Saving old cities: land use regression model for traffic emissions in the Historical Peninsula of Istanbul

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Abstract: This study aims to develop a pollution distribution model for estimating traffic related intra-urban concentrations of nitrogen dioxide (NO_2) levels. Weekly concentrations of NO_2 were measured at 45 different locations in the Historical Peninsula of Istanbul during spring, summer and winter seasons in 2010. The range of NO_2 was 14.2–155 μg/m^3. A land use regressing (LUR) model was developed to explore the impact of independent variables on the measured levels. Independent model variables were selected based on land use characteristics, traffic and road network information, and meteorological data. Results suggest that 150 metre range is the most effective buffer zone for NO_2 distribution characteristics in the study area. Average wind speed and temperature data have significant influences (up to 25%) on the prediction performances. Better estimations were produced for spring and winter seasons, particularly for in land stations compared with costal ones. As a result, the overall prediction performance of the constructed model is satisfactory ($R^2 = 0.64$).

Keywords: clean cities; air pollution; geographic information systems; spatial regression; exposure modelling.

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1 Introduction

The centre of ancient Istanbul, which is named as the Historical Peninsula, includes various historic sites which are among the masterpieces of the world cultural and historical heritage. Just as the Historical Peninsula is the cultural centre of Istanbul, Istanbul is the cultural centre city of Turkey. The Historical Peninsula of Istanbul draws international attention and attracts visitors from all over the world. Human presence in this region is very intense. It is estimated that more than 1.5 million people enter the Historical Peninsula each day. With the increase of population and extensive amount of traffic in the area, a research focusing on the anthropogenic effects on the delicate historical sites which are located within this region has become quite important. One of the most important problems threatening the historical and cultural heritage stocks in the area is air pollution (UNESCO, 2012).

Recent studies have demonstrated that air pollution is associated with deterioration, corrosion, soiling and other synergistic effects on cultural and historical materials in urban environments (de la Fuente et al., 2011; Nava et al., 2010; Ozga et al., 2011; Worobiec et al., 2010). The most important pollutants which cause deterioration on various materials are atmospheric sulphur dioxide, nitrogen dioxide and ozone (Ferm et al., 2005, 2006). Among numerous air pollutants, traffic-related emissions (particles, sulphur oxides, nitrogen oxides, carbon oxides, volatile organic compounds, etc.) are at the top of dangerous ones for urban environments. Atmospheric sulphur dioxide concentrations were decreased in urban regions as a consequence of concerted international policy actions. But despite the decreasing sulphur dioxide levels in most parts of Europe, elevated levels of nitrogen compounds, ozone and particulates became more important pollutants (Ferm et al., 2006).

Air pollution related risk assessment studies can be integrated into hazard identification, dose-response assessment, and exposure assessment studies. Exposure maps that demonstrate accurate and precise spatial distribution of risky pollutants are among the important tools in risk management applications (Crouse et al., 2009). Recent investigations demonstrated that more sophisticated exposure assessment methods are needed for better handling of intra-urban variability of pollutant concentrations. Among dispersion models, interpolation techniques and land use regression (LUR) methods are widely used where the later one has some advantages to fulfil the requirements of air quality management plans and strategies (Henderson et al., 2007; Rosenlund et al., 2008; Skene et al., 2010).

In related literature, there is no standard method for constructing a LUR model. In brief, linear regression models pollutant concentrations using predictive variables based on land use and meteorological data. Most of the studies use ad hoc procedures to determine sampling periods and sampler locations. NO_2 has selected a typical traffic emission parameter in multiple LUR studies (Hoek et al., 2008). A significant part of NO_2 concentrations present in the atmosphere is linked to primary traffic-related emissions, and it can be monitored relatively inexpensive measurement methods (Henderson et al., 2007). However, ambient NO_2 concentrations are mostly attributed to secondary production from NO, the dominant traffic emission parameter in the atmosphere through photochemical processes. NO_2 photochemistry is a complex process. Several atmospheric pollutants including volatile organic compounds, ozone, sulphur compounds, and CO determine the reaction rate and speed (Mavroidis and Chaloulakou, 2011). Although there is an inter-conversion process between NO and NO_2, nitrogen dioxide is considered more stable and homogenous one representing traffic-related emissions (Henderson et al., 2007).

This study has a particular aim to test the value of employing regional meteorology and land use data (e.g., elevation, and distance to sea) in a LUR model built on the spatially high-resolution monitoring network over a micro scale complex urban structure region.

2 Materials and methods

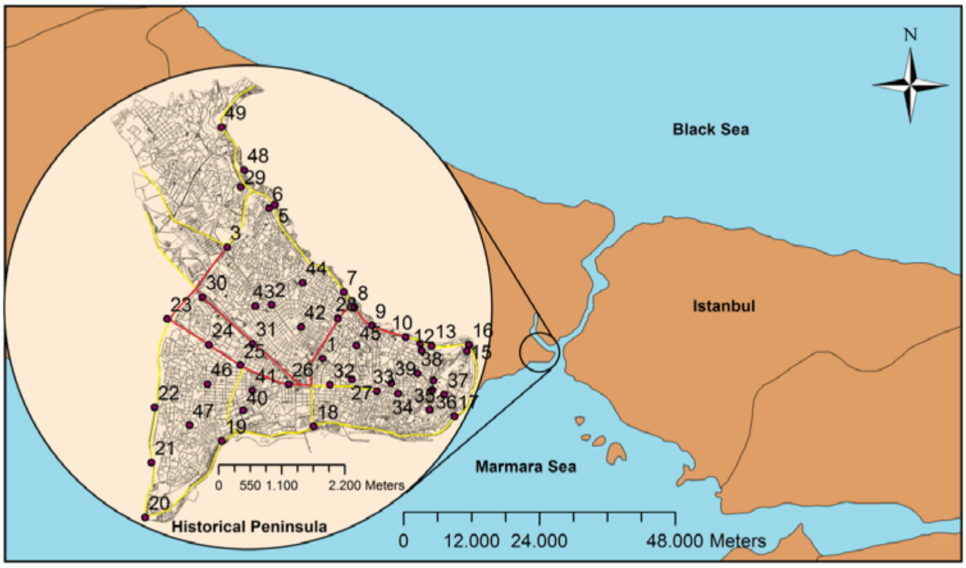
2.1 Study area

The location of Istanbul and the Historical Peninsula are given in Figure 1. 45 passive sampling stations were installed on the locations selected according to the systematic selection process over the peninsula (Popek, 2003). The same stations were used in a previous study to evaluate surface ozone distribution and its possible effect in the peninsula (Karaca and Öztürk, 2012). In this study, only nitrogen dioxide (NO_2) concentration values were used to model the traffic-relatedNO_2 exposures in the study area.

Based on the classification suggested by Cheng (2002), the spatial distribution and dimensions of the study area can be categorised as micro-scale. Micro scale based studies are quite limited in the literature and are considered promising to obtain higher level accuracy and to construct better local air quality management plans (Cheng, 2002). In addition to that, the surface characteristics of the Historical Peninsula are dominated by small-scale (geographical and structural) variations. Therefore the distribution of pollutants over the surface needed to be studied in a small operational scale. The cultural and historical stocks are distributed over the entire peninsula, let say; there are some in every street.

The selection procedure of the sampling locations for the passive samples was explained in details in the work of Karaca and Öztürk (2012), so we should only give some brief explanations in here. On a map, the Historical Peninsula was divided into grid squares 500 metres on a side, locating the sampling points just at the centre of each grid square. During the installation, some small alterations on the selected locations were unavoidable because of technical aspects, e.g., a proper street lamp or structural equipment. Coordinates of the stations were obtained using a geographical positioning system (GPS) module which was 1 m sensitive, recorded and then transferred into a GIS database. Locations of the sampling points or stations are given in Figure 1.

Figure 1 The Historical Peninsula of Istanbul and sampling locations (see online version for colours)



2.2 Sampling, chemical analysis, QC and QA

In this study, Radiello® type code 166 NO_2 passive samplers were used. For exposure studies, passive samplers are generally preferred due to their low cost and easy operation. Passive samplers are good candidates to be deployed in large-scale air pollution surveys with high spatial resolution requirements (Skene et al., 2010).

Samplers were placed in open field stations within the Historical Peninsula area (Fatih, Istanbul) ~2.5 m above ground level, with a minimum 50 m distance from any building structures or other obstacles. Some of the samplers were located in street canyons to predict direct emission rates from adjacent roads and arteries. Samplers were provided with rain shelters that also protected them from wind and direct sunlight exposure.

Three NO_2 measurement campaigns were performed during the spring, summer and winter periods in 2010 for seven consecutive days for each period at 45 different locations. Details of these campaigns are given in Table 1. We have six missing samples in summer and five missing samples in the spring season. The reason for the missing samples is attributed to vandalism.

The passive samplers are made of microporous polyethylene coated with triethanolamine (TEA). Nitrogen dioxide is chemiadsorbed onto TEA as nitrite ions (NO_2^{-1}), and then the adsorbed nitrite is quantified by ion chromatography (IC) analysis. The sampling rate of nitrite ions using passive samplers varies for different temperatures. There is a correlation method suggested by Radiello® for sampling rates under different temperatures. The nitrite amounts of the seasonal samples collected during different average temperature profiles (winter, summer and transitional periods) were corrected and the corrected concentrations were calculated using the calculation methods suggested by Radiello® (2007).

A Dionex® ICS 1100 model is an IC system equipped with an AS9-HC 4 mm anion exchange column (4 × 250 mm) and an IonPac® AG9-HC guard column (4 × 50 mm). The system consists of a gradient pump with online degassing, an anion self-regenerating suppressor ASRS® 300 (4 mm) in recycle mode of a 25-µl sample loop, and a DS6 thermostated conductivity detector. The Chromeleon® 6.5 sp10a data management system was used for controlling the system. The flow rate was set to 1.0 mL/min and 9.0 mM sodium carbonate eluent was used.

Table 1 Sampling campaigns and descriptive statistics

Information	*Campaigns 1*	*Campaigns 2*	*Campaigns 3*
Starting date	14.04.2010	23.07.2010	30.12.2010
End date	22.04.2010	29.07.2010	06.01.2011
Exposure time(min)	11,750	8,727	10,365
Average temperature (°C)	14	26	5.7
Numbers of missing data	5	6	2
Mean (µg/m^3)	80.5	63.2	74.9
Geometric mean (µg/m^3)	77.0	57.5	66.1
Standard deviation (µg/m^3)	22.6	25.9	38.2
Sample variance	509	673	1,458
Kurtosis	1.59	0.19	–0.35
Skewness	0.28	0.42	0.84
Minimum (µg/m^3)	21.8	14.2	23.5
Maximum (µg/m^3)	144.1	133.9	155.0

The precision of the method for all nitrite ions was evaluated by making repeated analyses of a fixed concentration (diluted samples of standard solution) on different days. The retention time dispersions of all the ions were quite insignificant (< 0.2%). Tree independent batches were prepared and injected three times thus making a total of nine injections (n = 9) at a particular concentration, and the relative standard deviation (RSD) was calculated. The RSD value was 1.8316 (in percent) indicating that the measurements were quite accurate. The detection level (DL) of the method was calculated to be three times of the standard deviation of blank samples. Solutions containing different concentrations of the ions in the calibration range were analysed and their concentrations were calculated using the calibration slopes. Linear calibration was used within the calibration procedure with an accuracy of 99.9 % level (offset is 0 and slope is 0.114). The linearity of the method was evaluated by plotting concentrations obtained by applying the method against introduced concentrations for each ion.

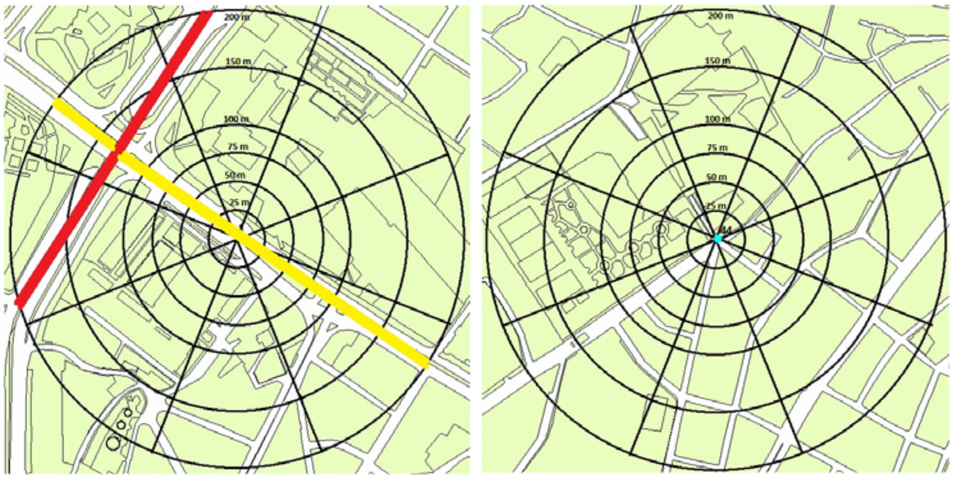
2.3 Selection of zonal buffers

Empirical models such as LUR are often used for predicting NO_2 concentrations which are accepted as a good marker for traffic-related air pollution. Traffic volume on road networks in the vicinity and landscape characteristics such as land use, elevation, population density is commonly used in such prediction models. But failing to capture variability in traffic volume can reduce the correctness of the model (Skene et al., 2010). As pointed out in the work of Rose et al. (2009) when valid traffic volume data is not available the model can include road densities within a measured buffer zone that might contribute to the pollution levels (Rose et al., 2009). Our model includes detailed road network data within a circular buffer zone for different radii from the central point where the NO_2 measurements were conducted. In Rose et al.'s (2009) work, the weighted road density within a 75 m radius was discovered to be better predictors of measured NO_2. In Skene et al.'s (2010) work where the measurements are conducted on residential areas the developed land within 500 m is associated with increased levels of NO_2. The road network density of the Historical Peninsula of Istanbul is very high due to a large number of historical and commercial zones. With such high road network density, we can expect that the near roads will contribute relatively more to the air pollution suppressing the far ones. Considering that the road densities in our study are closer to Rose et al.'s (2009) study we measured the road lengths within the radii of 25, 50, 75, 100, 150 and 200 metres. The concentric rings and their sizes of the buffer zones can be observed in Figure 2.

2.4 Road classification

While examining the roads in the buffer zones, one can observe that roads in different sizes and shapes exist. Classifying the roads according to the known or expected traffic counts and assigning relative weights to these roads is an acceptable way of calculating a weighted road density variable that will be used in our model. In Rose et al.'s (2009) work roads are classified into three major types where motorways, primary roads, and arterial roads are considered as type one roads with very high traffic volume. Distributor roads are considered as the type two roads where traffic volumes are considerably less than the type one roads but still significant. Local roads are labelled as type three roads where traffic density is considered to be low. Examining the road network of the Historical Peninsula a similar approach was followed. We classified the roads into four types where primary roads are considered as type one roads (R1). Primary roads stretch between major commercial zones. The type two roads are the arterial roads (R2). The traffic volume on type one roads is significantly greater than the type two roads which is different than Rose et al.'s (2009) classification. In Figure 1 type one roads are drawn with red lines and type two roads are drawn with yellow lines. Type three roads are distributor roads (R3) where the traffic volume is considerably lower than the first two types but still significant. Type four roads are local roads (R4) with low traffic volumes.

Figure 2 Selection of the buffer zones for road density calculations. sampling station buffer that (a) includes primary (red line) and arterial roads (yellow line) (b) no primary or arterial but only local roads (see online version for colours)



(a) (b)

In the proposed model, the measured road lengths of each type within the buffer zones specified in the previous section constitute an important part. Each road type is multiplied by a specific weight that is based on average traffic counts. We name this weight as road weight.

2.5 Traffic and meteorological data

Limited traffic count data was obtained from the traffic control centre (TKM) of the Istanbul Metropolitan Municipality. TKM monitors primary and arterial roads using several automatic road radar sensors. These are special sensors which are mounted to specific parts of roads (7 m behind and 7 m up from the road) and can measure up to eight lanes. Traffic data was obtained from #184, #187, #189, #190, # 208, #219 and #375 road radar sensors (online traffic data is available at http://tkm.ibb.gov.tr/en-EN/its/itsSensor.aspx). The daily average traffic count on one of our selected primary roads (Adnan Menderes Bul.) is 112,000 vehicles. The daily average traffic count on the coast road (Yenikapı-Sirkeci part) is 46,000 vehicles, where most of the coast road is classified as type two. The daily average traffic count of another type two road (Samatya-Yenikapı) is 73,000 vehicles. From time to time the traffic counts of type two roads can approach a type one road. We could not obtain any traffic count data for the distributor and local roads. We assume that the traffic count on distributor roads will be significantly less than the primary and arterial roads. We also assume that the traffic counts of local roads will be less than 10,000, maybe on the range of thousands. The previously mentioned road weights that will be used in our model will be represented in quadruples

(WR1-WR2-WR3-WR4) where the first weight is related to type one roads and the last weight is related to type four roads.

To add wind direction information into the model, residential buffers were divided into eight directions to use prevailing wind data as an input parameter. Hourly wind directions were used to compute cumulative seasonal wind frequencies. In addition to wind frequencies, the average hourly wind speeds were also calculated and used to check their effects on model performances. Unfortunately, there are not any local meteorological stations located over the Historical Peninsula. In this study, we used meteorological data obtained from Göztepe meteorological station operated by Turkish State Meteorological Service which is the closest station (about 5 km far) to the Historical Peninsula.

2.6 Distance weights

In addition to road weights, an extra weight for each buffer zone according to their distance to the centre point was used. In Skene et al.'s (2010) work, a step function relating isotropic NO_2 dispersion to traffic volume in concentric buffers is used. Our distance weight function can mimic this kind of step functions by adjusting weights for the concentric buffers in our model as well. In this study, linear weights were selected based on the reciprocals of buffer distances.

2.7 Regression modelling

The proposed LUR model is based on measured road lengths within the concentric buffer zones, road weights that are adjusted to traffic volume, wind frequencies for eight different directions and distance weights incorporating a dispersion model for NO_2 levels.

The road lengths of each type of road within a buffer zone are known. These lengths are multiplied by the related road weights and added to calculate the total road density. Road densities are multiplied by distance weight parameters and wind frequency parameters explained above. To include a buffer zone as a variable for the final model one must include all the concentric inner zones closer to the centre. For example to include the 50–75 metre buffer zone as a variable in our model the buffer zones for 0–25 and 25–50 metres should be added. We also developed a multivariate regression model where we included temperature, elevation and a distance to sea parameters.

3 Results and discussions

3.1 NO_2 measurements

Istanbul is typically under the effects of three dominant seasonal characteristics; namely winter, summer and transitional periods. The fall and spring seasons can be categorised as transitional periods. During both seasons average temperature, humidity and other meteorological factors are very similar. But air flow directions can be different due to the local effects of mesoscale meteorology. In literature, some researchers preferred to include seasonal measurements to evaluate the characteristics of NO_2 concentrations which show significant differences in hot summer days and cold winter days (Skene et al., 2010). As a result, we decided to conduct three different sampling periods to characterise the behaviour of traffic-related pollution exposure levels over the Historical Peninsula.

Descriptive statistics, calculated separately for each season, are given in Table 1. Measured NO_2 levels ranged from 14.2 to 155.0 μg/m^3 after the corrections for blank concentrations. The minimum average concentration was observed during summer while the maximum one was during the spring season. All measured seasonal average concentrations were also compared to a central monitoring station located in the Historical Peninsula of Istanbul. The central monitoring station is operated by the Istanbul Metropolitan Municipality and its data is available online (http://www.ibb.gov.tr). There is a good agreement in the trends between our measurements and the Aksaray station, but this central monitoring station's seasonal mean values are about 30% higher than our mean values. The maximum difference is observed in spring (38%) while the minimum is in fall (26%). The Aksaray station is located on a main arterial road canyon in the peninsula that explains the 30% elevated concentrations. The yearly average of the NO_2 concentration measured by the Aksaray central air quality station is 90.9 μg/m^3, which is considerably higher than the comparable studies shown in Table 2. Only Rosenlund et al. (2008) reported a higher average concentration level stating that they collected NO_2 measurement data from a central air quality monitoring station located in an urban environment (Rome, Italy) very close to street level traffic. One of the important challenges in our modelling study is that our NO_2 concentration range (~122 μg/m^3) is considerably higher than comparable studies (between 25–45 μg/m^3) (Table 2). Rosenlund et al. (2008) reported that there is a significant correlation (0.61 and 0.77) between their seasonal concentrations, but we obtained less significant correlations (0.57 and 0.64). The reason could be the greater seasonal fluctuations observed in the Historical Peninsula of Istanbul. The highest average concentration with the value of 80.5 μg/m^3 was observed in spring season while the lowest, 63.2 μg/m^3, in the summer season. Similar seasonal trends were also reported in the literature (Crouse et al., 2009; Henderson et al., 2007; Rosenlund et al., 2008; Skene et al., 2010). These seasonal differences can be attributed to seasonal atmospheric boundary levels, local meteorology, and photochemical oxidation, but this subject is not in the scope of this paper.

3.2 The univariate LUR model

Hourly wind records in eight major directions (N, NE, E, SE, S, SW, W, NW) were used to obtain three cumulative seasonal wind frequency profiles for spring, summer and winter periods (Table 3). Examinations of the wind frequencies reveal that prevailing wind directions have some typical differences. While there are two dominant directions for the spring sampling season which are north easterly and south westerly flows, there are dominating northerly flows in the fall and summer seasons. An anisotropic model can handle sharp fluctuations and differences in prevailing wind directions more efficiently than an isotropic model which is also noted in Skene et al.'s (2010) work. The performance of our anisotropic model using wind directions will be discussed in the following sections.

Table 2 Comparison of NO_2 values

Study	*Place*	*Sampling type*	*Mean NO_2 concentration ($\mu g/m^3$)*				
			Yearly	*Spring*	*Winter*	*Summer*	*Fall*
This study	Urban background, Istanbul, Turkey	Passive sampling		80.5	74.9	63.2	-
	Urban background very close to traffic at street level, Istanbul, Turkey	Central monitor	90.9	115.7*	91.6*	88.1*	74.8*
Rosenlund et al. (2008)	Residential, Rome, Italy	Passive sampling	46.8	52.4	-	42.5	45
	Urban background very close to traffic at street level, Rome, Italy	Central monitor	106				
Skene et al. (2010)	Residential, Connecticut, USA	Passive sampling	20.3		21.1**	10.1**	
Henderson et al. (2007)	Residential, British Colombia, Canada	Passive sampling		39.7			26.1
Rose et al. (2009)	Urban background, Sydney, Australia	Passive sampling	22.8				
Crouse et al. (2009)	Montreal, Canada	Passive sampling	24.1	28.4	25.5	18	

Notes: *These values were calculated for making a comparison between the sites. So only the values belonging to the same periods with the current study were used. **Indicated results are model outputs. ***Median values are reported instead of the mean value.

The independent variable of the univariate regression model is obtained using measured road lengths within the concentric buffer zones, road weights that are adjusted to traffic volume, wind frequencies for eight different directions and distance weights incorporating a dispersion model for NO_2 levels (see the Sections 2.3–2.7). The correlation coefficients between dependent and independent variables are summarised in Table 3, where the results of four different runs are given. In the first two runs, the proposed model was constructed with road weights based on traffic volume data obtained from the traffic control centre (TKM) of the Istanbul Metropolitan Municipality. But the traffic volume data obtained from the TKM is not comprehensive enough because it is only a rough average that does not distinguish seasonal differences. In addition, it does not include traffic volume data for local roads. By assigning traffic volume data to the corresponding road weights, the traffic data were normalised to [0, 1] as can be seen in the first column of Table 3. The road weight WR4 for local roads was arbitrarily set to a low value (0.04). In the last two runs, the road weights were set using the generalised reduced gradient (GRG) algorithm which is an optimisation technique used to solve smooth nonlinear optimisation problems. The GRG algorithm is part of the Excel Solver® (Frontline, 2012). The best coefficient results for the road weights WR1, WR2, WR3, and WR4 were found to be 0.80, 0.34, 0.51 and 0.16; respectively.

The wind frequency data mentioned before is another variable included in the proposed univariate regression model. The first and the third run in Table 3 include wind frequency data obtained from the Göztepe meteorological station. The second and the fourth run do not include real wind data, the wind data variables are equally distributed wind frequencies [0.125 (1/8) for each direction]. Contrary to our expectations, the results showed that wind data have no significant effect on the performance of the proposed regression model.

Table 3 Overall model performance and used coefficients

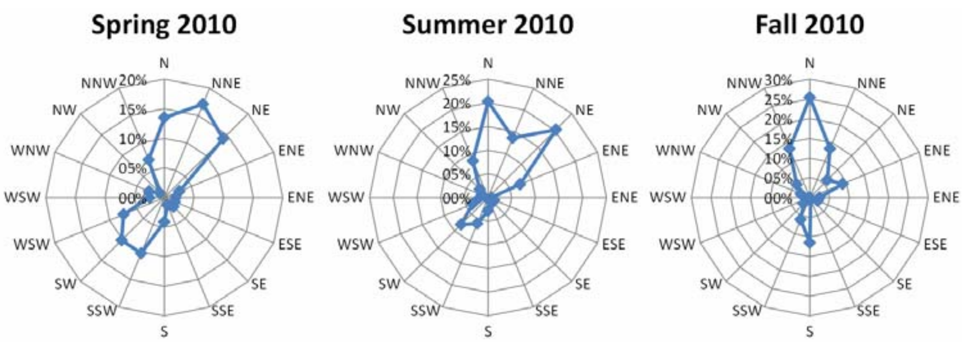
Relative road weights (WR1; WR2; WR3; WR4)	*Wind frequencies (N; NE, E; SE; S; SW; W; NW)*	*Correlation coefficient (R^2)*
TKM-based traffic loads (1.00; 0.66; 0.40; 0.04)	Measured wind frequencies	0.38 (150 m)
	(April: 0.10; 0.19; 0.08; 0.06; 0.25; 0.24; 0.04; 0.04)	
	(July: 0.31; 0.31; 0.05; 0.02; 0.06; 0.13; 0.04; 0.07)	
	(December: 0.15; 0.05; 0.01; 0.13; 0.39; 0.17; 0.08; 0.02)	
	0.125 (1/8) for each	0.38 (150 m)
Solved traffic roads (0.80; 0.34; 0.51; 0.16)	Measured wind frequencies	*0.44* (150 m)
	(April: 0.10; 0.19; 0.08; 0.06; 0.25; 0.24; 0.04; 0.04)	
	(July: 0.31; 0.31; 0.05; 0.02; 0.06; 0.13; 0.04; 0.07)	
	(December: 0.15; 0.05; 0.01; 0.13; 0.39; 0.17; 0.08; 0.02)	
	0.125 (1/8) for each	0.44 (150 m)

In Table 3, we can see that the univariate regression model based on traffic volume data from TKM and real wind frequency data produced an R^2 value of 0.38. Using optimised road weights improved the R^2 value to 0.44 which is a 15% increase. Inspecting the road weights suggested by the optimisation algorithm we can observe that the primary and arterial roads while still important are assigned smaller weights. Distributor and local roads are assigned higher weights. This is an important indicator that one should include distributor and local roads in their LUR models to estimate traffic-related pollutants where the road network is very dense as in our study area. In Table 3, the buffer zone ranges for the best regression results are reported as well. It can be observed that in all trials the 150-metre range is found to be the most effective buffer zone.

3.3 Inland vs. costal

The estimation of a regression model presented in Table 3 is not satisfactory ($R^2 < 0.5$, $p > 0.05$). In order to evaluate the distribution characteristics of measured NO_2 concentrations, all the measured concentrations were illustrated relatively in Figure 3 using bar charts where the longest bar indicates the maximum observed concentration within all the sampling campaigns. Inspecting the land use characteristics and the road network properties for the coastal and the inland areas it can be observed that there are distinguishable differences. In order to evaluate the effects of these different land use characteristics we divided the study area into two main sections namely; inland and costal. As can be observed in Figure 3 stations numbered 5, 6, 7, 8, 9, 10, 12, 13, 15, 16, 17, 18, 19, 20, 29, 48, and 49, which constitute 40% of the stations were categorised as coastal and the rest as inland. The same univariate regression modelling methodology is followed for the grouped stations. The obtained results are summarised in Table 4.

Figure 3 Relative NO_2 concentrations measured over the study area (see online version for colours)



Looking at Table 4, we observe that the proposed regression model produces better R^2 values for the spring and winter seasons. Especially the regression model constructed with the inland station group and the TKM traffic data produces R^2 values as high as 0.71. Using optimised road weights the R^2 value goes up to 0.75. The regression model constructed with coastal stations and TKM traffic data produces an R^2 value of 0.27. Only for the winter season, this number goes up to 0.52. Using optimised road weights, in this case, improves the produced R^2 values significantly (0.64). The optimised road weights of the arterial and distributor roads are considerably lower than the TKM-based road weights. The effect of the wind data is small and inconsistent for the majority of the constructed models.

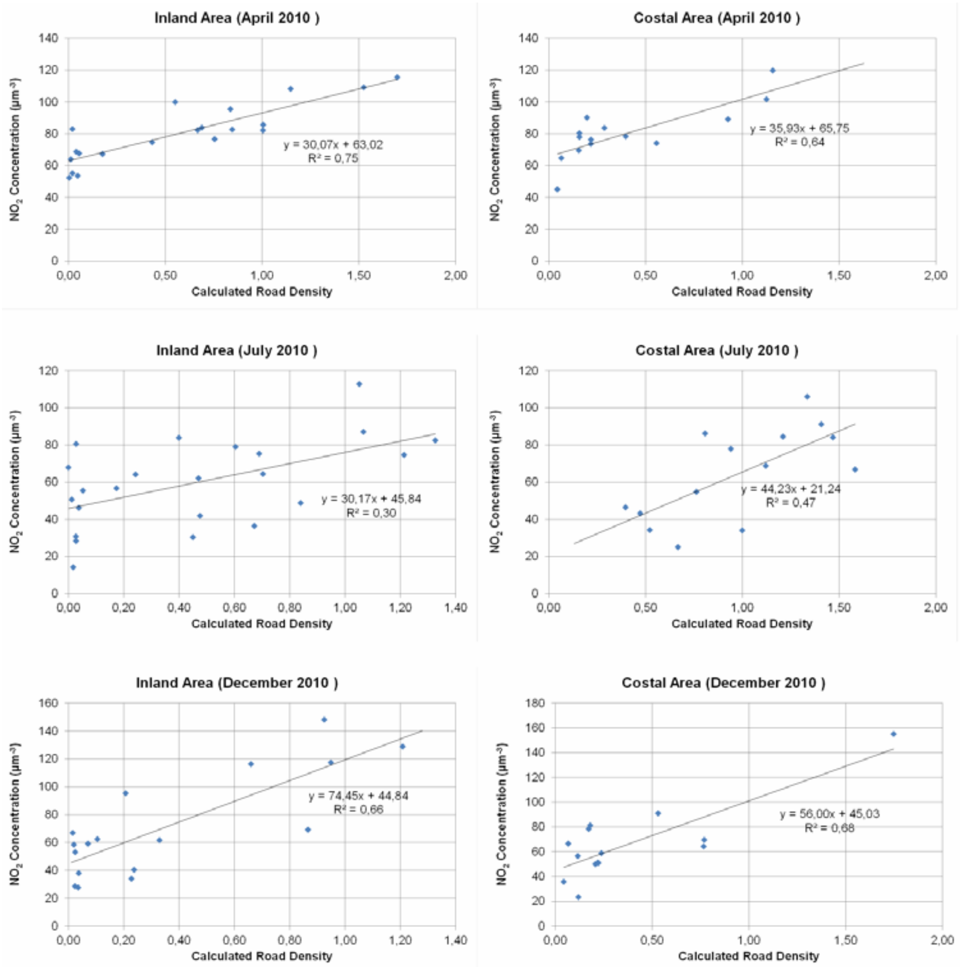
Table 4 LUR model results for separated inland and costal stations

Relative road weights (WR1;WR2; WR3; WR4)	*Wind frequencies (N; NE, E; SE; S; SW; W; NW)*	*Inland (R^2)*	*Coastal (R^2)*
	April 2010		
TKM-based traffic loads (1.00; 0.66; 0.40; 0.04)	Measured wind frequencies (0.10; 0.19; 0.08; 0.06; 0.25; 0.24; 0.04; 0.04)	0.71 (75 m)	0.27 (50 m)
	0.125 (1/8) for each	0.68 (75 m)	0.31 (50 m)
Solved traffic roads for best fit (Inland: 0.85; 0.70; 0.60; 0.04 Coastal: 0.85; 0.15; 0.09; 0.12)	Measured wind frequencies (0.10; 0.19; 0.08; 0.06; 0.25; 0.24; 0.04; 0.04)	*0.75* (75 m)	*0.64* (50 m)
	0.125 (1/8) for each	0,73 (75 m)	0.55 (50 m)
	July 2010		
TKM-based traffic loads (1.00; 0.66; 0.40; 0.04)	Measured wind frequencies (0.31; 0.31; 0.05; 0.02; 0.06; 0.13; 0.04; 0.07)	0.14 (25 m)	0.27 (200 m)
	0.125 (1/8) for each	0.18 (25 m)	0.26 (200 m)
Solved traffic roads for best fit (Inland: 0.85; 0.70; 0.60; 0.04 Coastal: 0.85; 0.15; 0.09; 0.12)	Measured wind frequencies (0.31; 0.31; 0.05; 0.02; 0.06; 0.13; 0.04; 0.07)	*0.30* (25 m)	*0.47* (150 m)
	0.125 (1/8) for each	0.30 (25 m)	0.47 (150 m)
	December 2010		
TKM-based traffic loads (1.00; 0.66; 0.40; 0.04)	Measured wind frequencies (0.15; 0.05; 0.01; 0.13; 0.39; 0.17; 0.08; 0.02)	0.64 (150 m)	0.52 (150 m)
	0.125 (1/8) for each	0.67 (150 m)	0.38 (150 m)
Solved traffic roads for best fit (Inland: 0.85; 0.70; 0.60; 0.04 Coastal: 0.85; 0.15; 0.09; 0.12)	Measured wind frequencies (0.15; 0.05; 0.01; 0.13; 0.39; 0.17; 0.08; 0.02)	*0.67* (150 m)	*0.68* (150 m)
	0.125 (1/8) for each	0.67 (150 m)	0.50 (150 m)

The proposed regression models produce low R^2 values for the summer season. The reason for this could be related to local meteorology and photochemical oxidation which affects the atmospheric dispersion and conversion processes of NO_2. Although the regression models constructed with TKM-based road weights are close, the best model performances were obtained for solved road weights in each of the periods. The scatter plots of the independent parameter (calculated road density) and NO_2 concentrations for the best solutions are given in Figure 4. In Table 4, we can also observe the buffer zone ranges for the best regression results. The ranges seem to be season dependent. In spring, the better results are produced for 50–75 metres. In winter, this range goes up to 150 metres. In summer, there is a significant gap between the coastal and inland stations (25–200 metres). This can be a result of the summer time sea breeze effect and the higher level of atmospheric dispersion. All these analyses showed that a LUR model using one independent variable is not powerful enough to comprehensively explain the NO_2

concentrations over the Historical Peninsula of Istanbul. We decided to develop a multivariate regression model where temperature, elevation and a distance to sea variables should be included.

Figure 4 The scatter plots of the independent parameter (calculated road density) and NO_2 concentrations for the best solutions (see online version for colours)



3.4 The multivariate LUR model

The correlation coefficients (R^2 values) between the NO_2 concentrations and average wind speed (km/h), elevation (m), average temperature (C°) and distance to sea (m) are –0.18, –0.16, –0.09, and 0.32 respectively. This correlation analysis indicates that only the distance to sea level variable has a positive correlation while the other independent variables have negative correlations. The positive correlation value indicates that the pollution level decreases as a station gets closer to the sea. We believe that an important factor is the difference in the road network densities. On the other hand, wind speed and elevation showed negative correlations with the NO_2 levels.

The multivariate regression model was constructed by including all the variables mentioned without differentiating between geographical and seasonal measurements. The results are summarised in Table 5. The overall prediction performance of the constructed model is moderate (R^2 = 0.64). The higher p values indicating the lowest influences on the model were calculated for the elevation and distance to sea variables. According to the model, the average wind speed and the average temperature have significant of influences on the prediction performances.

Based on the statistical measures given in Table 5 the independent variables can be ordered according to their influences as follows; total road lengths (wind direction and distance weighted) (150 m), average wind speed (km/h), average temperature (C°), distance to sea (m) and elevation (m).

Table 5 Multivariate LUR model results (R^2 = 0.64)

	Coefficients	*Standard error*	*T-stat*	*P-value*
Intercept	174	29.2	5.979	0.000
Total road lengths (Wind direction and distance weighted) (150 m)	20.5	3.38	6.075	0.000
Distance to sea (m)	0.013	0.005	2.539	0.013
Average wind speed (km/h)	–6.62	1.66	–3.997	0.000
Elevation (m)	–0.09	0.04	–2.239	0.028
Average temperature (C°)	–0.91	0.27	–3.403	0.001

4 Conclusions

Risk assessment is an important part of management strategies for preserving and protecting cultural and historical heritages. Evaluating pollution exposure levels to develop risk assessment plans is one of the most important steps of this process.

For a particular location having a small number of interest items, monitoring exposure levels with few monitoring stations might be a convenient solution. But for a larger area where several cultural and historical heritages are spatially distributed over a complex terrain, this solution can become very expensive and might be impossible to monitor. In this case, model-based approaches can become a valuable alternative to predict the spatial distribution of pollutants which is risk parameter. We believe that the model-based alternative is a convenient solution for the risk assessment of the numerous cultural and historical heritages distributed over the Historical Peninsula of Istanbul.

In literature, most of the LUR modelling is used at ‘simple’ places or in larger scales, as a consequence of the difficulties and limitations of using a LUR-model to determine air pollution concentrations in a complicated compact urban environment with street canyon dispersion. The endeavour of this study is to develop a LUR model to estimate traffic-related pollution levels over a complex urban terrain, the Historical Peninsula of Istanbul. The topography of the study area is densely structured, surrounded by sea and just located at the middle of the Bosporus strait, which is a natural air corridor, and the land use variation over the intra-urban environment shows extreme local variations. To assure the LUR model is able to represent these extreme local variations in land use variation and pollution concentrations, several sampling stations (45) were installed over a micro-scale, 2.5 km ×2.5 km, study domain, to capture emission distribution characteristics of the road types and compositions. Such LUR studies are quite limited in the literature and are considered promising to obtain higher level accuracy and to construct better local air quality management plans for the places having plentiful cultural heritage stocks at risk.

This study demonstrates that the land use regression model (LUR) approach is a practical, time saving and considerably inexpensive method to predict traffic-related pollution exposure. Although sharp increases in model performances were not observed, the advantage of the proposed LUR model is that it includes measured wind frequencies as an independent variable. Another important challenge in our modelling study is that our NO_2 concentration range (~122 $\mu g/m^3$) is considerably higher than comparable studies. Also, the terrain of the study area is very complex, surrounded by sea and just located in the middle of the Bosporus strait, which is a natural air corridor. These factors bring additional difficulties in prediction and possibly decrease the performance of the proposed regression model. This LUR modelling challenge showed that, seasonal fluctuations bring extra difficulties to define or model the spatial distribution of pollution. In this case, some seasonal factors such as average temperature and wind direction profiles become more important and their possible effects on the model performance.

In conclusion, the obtained results suggest that our LUR model explains the traffic-related air pollution levels with reasonable accuracy. Thus, this model has a potential to be used in risk assessment studies.

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