social amenities of the house neighborhood such as recreation parks, police community units UPCs, health centers, education centers, among others. The $X_h = X_{h1}, \ldots, X_{hn}$ is a vector representing the house environmental attributes such as air quality, noise levels, among others.

According to Gottlieb (1966), there are several hedonic functions that may be used in order to estimate the impact of the environmental nuisance on house properties such as lineal, quadratic Box-Cox, Log-Lineal, and Semilog-Lineal. When all attributes are observed to be linear and quadratic, then the Box-Cox functions perform best on the normalized mean and standard deviation of error criteria, as pointed out by Cropper et al. (1988).

Due to limited information regarding house markets prices, we have used housing listing prices, as defined by Knight (2002)

and Beracha and Seiler (2014), being the price prior any transactional negotiation. This is a "just below" strategic from the seller in order to receive a fair price for his property (Beracha & Seiler, 2014). In addition, and as a result of some house attributes do not have a linear relationship with price, we considered a log-log function (Gujarati & Porter, 2010). Gujarati and Porter (2010) introduced the no lineal regression model based on the Cobb-Douglas production function, which are intrinsically lineal function. The log-log function can be expressed as:

$$lnP_h = \beta_{h1} lnX_h^{\beta_2} + \varepsilon \tag{2}$$

Where the natural log of the price of a house P_h is a function of the J characteristics assumed to influence price, while ^β is the coefficient to be estimated, and ε is a normally distributed error term. One of the reasons for using the log-log model has been to estimate partial elasticity of price housing characteristics (Gujarati & Porter, 2010). According to Gujarati and Porter (2010) such elasticity represents the marginal willingness to pay for additional upgrading of housing characteristics.

Data collection

In the study hedonic model, price was the dependable variable, representing the listing house price. The independent variables are structural, neighborhood, environmental attributes, the latter of which is measured as the distance between selected properties and the contamination control centers of the DMQ. Structural attributes are nominal variables, meaning the value assigned for each structural characteristic according to the house market value. Additionally, five independent dummy variables were settled with the available GIS tools, as well as location, in order to indicate to which parish each house belongs. The specific hedonic pricing model to estimate the effects of air contamination is best expressed with the following equation:

$$
\begin{aligned}
Ln(P) = {} & \beta_0 + \beta_1 ln(AC) + \beta_2 ln(An) + \beta_3 ln(Ar) + \beta_4 ln(AT) + \beta_5 ln(Ba) + \\
& \beta_6 ln(Cu) + \beta_7 Ga + \beta_8 ln(Ha) + \beta_9 Ja + \beta_{10} ln(Ma) + \beta_{11} ln(Wa) + \\
& \beta_{12} \ln(FL) + \beta_{12} Te + \beta_{13} \ln(DB) + \beta_{14} \ln(DS) + \beta_{15} ln(DE) + \beta_{16} ln(DA) + \\
& \beta_{17} ln(DM) + \beta_{18} ln(DV) + \beta_{19} ln(DHe) + \beta_{20} ln(DU) + \beta_{21} ln(PM_{2.5}) + \\
& \beta_{22} ln(SO_2) + \beta_{23} ln(CO) + \beta_{24} ln(O_3) + \beta_{25} ln(NO_x) + \beta_{26} ln(T) + \beta_{27} ln(V) + \varepsilon
\end{aligned} \tag{3}
$$

All variables used concern those attributes or characteristics that are closely associated with the physical structural composition of a house residence, as well as neighborhood characteristics and environmental attributes regarding levels of contamination. For the inventory of structural composition, the different online property search engines were used. That is, in each of the search engines, first the area/neighborhood of the city was chosen, then, the type of property (house, apartment, land, etc.), while the search engine returned results with those aforementioned conditions. These web pages have had the option of geolocation of the property, therefore once the property (house) had been

chosen, the geographical coordinates were noted. The environmental variables used in the model were measured in micrograms per cubic meter (μg/m³) and included Particulate Matter $PM_{2.5}$, Ozone (O_3), Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), and Sulfur Dioxide (SO_2). This process was performed with each of the study areas and was conducted in the months of March, April, and May 2019. All variables of the econometric model are presented in Table 1 with corresponded measurement units.

From the three filtered databases, a Log-Log econometric hedonic model was developed for each pollutant in order to

Table 1. Description of Econometric Model Variables.

VARIABLE	CODE	DESCRIPTION	UNIT
Price	Ln(P)	Market housing sale prices (sales prices in US$)	$
Construction area	Ln(AC)	House construction area in square meters	m^2
House age	Ln(An)	House unit age	years
Construction materials	Ln(Ar)	House' construction materials $j = 1,..,5$ (Steel/metal structure = 1, Adobe bricks/rammed earth = 2, Concrete structure = 3, Bricks/concrete bricks = 4, Timberwood = 5)	Nominal
Parcel land	Ln(AT)	Bare land size where building stands in square meters	m^2
Number of bathrooms	Ln(Ba)	Number of bathrooms of house unit	Nominal
Roof	Ln(Cu)	House' roofing materials $j = 1, . . .,8)$ (Asbestos cement = 1, Ceramic roof tile = 2, Concrete slab = 3, Steel roofing = 4, Asphalt tile = 5, Clay roof tile = 6, Industrialized roof tile = 7, Zinc sheets = 8)	
Garage	Ga	Doomy variable (1 unit house has a garage, otherwise 0)	Ordinal
Number of bedrooms	Ln(Ha)	Number of bedrooms of house unit	Nominal
Garden	Ja	Doomy variable (1 unit house has a garden, otherwise 0)	Ordinal
Masonry	Ln(Ma)	House' masonry $j = 1, 2, 3$ (Adobe bricks/rammed earth = 1, Bricks/concrete bricks = 2, Prefabricated = 3)	
Finish wall	Ln(Wa)	Finish work of walls of housing unit $j = 1, . . .,7$ (Paintless plaster = 1, Plastered and painted = 2, Ceramic/espacato/wall cladding = 3, Masonry without plastering = 4, Textured (chamfered, graphed, plated) = 5, Glass (structural glass, curtain wall) = 6, Painted on masonry/plastered = 7)	
Number of floors	Ln(FL)	Number of floors per house unit	Nominal
Balcony	Te	Doomy variable (1 unit house has a balcony, otherwise 0)	Ordinal
Garbage cleaning services	Ln(DB)	Distance from the house unit to the garbage containers	m
Neighborhood risk	Ln(DS)	Distance from the house unit to actual assault and car and homes' theft	m
Education services	Ln(DE)	Distance from the house unit to the closest education center o institution	m
Recreational areas	Ln(DA)	Distance from the house unit to closest the recreational areas	m
Supermarket/grocery markets	Ln(DM)	Distance from the house unit to closest supermarket or marketplace	m
Public transportation and mobility	Ln(DV)	Distance from the house unit to the closest public transportation stop and parking services	m
Public health services	Ln(DHe)	Distance from house unit to the closest health center	m
Neighborhood security	Ln(DU)	Distance from house unit to the closest police station	m
Particulate matter	Ln($PM_{2.5}$)	Mixture of solid particles and liquid droplets found in the air with diameters that are generally 2.5 µm and smaller.	µg/m^3
Carbon monoxide	Ln(CO)	Carbon monoxide (CO) intoxication is a tasteless, odorless, nonirritating but highly toxic gas.	µg/m^3
Nitrogen oxides	Ln(NO_X)	Nitrogen oxide (NO_x) is one of a group of highly reactive gases.	µg/m^3
Ozone	Ln(O_3)	Ground-level ozone is a harmful air pollutant, because of its effects on people and the environment, and it is the main ingredient in "smog."	µg/m^3
Sulfur oxides	Ln(SO_2)	Sulfur Oxides is the component of greatest concern and is used as the indicator for the larger group of gaseous sulfur oxides SO_2 can affect both health and the environment.	µg/m^3
Temperature	Ln(T)	Average temperature in Celsius degrees	°C
Wind velocity	Ln(V)	Wind velocity in meters per second	m/s

Note. Description of econometric model variables.

explain the functional relationship between the price of house residence units and its respective explanatory variables (physical, social, and environmental). Additionally, all explanatory variables statistically significant were selected to assemble the final econometric model which explains better the dependent variable. This final model passed through a validation process in which some statistical tests were conducted in order to detect possible issues of multicollinearity, self-correlation, and heteroscedasticity through the Breusch-Pagan-Godfrey White tests (Breusch, 1978; Breusch & Pagan, 1979; Godfrey, 1978; White, 1980). This would allow to validate the coefficients fitness and model predictive test capacity (Gujarati & Porter, 2010).

As some inconsistencies appeared in the first regression model, we did not consider some variables due to some collinearity and their statistical insignificance. Some of the physical house variables and almost all social (neighborhood) variables were not statistically significant, therefore they were eliminated from the regression model. A Dubbin–Watson test was conducted to correct any autocorrelation problem (Durbin & Watson, 1950, 1951). Therefore, the final hedonic price log-log model was expressed as follows:

$$lnP = \alpha_0 + \alpha_1 ln(DE) + \alpha_2 ln(DM) + \alpha_3 ln(AC) + \alpha_4 ln(AT) + \alpha_5 ln(Ba) + \alpha_6 ln(Ha) + \alpha_7 Ja + \alpha_8 ln(An) + \alpha_9 ln(PM_{2.5}) + \alpha_{10} ln(CO) + \alpha_{11} ln(NO_x) + \alpha_{12} ln(O_3) + \alpha_{13} ln(T) + \epsilon \quad (4)$$

Where,

Ln(P)	Natural log of market housing sale prices (sales prices in US$)
Ln(DE)	Natural log of the distance from the house unit to the closest education center or institution
Ln(DM)	Natural log of the distance from the house unit to closest supermarket or marketplace
Ln(AC)	Natural log of house construction area in square meters
Ln(AT)	Natural log of bare land where building stands in square meters
Ln(Ba)	Natural log of number of bathrooms of house unit
Ln(Ha)	Natural log of number of bedrooms of house unit
Ja	Doomy variable (1 unit house has a garden, otherwise 0)
Ln(An)	Natural log of the house unit age
Ln(PM_{2.5})	Mixture of solid particles and liquid droplets found in the air with diameters that are generally 2.5 μm and smaller.
Ln(CO)	Carbon monoxide (CO) intoxication is a tasteless, odorless, nonirritating but highly toxic gas.
Ln(NO_2)	Nitrogen oxide (NO$_x$) is one of a group of highly reactive gases.
Ln(O_3)	Ground-level ozone is a harmful air pollutant, because of its effects on people and the environment, and it is the main ingredient in "smog."
Ln(T)	Average temperature in Celsius degrees

Study area

The current study determined the effects of contamination on house residences of three parishes of the DMQ, being Calderón, Belisario Quevedo, and Guamaní (Figure 1). As previously mentioned, price was the dependable variable, representing the house unit listing price. The independent variables are structural, neighborhood, environmental attributes, the latter of which is measured as the distance between selected properties and the contamination control centers of the DMQ. The Red of the Environmental Monitoring of the DMQ Network (REMMAQ) has nine air monitoring stations distributed along the city. The DMQ has the Quiteño Air Quality Index (IQCA), which is based on the US regulations (AQI), and indicates daily maximum concentrations (Hernandez et al., 2020; Quiroz et al., 2020; Ruggieri & Plaia, 2012).

From each parish, a ratio of a 3 km buffer zone was established in respect to each air monitoring station and selected all properties from de DMQ District cadaster using ArcGis 10.2 (Figure 1). Furthermore, all individual one or two floors house units were selected, while apartment housing units or mixed commercial and residential units were not considered in the hedonic model. A total of 51,766 residential house units were part of our population residential units (Table 2), from which a sample was selected.

The housing sample was obtained from the Weimer's formula, which is used when the population is finite and a confidence interval is estimated, for the average of the sample (Weimer, 2011).

$$n = \frac{N*Z^2*p*(1-p)}{(N-1)*e^2 + Z^2*p*(1-p)} \quad (5)$$

Where,
n is the residential house unit's sample,
N is the population size,
Z is the Z parameter (at 95% level of significance),
e is the error range (5%),
p is the expected probability.

The housing sample yielded 803 housing units, but only a total of 667 housing units were analyzed during the current study, as those units were the only ones on sale during a 3 months period in 2019 time when this study was performed. The sample was divided for three parishes subject of this study and both hedonic models were used in this sample. A total of 267 observations for Calderón Parish, while further 268 each observation was accounted for Belisario Quevedo and Guamaní Parishes. The sample needs to include information on the value of real estate and air pollution in the area where it is located.

GIS interpolation

In order to estimate the economic impact of air contamination on the selected areas, an interpolation is required by using GIS tools. There are several kinds of interpolation techniques inbuilt in GIS, which include inverse distance weighting
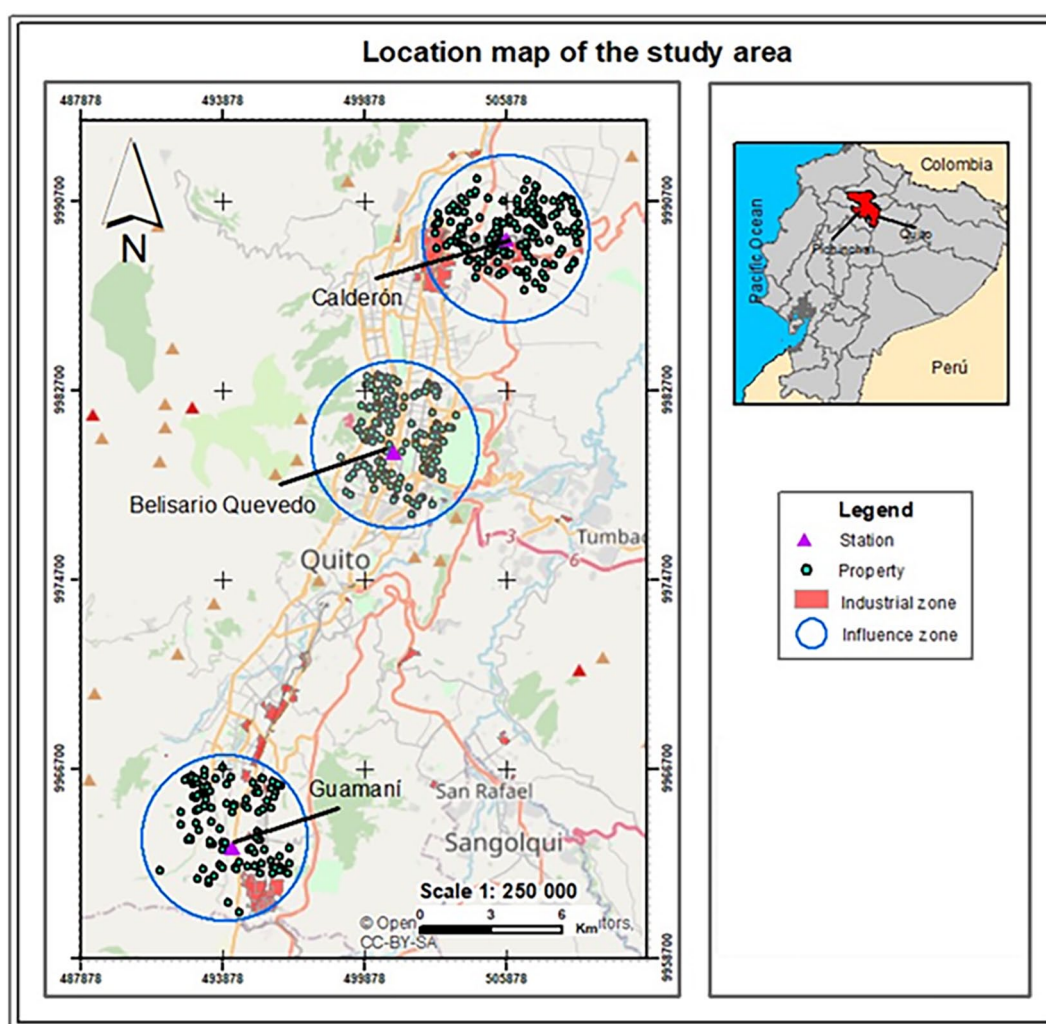
Figure 1. Study area.

Table 2. Population House Residential Units.

PARISH	HOUSE RESIDENTIAL UNITS	AVERAGE RESIDENTIAL UNIT SIZE (M²)	AVERAGE PRICE (US$/M²)
Calderón	14,288	163.47	612.84
Belisario Quevedo	18,509	404.19	887.63
Guamaní	18,969	163.51	459.28

Source. DMQ cadaster.
Note. Population house residential units.

(IDW), Kriging, and spline (Childs, 2004). Childs (2004) asserts that the IDW determines the cell values using a linear weighted combination set of sample points and the weight is assigned as a function of distance of an input point from the output cell location. The greater the distance, the less influence the cell has on the output value. These techniques are mostly used in air pollution studies (Jha et al., 2010, 2011). Evaluation of interpolation technique for air quality parameters in Port Blair, India (Wong et al., 2004). When the set of points is dense enough to capture the extent of local surface variation needed for the analysis, then the IDW is used.

Spline estimates values for unknown points using a mathematical function that minimizes the overall surface curvature (Greiner, 1991). This results in a smooth surface which passes exactly through the points. In this respect, Childs (2004) remarks the regularized spline incorporates three derivatives, of which the first is the slope, the second is the rate of change in the slope, and the third is the rate of change of the second derivative. This method is a special type of piecewise polynomial interpolation and best for gently varying surfaces. It is often preferred with a small interpolation error even when using low degree polynomials for the spline. Hereby, this

method is able to predict ridges and valleys in the data, being the best method for representing smoothly varying surfaces of phenomenon (Childs, 2004).

Kriging is a powerful statistical method of interpolation for which the interpolated values are modeled by a Gaussian process governed by prior covariances (Bailey & Gatrell, 1995). It is a stochastic method that is used for diverse applications such as health science, geochemistry, and pollution modeling (Griffith, 1988). It assumes that the distance or direction between sample points reflects a spatial correlation that represents variation in surface. Hereby, it produces better estimates to consider explicitly of the effect of random noise. Also, it is less susceptible to use in arbitrary decision and indication of the estimates (Childs, 2004). The tool predicts the values for all locations within a specified radius as a function of specified number of points or all points. Furthermore, it uses a sophisticated weighted average technique in order to predict values from observed samples. There are many types of Kriging, such as ordinary, spherical, and Gaussian. The mathematical formulation is been given in the following equation:

$$Z^*(u) - m(u) = \sum_{i=1}^{n(u)} \lambda_i \left[Z(u_i) - m(u_i) \right] \qquad (6)$$

where u and u_i are location vectors for estimation point and one of the neighboring data points, indexed by i; $n(u)$ is the number of data points in the local neighborhood used for estimation of $Z^*(u)$; $m(u)$ and $m(u_i)$ are expected values (means) of $Z(u)$ and $Z(u_i)$; and $\lambda_i(u)$ is the Kriging weight assigned for datum $Z(u_i)$ for estimation of location u. The same datum will receive a different weight for different estimation location. Kriging is more appropriate technique when the spatial correlated distance is known (Childs, 2004).

Results

Air contamination, as an environmental attribute was expected to have an effect on residence house units. The levels of contamination were from the atmospheric monitoring stations of the DMQ. A prediction map was used in order to better represent the environmental problem that occurs in a parish. The environmental attributes were the levels of each air pollutant ($PM_{2.5}$, SO_2, CO, O_3, and NO_2) and evaluate which of all these contaminants may has an effect on residence house units. We adjusted the IQCA to air pollutant levels and the colors for each category (Table 3) were based on the study of Corporation for the Air Quality Improvement of Quito (CORPAIRE, 2004).

Table 3. Air Contamination in the DMQ From IQCA (μg/m³).

RANGE	AQI LEVELS OF HEALTH CONCERN	CO[A]	O₃[B]	NOₓ[C]	SO₂[D]	PM₂.₅[E]
0–50	Good	0–5,000	0–80	0–75	0–175	0–33
50–100	Moderate	5,001–10,000	81–160	76–150	176–350	34–65
100–200	Unhealthy for sensitives	10,001–15,000	161–300	151–1200	351–800	66–150
200–300	Unhealthy	15,001–30,000	301–600	1,201–2,300	801–1,600	151–250
300–400	Very unhealthy	30,001–40,000	601–800	2,301–3,000	1,601–2,100	251–350
400–500	Hazardous	>40,000	>800	>3,000	>2,100	>350

[a]An average concentration of 8 hours.
[b]Average concentration in 1 hour of photochemical oxidants named as ozone.
[c]Maximum concentration during 24 hours of nitrogen oxides names as NO_2.
[d]Average concentration in 24 hours.
[e]Maximum concentration of particles in 24 hours; based on the United States AQI.

Air contamination levels for each pollutant are illustrated in Figure 2. In relation to $PM_{2.5}$, the results yielded that in the El Camal station surroundings appeared at hazardous level characterized by a red color according to IQCA levels, while, for the surroundings of the stations of Calderón, Guamaní, El Centro have unhealthy levels represented by an orange color in Figure 2. The Cotocollao Station comprised an unhealthy range for sensitive groups, indicated by the green color in Figure 2. Finally, the environments of the Tumbaco and Los Chillos stations indicated good to moderate levels showed with gray color in Figure 2. Similar results were encountered with NO_2. This pollutant is fundamental as it is the only one that people are

able to perceive. The El Camal station surroundings exhibited again hazardous levels (indicated by a red color in Figure 2), but the rest of control stations were in the range between good to unhealthy for sensitive groups (gray and green colors in Figure 2). Similar to NO_2, SO_2 levels of contamination emerged at the hazardous level at the El Camal station represented by red color in the surroundings of the station (Figure 2). The other two pollutants, such as O_3 and CO appeared between good and unhealthy for sensitive people in almost the entire city, but had hazardous levels of O_3 at the Guamaní station indicated by a red color in Figure 2 and hazardous effects of CO close to the Cotocollao station also represented by a red
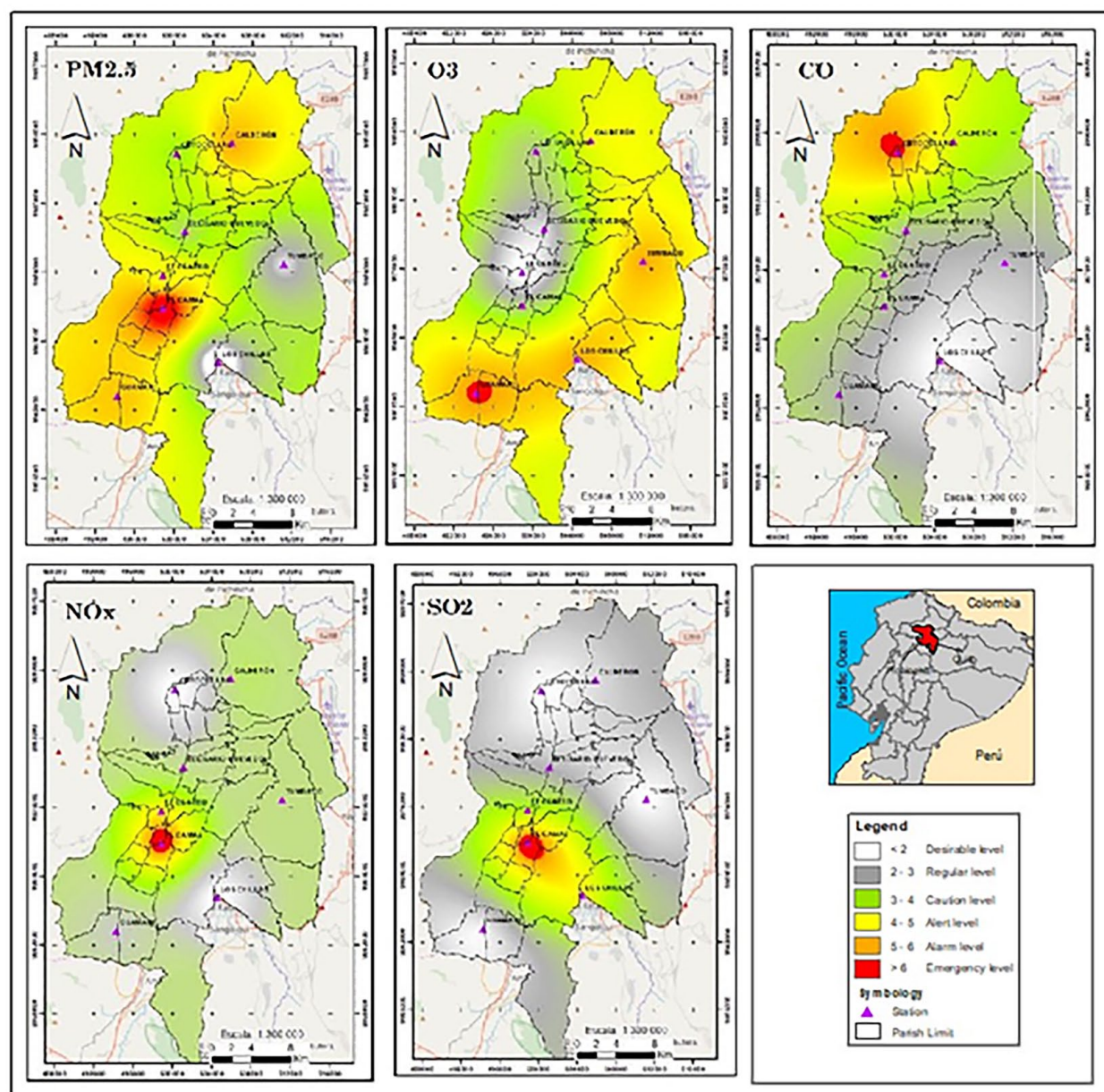
Figure 2. Contamination levels of the DMQ.

color in Figure 2. The hazards levels of the Camal station for $PM_{2.5}$, NO_x, SO_2 may be a consequence of industrial clustering in this area. The other industrial clustering is located to the north of Quito, relatively close to Cotocollao station. However, this station did not show high levels of unhazarded levels of for these pollutants.

The three main data stations for this study support the interpolation results of DMQ pollution levels displayed in Figure 2. The $PM_{2.5}$ indicates similar pollution levels in these three stations, as well as NO_2. Whereas, CO yielded higher pollution levels at Calderón station and O_3 within surroundings of Guamaní station (Figure 3). On the other hand, SO_2 appears at low pollution levels in all three stations (Table 4).

Consequently, the results demonstrated that air pollution as an environmental attribute at the DMQ had influenced the

prices of the residence house unit (Table 5) as validated by using the logarithmic functional form (Log-Log). The environmental variable ($PM_{2.5}$, SO_2, CO, O_3, and NO_x) have been performed in the EViews 10 program separately for each of the pollutants. Hereby, the econometric log-log model fitted almost perfectly with data, as the adjusted R^2 yielded about 0.923.

The CO and NO_x gases coefficients were obtained with a negative sign and were significant at 95%. On the other hand, for $PM_{2.5}$ and O_3 their coefficients were of negative sign and were not significant at 95%. In similar studies the logic of thought of all pollutants were expected to have negative sign coefficients, since the higher the amount of air pollution by the polluter, the lower the price of residence house unit would be. In other words, the relationship between the pollutant and the
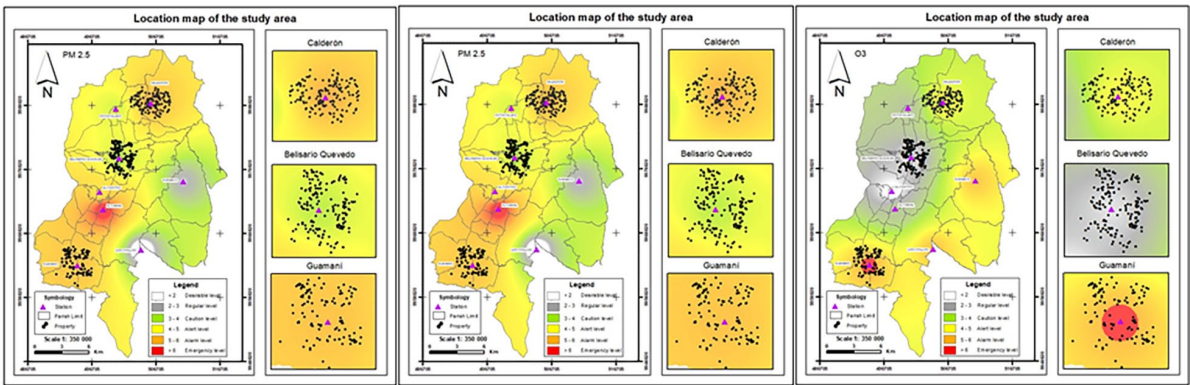
Figure 3. Contamination levels within the three main stations of the DMQ.

Table 4. Contamination Levels of Major Pollutants in the DMQ.

	BELISARIO QUEVEDO (μG/M^3)	CALDERÓN (μG/M^3)	GUAMANÍ (μG/M^3)	SAMPLE AVERAGE (μG/M^3)	SAMPLE *SD*
PM$_{2.5}$	17.4	17.4	17.4	17.96	1.19
CO	4.3	5.5	4.1	4.85	0.67
NO$_X$	23.5	23.6	22.4	23.26	0.59
O$_3$	19.4	24.9	27.9	23.78	2.78
SO$_2$	2.8	2.3	2.1	2.52	0.29

Note. Contamination levels of major pollutants in the DMQ.

Table 5. Original Hedonic Price Log-Log Model.

VARIABLE	STATISTICS	SIGNIFICANCE	VARIABLE	STATISTICS	SIGNIFICANCE
(Constant)	17.620 (−7.136)	***	Ln(Ba)	0.135 (−3.335)	***
Ln(DE)	0.022 (−0.03)		Ln(Ha)	0.156 (−3.152)	***
Ln(DHe)	0.022 (−1.249)		Te	0.029 (−1.42)	
Ln(DU)	0.008 (−0.495)		Ln(FL)	−0.033 (−0.832)	
Ln(DS)	0.007−0.336		Ga	0.037 (−0.733)	
Ln(DA)	−0.012 (−0.626)		Ja	0.095 (−4.427)	***
Ln(DB)	0.0002−0.012		Ln(An)	−0.029 (−3.534)	***
Ln(DM)	−0.048 (−2.272)	**	Ln(PM$_{2.5}$)	−1.551 (−1.273)	
Ln(DV)	0.029 (−1.465)		Ln(CO)	−1.047 (−2.391)	**
Ln(Ar)	0.031 (−0.523)		Ln(NO$_X$)	−2.806 (−2.120)	**
Ln(Ma)	−0.01 (−0.121)		Ln(O$_3$)	−0.67 (−1.086)	
Ln(Wa)	0.029 (−1.216)		Ln(SO$_X$)	0.059 (−0.283)	
Ln(Cu)	−0.014 (−0.649)		Ln(T)	2.592 (−3.536)	***
Ln(AC)	0.493 (−11.044)	***	Ln(*V*)	−0.375 (−0.680)	
Ln(AT)	0.248 (−6.975)	***			
			Adjusted *R*^{2}	0.92	
			Dubbin–Watson	1.913	
			F-stat	214.419	***
Ln(Cu)	−0.014 (−0.649)		Ln(*T*)	2.592 (−3.536)	***

Note. Original hedonic price log-log model.
***99% of significance, **95% of significance, *90% of significance.

Table 6. Final Hedonic Price Log-Log Model.

VARIABLE	STATISTICS 1% INCREASE POLLUTION	SIGNIFICANCE
(Constant)	18.729 (10.957)	***
Ln(DE)	0.038 (1.938)	*
Ln(DM)	-0.030 (-1.906)	*
Ln(AC)	0.491 (11.686)	***
Ln(AT)	0.256 (7.694)	***
Ln(Ba)	0.141 (3.741)	***
Ln(Ha)	0.145 (3.007)	***
Ja	0.096 (4.661)	***
Ln(An)	-0.032 (-4.029)	***
Ln(PM$_{2.5}$)	-1.733 (-2.113)	**
Ln(CO)	-1.103 (-3.431)	***
Ln(NO$_X$)	-2.765 (-2.890)	***
Ln(O$_3$)	-0.857 (-1.935)	*
Ln(T)	2.641 (4.485)	***
Adjusted R^2	0.921	
Dubbin–Watson	1.932	
F-stat	481.675	***

Note. Final hedonic price log-log model.
***99% of significance, **95% of significance, *90% of significance.

house price is inversely proportional or negative. However, unexpectedly, the results regarding SO$_2$ were not significant and its coefficient resulted with a positive sign. This unexpected outcome may be as a result of the low levels of contamination as it is illustrated in Table 4.

The results of other house features were as anticipated. Variables such as construction area, parcel size, number of bedrooms, number of bathrooms, house's age, and presence of a garden were significant at 99%. Among neighborhood characteristics, only distance to closest market was significant at 95%.

We selected all significant variables with the environmental variables and ran again the final regression model with an increase of 1% of pollution levels for each pollutant. As in the original regression, all physical and neighborhood characteristics such as construction area, parcel size, number of bedrooms, number of bathrooms, house's age, and presence of a garden were significant at 99%. Yet, in this second regression, distance to closest market place were only significant at the 90% level. Distance to education centers appeared significant also at about 90%, which was not significant in the original regression (Table 6).

The results were interesting as all environmental variables were significant (Table 6), including O$_3$ and PM$_{2.5}$, which in

the original lacked to be statistically significant. The new hedonic model had an adjusted R^2 of 0.921, meaning that it fits with most of the data. Furthermore, the given results demonstrate that air pollution has a significant negative effect on residence values, while house market values will decrease proportionally with 1% increase on air pollutants.

The most significant among them was the NO$_2$ with a coefficient of −2.765, meaning that an increase in 1% of this pollutant will have a 2.8% decrease in the property price (Table 6). As aforementioned, the NO$_x$ is one of the very few air pollutants that people are able to perceive. This result is significant since the average residence value is 865.13 US\$/m², meaning a reduction in house value of 23.92 US\$/m². The other one is O$_3$, which was also statistically significant, but only at 10%. The impact of increasing 1% in concentration of O$_3$ will affect by decreasing the residence value in 7.41 US\$/m². The other two air pollutants are significant as these are gases that people are not able to perceive, as these are odorless. The most dangerous of all gases being PM$_{2.5}$, had a coefficient of −1.733 and was statistically significant at 95%. This means that an increase in 1% in PM$_{2.5}$ concentrations will reduce a property value in 14.99 US\$/m². The CO, also a very hazardous gas, had a coefficient of −1,103 and 99% of significance, meaning that an increase of CO concentrations will affect in reducing the house value in 9.54 US\$/m² (Table 6).

The results clearly support our initial assumption that air contamination significantly affects property values. As expected, all physical features included in the final regression model had a positive impact on residence house prices and were statistically significant. House size (LnAC) and parcel size (LnAT) were the most important in terms of house prices. As a final point, we note that our study is not exclusively opted for residential area, rather fit also for commercial buildings such as malls and restaurants. However, we did not consider these buildings in our hedonic price model.

Discussion

Using GIS tools allowed us to estimate the impact of air contamination in the city of Quito through GIS interpolation. The levels of contamination were hazardous particularly in the El Camal control station surroundings. This area was particular at risk in at least three out of five pollutants considered. This study was limited to demonstrate the range of contaminants, but it did not consider the reason why this area is particularly risky.

The Hedonic Regression model allowed us also to estimate the effect of air contamination on residence housing. As a tool, the hedonic price model combined with GIS tools enabled to determine the correlation between house environmental characteristics and the sale price. The results illustrate that air contaminants such as NO$_x$ and O$_3$, pollutants that people are able to perceive, and PM$_{2.5}$ and CO which people cannot smell, have a negative α coefficient with price. This means that the price of a

residential house unit located in areas of high concentration of all these contaminants is significantly lower than other residential properties located outside of the area of influence of the air control stations. We determined that the price of a residential house will increase between 7.41 up to 23.92 US$ by rise of 1% of the pollution levels depending of the type of pollutant. In addition, price of house increases between 1.1% and 2.8% when house distance apart from air pollutants high concentration. Palmquist and Israngkura (1999) encountered a 4% increase in house price for α. Nourse (1967) findings indicate a decrease in value of 3.9%, assuming an increase of 0.5 mg of sulfur trioxide (SO_3) per square meter per day. The study by Nourse (1967) was a time series between 1957 and 1964. Our study was settled for 1 year analysis and sulfur dioxide (SO_2) was not statistically significant. Nelson (1978) indicated damages between 60 and 70 US$ for an increase of 1 $\mu g/m^3$/day in suspended particles with a coefficient of −0.019. Liu et al. (2018) encountered a decrease in selling house price of 3.97% if the quality index rises by 0.1. Their study also used sales house price as a dependent variable. On the other hand, Bajari et al. (2012) yielded that an increase of 1 ppb in SO_2 would affect house annual return by 0.013%. All these studies determined pollutant concentration or variations of pollutant concentrations instead of distance from main source point as demonstrated in our current study. We realized that the price of a residential house will decrease between 1.9% and 6.0% in value by increasing 1% of pollution, depending on the contaminant.

The results are significant because with an average housing price of 184,620.00 US$, the loss between 1,846.20 and 4,984.74 US$ represents a significant drop in property value. If we forecast this drop in value for all 51,766 residential properties of all three areas involved in the current study, the lost value would rise up to 95,570,389.20 US$ as the lowest bound. This is a tremendous loss in property value as an effect of air contamination. Policy makers should consider such value in order to design policies that make sense in terms of control of air contamination.

Conclusions

The results of the present study demonstrated the impact of air pollution on house properties and combined with GIS interpolation indicated the potential effect of pollutants across all city. This is particular interesting as the results from all three parishes are able to be extrapolated for the entire city. The GIS interpolation allowed to demonstrate one particular characteristic of air pollutants, which is that there are not uniformly distributed. Secondly, an increase of 1% of each contaminant varies the impact of residential housing and most importantly, this study yield such impact with those contaminants that are not perceived by potential buyers. This is particular of interest as the marginal willingness to pay by buyers depends upon their perception of all house characteristics, including environmental disamenities.

Furthermore, we were able to indicate the potential loses of the city regarding property taxes. The DMQ has a range from 2.25/1,000 to 5/1,000 as property taxes depending on the city's area and house characteristics. The loss in property value between 1,846.20 and 4,984.74 US$ means that DMQ lacks to collect between 215,000 to over 1,000,000 annually in property taxes from these three parishes, and several uncollected millions of dollars for the entire city.

Improving air quality is worth by no means for a city not only increasing city's revenues, but also declining loss of property value and reducing health problems and premature deaths. Several recent studies have demonstrated that reducing main source of pollution during the lockdown in many countries improves air quality between 15% and 36% depending on the pollutant (Amouei Torkmahalleh et al., 2021; Kumar et al., 2020; Othman & Latif, 2021; Pacheco et al., 2020; Venter et al., 2020; Zalakeviciute et al., 2020). All these studies proved that in short period of time during COVID-19 lockdown (Abbas et al., 2021; Azizi et al., 2021; Su et al., 2021; Wang et al., 2021), few weeks according to these authors, air pollution declined rapidly, with exception of O_3. In terms of economic and environmental policies, any policy to prevent air contamination will be undeniably worth it.

There are some limitations in our analysis since we did not consider insurance premium information, partially because of lack of information, but also due to a limited market for this type of insurance on property values in the residential area of DMQ.

We did not consider either a time series study due to restricted information regarding housing market of our study area. Based on the information from Real Estate firm's web site of sales during the time of the current study, our results are site-specific. Therefore, our data analysis may not be suited to any generalization regarding policy making.

The reasons why O_3 is severely concentrated in the Guamaní control station area remains unknown to date, as well as the concentrations of CO in the Cotocollao control station. Additional studies are required in order to understand such particular distributions of air pollutants in the DMQ. Furthermore, it would be very interesting to know if there is any correlation between coefficient values of each pollutant with the interpolation values estimated in this study.

However, our results are significant enough to call the attention of policy makers in order to start more profound studies regarding air contamination in the Metropolitan District of Quito.

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Rodríguez-Espinosa Conceptualization, Methodology, Data analysis and interpretation, Writing-Original draft preparation. Marcos Luna- Ludueña Data spatial modelling analysis, Data interpretation and Data validation, and Formal Analysis. Theofilos Toulkeridis Writing, Reviewing and Editing.

Availability of Data and Materials

The data were gathered from Real Estate business companies, which are included in the paper's Reference List.

Consent of Publication

The main goal of authors of this research was, and still is, to get published as it is clearly included in "cover letter" where authors are declaring their consent.

Declaration of Conflicting Interests

The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: We ensure, that our manuscript has NOT been submitted simultaneously for publication anywhere else, containing original data and a paper not presented previously at any congress as it was stated in the author's "cover letter." We do not have any material (figures, images, or tables) included in the manuscript that may require to obtain permission to reproduce copyrighted material from other sources, and there is no conflict of interest with any party.

Ethical Approval and Consent to Participate

Not applicable. The present study was designed using public information and data, as a result, it did not require consent to participate. Additionally, the econometric model has no ethical implications and did not affect any person that might require ethics approval.

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