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ORIGINAL PAPER

Air pollution and hospital admissions for cardiorespiratory diseases in Iran: artificial neural network versus conditional logistic regression

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Abstract This study was conducted to evaluate the relationship between air pollutants (including nitrogen oxides [NO, NO_2, NO_X], sulfur dioxide [SO_2], carbon monoxide [CO], ozone [O_3], and particulate matter of median aerometric diameter <10 μm [PM_{10}]) and hospital admissions for cardiovascular and respiratory diseases. The study had a case–crossover design which was conducted in Tabriz, Iran. Daily hospital admissions and air quality data from March 2009 to March 2011 were analyzed using the artificial neural networks (ANNs) and conditional logistic regression modeling. The results showed significant associations between gaseous air pollutants including NO_2, O_3, and NO and hospital admissions for cardiovascular disease. Gaseous air pollutants of NO_2, NO, and CO were associated with hospital admissions for chronic obstructive pulmonary disease, while PM_{10} was associated with hospitalizations due to respiratory infections. PM_{10} and O_3 were also associated with asthmatic hospital admissions. There was no significant association between SO_2 and studied health outcomes. Comparing the results of logistic regressions and ANNs confirmed the optimality of the ANNs for detection of the best predictors of hospital admissions caused by air pollution. Further research is required to investigate the effects of seasonal variations on air pollution-related health outcomes.

Keywords Case–crossover analysis · Cardiorespiratory health effects · Hospital admissions · Air pollution

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Introduction

It has been estimated that air pollution is responsible for approximately 800,000 deaths annually worldwide including 5 % of deaths from respiratory cancer, 3 % from cardiovascular disease, and 1 % from acute respiratory infections (Kalantzi et al. 2011). Over the past two decades, a number of studies have evaluated the associations between outdoor air pollution and adverse health effects such as cardiovascular and respiratory diseases in different parts of the world including North America (Li et al. 2011; Lin et al. 2008; Rodopoulou et al. 2014; Wilson et al. 2004), Europe (Kalantzi et al. 2011; Di Ciaula 2012; Rushworth et al. 2014), Australia (Hansen et al. 2012), and some Asian countries including China, Taiwan, and India (Cao et al. 2009; Chang et al. 2005; Chen et al. 2010; Ge et al. 2011; Gurjar et al. 2010; Lin et al. 2013; Tao et al. 2014). These studies have shown an increase in mortality and/or hospital admissions for cardiovascular and respiratory diseases due to short- and long-term exposure to air pollutants. Unlike many studies that have focused on mortality compared with hospitalization prior to 2005 (Chang et al. 2005), there are an increasing number of studies that have been conducted to evaluate the association between air pollution and hospital admissions during the recent decade. These epidemiological studies have reported associations between daily variations in air pollution and hospital admissions for cardiovascular and respiratory diseases (Cao et al. 2009; Chang et al. 2005; Chen et al. 2010; Di Ciaula 2012; Ge et al. 2011; Gurjar et al. 2010; Hansen et al. 2012; Kalantzi et al. 2011; Li et al. 2011; Lin et al. 2013, 2008; Rodopoulou et al. 2014; Tao et al. 2014; Wilson et al. 2004; Liu et al. 2013).

However, very few studies have been conducted on this issue in Iran. In one of the few attempts, the effect of carbon monoxide (CO) in ambient air on hospitalization for angina pectoris was evaluated in Tehran using time series approach and it was found that each unit increase in CO level resulted in a 1.00934 increase in the number of hospital admissions for angina pectoris (Hosseinpoor et al. 2005). Moreover, a significant correlation between CO and particulate matter of median aerometric diameter <10 μm (PM_{10}) concentrations with hospital admissions for cardiovascular disease was reported from Kermanshah Province in the western part of Iran (Khamutian et al. 2014). In another study, a significant association was reported between the risks of acute coronary syndrome and elevated concentrations of CO in Tehran (Qorbani et al. 2012).

It is important to conduct epidemiological studies in those regions that are exposed to high levels of air pollution. This is the case for Tabriz, the third largest megacity in Iran, where there are high levels of air pollution due to motor vehicles as well as the heavy industries including petrochemical, refinery, thermal power plant, and thousands of large and small industrial units. However, the impact of air pollution on cardiovascular and respiratory diseases has still not been documented in Tabriz. The findings from research in this area will help to better understand the relationship between air pollution and hospital admission for cardiovascular and respiratory diseases.

Additionally, conditional or mixed model logistic regressions, accounting for correlation between case and control records, are commonly used to model the relation between air pollution and meteorological data with adverse health effects (Chan and Ng 2011; Chang et al. 2005; Chen et al. 2010; Gleason et al. 2014; Guo et al. 2009; Hansen et al. 2012; Kan and Chen 2003; Lee et al. 2008; Li et al. 2011; Lin et al. 2013; Qorbani et al. 2012; Tobías et al. 2011; Villeneuve et al. 2012; Wendt et al. 2014; Wong et al. 2014; Yang et al. 2004). However, the artificial neural networks (ANNs) were also used for modeling in the present study. Owing to the nonlinear nature of models, the ANN smacks the model more flexible compared to logistic regression (Dreiseitl and Ohno-Machado 2002). ANNs contain more multifarious structures by using the hidden nodes, and this complexity proposes ANNs with the power to classify any data with complex relations. Moreover, regression models require that rigorous statistical assumptions to be fulfilled in order to achieve reliable results, while this is not the case for ANNs (Kutner et al. 2005). It is also feasible to test the statistical significance of the coefficients in the logistic regression models using *P* values (Hosmer Jr and Lemeshow 2004), and therefore the importance of variables is defined in terms of the statistical significance of the coefficients for the variables. However, this criterion can vary depending on the amount of available data, and particularly if the number of observations is very large, predictors with small effects on the outcome are likely to be significant. However, due to the nonlinear nature of ANNs, automatic relevance determination (Bishop 1995) could be used to exploratorily assess the importance of input variables to classify the output and solve the problem of over-sensitivity of the logistic regression in large data.

Based on the above-mentioned background, the aims of this study were to evaluate the relationship between air pollutants (including nitrogen oxides [NO, NO_2, NO_X], sulfur dioxide [SO_2], carbon monoxide [CO], ozone [O_3], and particulate matter of median aerometric diameter <10 μm [PM_{10}]) and hospital admissions for cardiovascular and respiratory diseases using both logistic regression and ANNs models.

Materials and methods

Study design

The study had a case–crossover design. In this design, that is very close to matched-pair case–control study, each study participant as a case is considered to be his/her control in another time window. This design simultaneously controls the effect of multifactorial confounders by matching in the design of the study (Kwon et al. 2001). In other words, potential confounding by individual characteristics would be controlled by self-matching (Bateson and Schwartz 2004; Qorbani et al. 2007). A lag time of 5 days was considered in the present study, so that the mean value of air pollution indices in the hospitalization day ±2 days was calculated as the case times and the mean value of air pollution indices during the rest days of the month was considered as control days. Since it was possible that the metrological data including temperature and relative humidity might be changed during this time window, thus they were adjusted in the analyses.

Setting and study period

The study was conducted in Tabriz, the fourth largest city in Iran and the capital of East Azerbaijan Province in

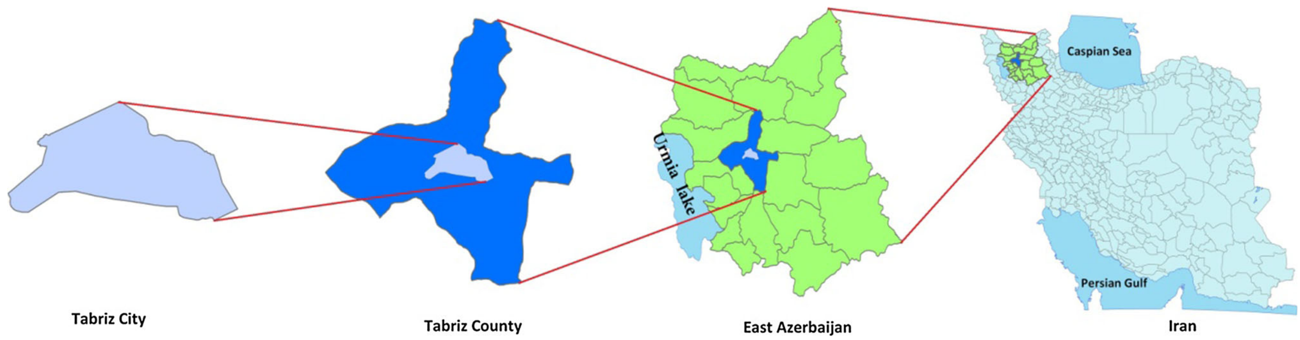

Fig. 1 Location of Tabriz in the northwest of Iran

northwest Iran. It has an area about 324 km^2 (Fig. 1) and an estimated population of 1.5 million. The study included seven urban districts (out of ten districts) in the study region, with an approximately 1.1 million permanent residents as the target population of the study. Three urban districts were excluded from the study due to the lack of air pollution monitoring stations in those areas. The study period was from March 2009 to March 2011 (based on Iran's calendar year).

Data collection

Daily hospital admission records were obtained from five hospitals in Tabriz (Ali Nasab, Amir Almomenin, Imam Reza, Madani, and Tabriz Children's Hospital). The data included the date of admission, gender, age, and the diagnostic code. The causes of hospital admissions were coded according to the International Classification of Diseases, Revision 10 (ICD-10): cardiovascular disease (CVD; I20, I21, and I21.9), asthma (J45), respiratory infections (J06, J42, J12, J18, J20, J21, J22, and J30), and chronic obstructive pulmonary disease (COPD; J44.8 and J44.9).

Air pollution and meteorological variables

Air quality data including hourly measurements of nitrogen oxides (NO, NO_2, NO_X), sulfur dioxide (SO_2), carbon monoxide (CO), PM_{10}, and ozone (O_3) were obtained from six fixed online air quality monitoring stations operated by East Azerbaijan Environmental Office (EAEO). The measurement methods of air pollutants are summarized in Table 1. Figure 2 represents a map of Tabriz City including the locations of the EAEO monitoring sites. Daily average concentrations for nitrogen oxides, SO_2, CO, and PM_{10} as well as the 8-h maximum levels for O_3 were derived from the corresponding hourly datasets taken from each station and were considered valid if at least 75 % of the 1-h values were available during that particular day for each monitoring site. The daily mean temperature and relative humidity data for the same period were obtained from the East Azerbaijan Meteorological Bureau.

Table 1 Measurement methods of air pollutants

Pollutant	Measurement method
Nitrogen oxides	Chemiluminescence
CO	Nondispersive infrared radiation (NDIR)
PM_{10}	Beta attenuation monitoring (BAM)
SO_2 and O_3	UV photometry

Statistical analysis

The required sample size was determined using primary information obtained from a pilot study. Considering an odds ratio of 1.2, the smallest possible effect size, 95 % confidence, and a power of 80 %, the minimum sample size required was computed as 1741 by G-Power (version 3.1.2) software (Franz Faul, Keil University, Germany). However, the sample was increased to 2777 samples implementing the design effect.

Data are summarized and presented using mean [standard deviation (SD)] for quantitative variables and frequency (percentage) for qualitative variables (Asghari Jafarabadi and Mohammadi 2013). The ANNs method was applied to model the relation between the air pollution parameters as independent variables and health outcomes wherein the meteorological data, age, and sex were adjusted for. This method is very useful when the relationships are difficult to describe adequately with conventional approaches. The models were fitted, and the quality of models was tested using common measures of discrimination (i.e., sensitivity, specificity, accuracy, and the area under the receiver operating characteristic [ROC] curve) (Dreiseitl and Ohno-Machado 2002). Multilayer perceptron (MLP) ANN was used, where the inputs and output of this model correspond to the predictor and outcome variables, respectively, in a logistic regression model.

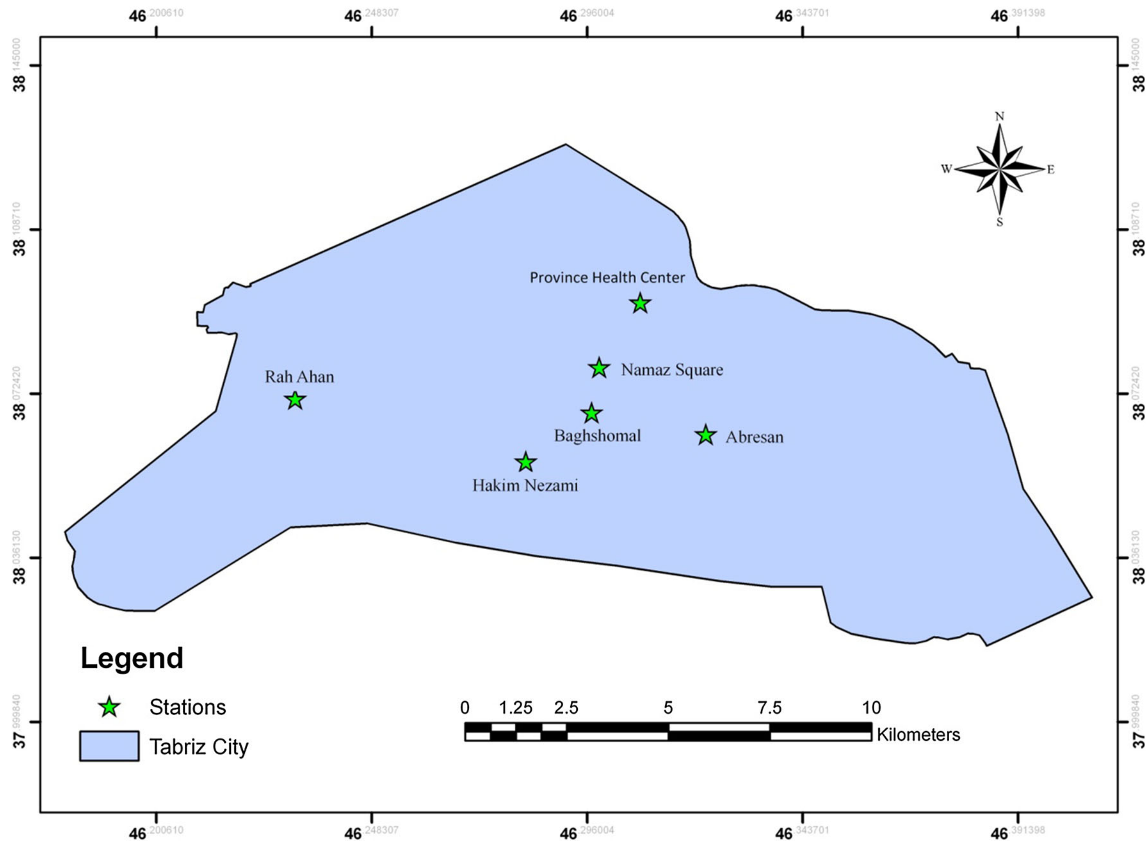

Fig. 2 Locations of six fixed air pollution monitoring stations in Tabriz

The nodes in the hidden layer (hidden nodes) contain intermediate values which are calculated by the network that do not have any physical meaning. The hidden nodes allow the ANN to model complex relationships between the input variables and outcomes. The model is as follows:

$$f(x) = K\Sigma[wg(x)]$$

where K is activation function, w is weights, and g is function of input variables.

The model parameters were estimated using maximum likelihood estimation. The estimation of the optimal parameter values requires the maximization of likelihood function. To estimate the optimal weights, the back-propagation algorithm (Rumelhart et al. 1988) was used for training ANNs which is based on the idea of adjusting connection weights to minimize the difference between real and predicted outcomes (error) by propagating the error in a backward direction. Afterward, automatic relevance determination (Dreiseitl and Ohno-Machado 2002) was used to exploratorily assess the importance of air pollutants and meteorological variables to predict the causes of hospital admissions. In this case, the raw and normalized weights were computed, and thus the importance of the independent variables in predicting the causes of hospital admissions was classified based on quartiles as (very low <25 %, low 25–50 %, moderate 50–75 %, and high 75–100 %). Based on CVD, respiratory infections, COPD, and asthma as the causes of hospital admissions (output variables), ANN models were fitted on data, and in each model, air pollutants including O_3, NO_2, PM_{10}, SO_2, CO, NO, and NO_X (as input variables) were entered in the model. Additionally, meteorological data including mean temperature and relative humidity with the length of stay (LOS) in the hospital were adjusted. To taking into account the effect of gender and age of the subjects, the effect of these variables was also adjusted in the model. The standardized rescaling method for covariates, with one hidden layer, hyperbolic tangent activation function in the hidden layer, softmax activation function in the output layer, and cross-entropy error function was used. To avoid over-fitting and provide the generalizability of the model results, a cross-validation using test sets was performed considering 30 % of data for testing sets. Analyses of logistic regressions and ANNs were performed using SPSS 16 software (SPSS Inc., IL, Chicago, USA). The adjusted weights of the ANN models were depicted by radar plots which were drawn using MS Excel 2007. Additionally, the area under the curve (AUC) of the logistic regressions and ANNs was compared based on DeLong method (DeLong et al. 1988) (STATA corp., College station, Texas, USA).

Results and discussion

Study population, air pollution, and meteorological characteristics

A total of 4862 subjects were assessed for eligibility in the study, of which 2085 cases did not meet the study criteria and were excluded. Of the 2777 study subjects, 1676 were males and 1101 were females. There were no missing values for the data entered in the analyses (Fig. 3). The distribution of the causes of hospital admissions showed COPD and asthma as the most ($n = 987$, 35.5 %) and least ($n = 387$, 14.0 %) prevalent causes of hospital admission, respectively. The information concerning the districts coverage of the stations, air pollution, and meteorological variables is also presented in Table 2.

Comparison of the fit of logistic regression and ANN models

The results of modeling logistic regressions and ANNs confirmed the optimality of the ANNs for detection of the best predictors of hospital admissions due to air pollution. Additionally, based on ANN modeling, the findings of this study demonstrated that after adjusting for age, gender, LOS, mean temperature, and relative humidity, the most important predictors of hospital admissions for CVD were NO, O_3, and NO_2, for respiratory infections was PM_{10}, for COPD were NO_2, NO, and CO, and for asthma were PM_{10} and O_3 concentrations in the ambient air in Tabriz. The results of comparison of the quality of logistic regression and ANN models based on discrimination measures are presented in Table 3. The results showed that AUC of ANN models were significantly better than that of the logistic regression for all models (all $P < 0.05$ and $P = 0.053$ for COPD model). Although the specificity of the models was slightly better for two models in logistic regression analyses (asthma and respiratory infections), the sensitivity and accuracy of all models were higher for ANNs. Thus, this led us to use ANNs because of optimal performance in our data.

The results of the evaluation of ANN models showed a close estimate of quality measures for testing sets compared to training sets so that the accuracy of the model for CVD (training 74.3 % vs. testing 76.0 %), respiratory

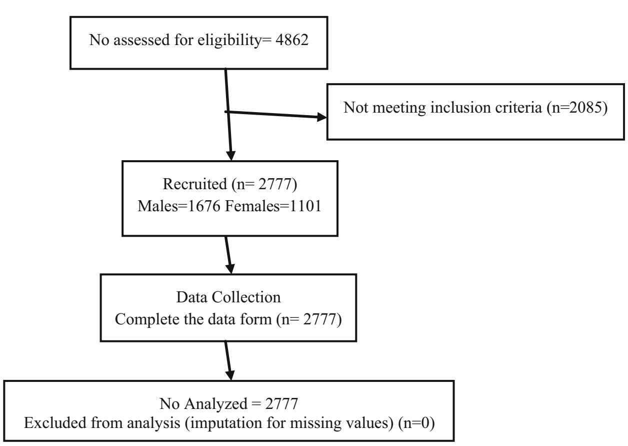

Fig. 3 Study flowchart

Table 2 Summary statistics of study variables during 2009–2011

	Summary statistics
Causes of hospital admission	
CVD	763 (27.5 %)
Respiratory infections	640 (23.0 %)
COPD	987 (35.5 %)
Asthma	387 (14.0 %)
Hospitals	
Ali Nasab	919 (33.1 %)
Amir Almomenin	100 (3.6 %)
Imam Reza	397 (14.3 %)
Children	536 (19.3 %)
Madani	825 (29.7 %)
Stations	
Abresan	765 (27.5 %)
Baghshomal	204 (7.3 %)
Province Health Center	881 (31.7 %)
Hakim Nezami	299 (10.8 %)
RahAhan	389 (14.0 %)
Namaz square	239 (8.6 %)
Air pollution and meteorological variables	
Mean temperature (°C)	10.94
Relative humidity (%)	52.00
O_3 (ppm)	20.01
NO_2 (ppm)	13.22
PM_{10} (μg/m^3)	79.29
SO_2 (ppm)	7.70
CO (ppm)	1.82
NO (ppm)	11.86
NO_X (ppm)	24.06

Cardiovascular diseases (CVD; including I20, I21, and I21.9; ICD-10 codes), asthma (J45), respiratory infections (including J06, J42, J12, J18, J20, J21, J22, and J30; ICD-10 codes), and chronic obstructive pulmonary disease (COPD; including J44.8 and J44.9; ICD-10 codes)

For air pollution and meteorological variables, the mean values and for other variables n (%) are presented

Table 3 Comparison of the quality of logistic regression and ANN models based on discrimination measures

Models	AUC			Sensitivity		Specificity		Accuracy	
	LR	ANN	P value[#]	LR (%)	ANN (%)	LR (%)	ANN (%)	LR (%)	ANN (%)
CVD	0.71	0.83	<0.001	24.0	38.3	87.4	92.1	66.9	74.3
Respiratory infections	0.74	0.80	<0.001	38.7	43.8	95.8	95.2	83.9	85.0
COPD	0.79	0.80	0.053	48.1	48.7	83.8	86.1	71.9	73.7
Asthma	0.78	0.81	<0.001	4.6	37.4	98.9	96.9	85.4	88.3

AUC area under curve

[#] *P* value based on DeLong method to compare the AUC

infections (training 85.0 % vs. testing 84.0 %), COPD (training 73.7 % vs. testing 96.0 %), and asthma (training 88.3 % vs. testing 87.4 %) were similar.

The effect of air pollution and metrological data on causes of hospital admission

The results of ANNs with importance analysis showed that the most important causes of hospital admissions for CVD were ambient NO, O_3, and NO_2 concentrations after adjusting for age, gender, LOS, mean temperature, and relative humidity. Other independent variables were in the moderate importance levels (Fig. 4). Significant association between NO_2 and CVD hospital admissions in the present study is in line with the findings of several previous studies such as those conducted in Shanghai using over-dispersed generalized linear Poisson model (Chen et al. 2010) and in Taipei by means of conditional logistic regression model (Chang et al. 2005). Interestingly, the findings from a study conducted in Santiago using conditional logistic regression model indicated that NO_2 was an ambient air pollutant with most adverse effects on CVD hospital admissions (Franck et al. 2014). A significant association between concentrations of O_3 in the ambient air and CVD hospital admissions has also been reported from Taiwan (Chang et al. 2005). Unlike the observed associations between NO_2 and O_3 with CVD hospital admissions, there is no agreement in the literature about the relation between NO and hospital admissions for CVD.

Regarding the hospital admissions for respiratory infections, the ambient PM_{10} was the most important predictor after adjusting for age, gender, LOS, mean temperature, and relative humidity. However, other independent variables were in the moderate and low levels of importance (Fig. 5). As shown in Fig. 5, there was an association between hospital admissions for respiratory infections and concentrations of PM_{10} in the ambient air. Similar effects of PM_{10} air pollutant on hospital admissions for respiratory infections were also observed in Lanzhou using Poisson regression model (Tao et al. 2014) and in Adelaide by conditional logistic regression model (Hansen et al. 2012).

For the COPD as another cause of hospital admissions, concentrations of NO_2, NO, and CO in the ambient air were in the high level of importance after adjusting for age, gender, LOS, mean temperature, and relative humidity. However, other independent variables were in the moderate

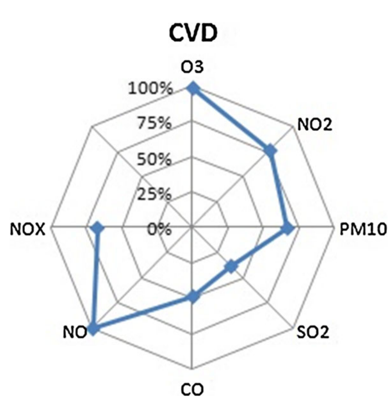

Fig. 4 Normalized importance of the independent variable in relation to CVD (adjusting for age, sex, LOS, mean temperature, and relative humidity)

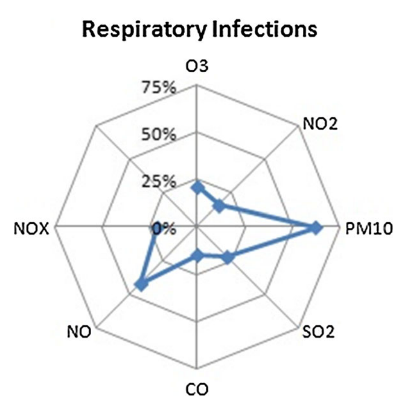

Fig. 5 Normalized importance of the independent variable in relation to respiratory infections (adjusting for age, sex, LOS, mean temperature, and relative humidity)

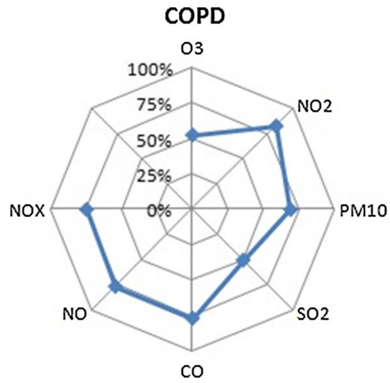

Fig. 6 Normalized importance of the independent variable in relation to COPD (adjusting for age, sex, LOS, mean temperature, and relative humidity)

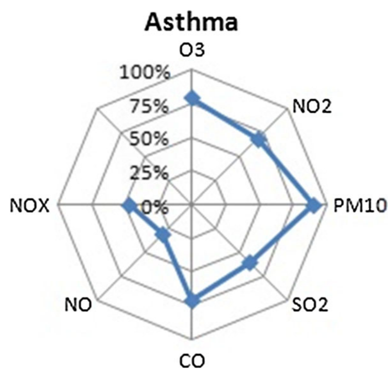

Fig. 7 Normalized importance of the independent variable in relation to asthma (adjusting for age, sex, LOS, mean temperature, and relative humidity)

level of importance (Fig. 6). Significant associations between NO_2 concentrations in the ambient air and hospital admissions for COPD have also been reported in studies conducted in India (Gurjar et al. 2010) and in Hong Kong (Qiu et al. 2013). However, there is no indication about the association between NO and CO with COPD hospital admissions in the literature.

Finally, after adjusting for age, gender, LOS, mean temperature, and relative humidity, concentrations of PM_{10} and O_3 in the ambient air were in the high level of importance for asthma. Other air pollutants including NO_2, SO_2, and CO were also in the moderate level. However, the NO and NO_X were in the low level (Fig. 7). A similar association showing an increase of 1.82 % in asthmatic hospitalizations due to elevated PM_{10} concentrations in the ambient air was recently observed in Shanghai (Cai et al. 2014). A summary of the most notable studies showing the associations between concentrations of different air pollutants in the ambient air and morbidity (hospital admissions and emergency room visits) is presented in Table 4.

In this study, considering the quality of models which were assessed based on the discrimination indices of sensitivity, specificity, accuracy, and the area under the ROC curve, the ANNs showed better fit. This is possibly due to the heterogeneity in our data, which leads to the deviation in the conventional regression assumptions. Moreover, ANNs include hidden layers in the model which take into account more complex relations in the data, and therefore this may be another possible explanation for better performance of the ANNs (e.g., more heterogeneity requires more complex system for modeling) (Kutner et al. 2005; Dreiseitl and Ohno-Machado 2002; Bishop 1995). On the other hand, this may lead the modeling to the problem of memorizing the dataset instead of identifying the underlying distribution or to over-fitting. Over-fitting is less of an issue in logistic regression, since the model complexity is already low, especially when no or few interaction terms and variable transformations are used, and this may cause a loss in the model flexibility. Compared to logistic regression, ANNs are more flexible and thus more susceptible to over-fitting (Dreiseitl and Ohno-Machado 2002). In this study, the complexity of model was reduced as much as possible to avoid the over-fitting of the models.

Additionally, as the functional form of likelihood differs for logistic regression and ANNs, the former is known as a parametric method, whereas the latter is sometimes called semi-parametric or nonparametric. This distinction is important because the input of parameters in logistic regression can be interpreted, whereas this is not always the case with the parameters of ANNs. Considering the design of this study, which was aimed to detect the best predictors of hospital admissions due to air pollution, the variables importance analysis method solved the problem. In other words, ANNs seems to be better than logistic regression models when it comes to identify the variables that are most likely to influence hospital admissions for air pollutants.

Conclusion

In conclusion, this case–crossover study demonstrated a significant association between gaseous air pollutants including NO_2, O_3, and NO and hospital admissions for CVD. Gaseous air pollutants of NO_2, NO, and CO were associated with hospital admissions for COPD, while PM_{10} was associated with hospitalizations due to respiratory infections. Concentrations of PM_{10} and O_3 in the ambient air were also found to be associated with asthmatic hospital admissions in Tabriz. These findings have important implications in terms of adverse health effects of air pollutants and establishing and developing policies for reducing cardiovascular and respiratory diseases caused by air pollution in

Table 4 Summary of articles presenting air pollutants' associations with morbidity (hospital admissions and emergency room visits)

References	City, nation	Model type	Years of study	Significant air pollutants	Health outcome
Current study	Tabriz, Iran	ANN, conditional logistic regression	2009–2011	NO, O_3, and NO_2	The most adverse effects on CVD hospital admissions
				PM_{10}	The most adverse effects on respiratory infections hospital admissions
				NO_2, NO, and CO	The most adverse effects on COPD hospital admissions
				PM_{10} and O_3	The most adverse effects on asthmatic hospital admissions
Khamutian et al. (2014)	Kermanshah, Iran	Poisson regression	2010–2011	PM_{10} and CO	Significant associations with CVD hospital admissions
Rodopoulou et al. (2014)	Dona Ana County, USA	Poisson generalized	2007–2010	$PM_{2.5-10}$	2.8–5.2 % increase in CVD and respiratory emergency room visits
Cao et al. (2009)	Shanghai, China	Over-dispersed generalized linear Poisson	2005–2007	For lag 3 10 μg/m^3 increase in	
				PM_{10}	0.01 % increase in emergency room visits
				SO_2	0.17 % increase in emergency room visits
				NO_2	0.08 % increase in emergency room visits
Chen et al. (2010)	Shanghai, China	Over-dispersed generalized linear Poisson	2005–2007	For lag 5 10 μg/m^3 increase in	
				PM_{10}	0.23 % increase in CVD hospital admissions
				SO_2	0.65 % increase in CVD hospital admissions
				NO_2	0.80 % increase in CVD hospital admissions
Kalantzi et al. (2011)	Magnesia, Greece	Poisson/count data models	2001–2007	PM_{10}, CO, NO, and O_3	Significant associations with cardiopulmonary diseases hospitalizations
Ge et al. (2011)	Shanghai, China	Generalized additive	2005–2008	$PM_{2.5}$	3.66 % increase in total hospitalizations
					4.06 % increase in CVD hospitalizations
					4.32 % increase in respiratory hospitalizations
Li et al. (2011)	Detroit, USA	Generalized additive, conditional logistic regression	2004–2006	SO_2 and $PM_{2.5}$	Significant increase in daily acute asthma
Qorbani et al. (2012)	Tehran, Iran	Conditional logistic regression	2007	PM_{10}	No significant association with hospital admission for acute coronary syndrome
				CO	Significant associations with hospital admissions for acute coronary syndrome
Chang et al. (2005)	Taipei, Taiwan	Conditional logistic regression	1997–2001	PM_{10}, NO_2, CO, and O_3	Significant associations with CVD hospital admissions
Hosseinpoor et al. (2005)	Tehran, Iran	Poisson regression	1996–2001	CO	Significant relations with daily admissions due to angina pectoris
				NO_2, O_3, SO_2, and PM_{10}	No significant relations with daily admissions due to angina pectoris
Lin et al. (2008)	New York, USA	Two-stage Bayesian hierarchical	1991–2001	O_3	Positive associations with respiratory hospital admissions
Gurjar et al. (2010)	Delhi, India	Ri-MAP	1998–2005	SO_2, NO_2, and TSP	About 1500/yr excess COPD hospital admission
Tao et al. (2014)	Lanzhou, China	Poisson regression	2001–2005	PM_{10}, SO_2, and NO_2	Significant associations with respiratory hospital admissions
Hansen et al. (2012)	Adelaide, Australia	Conditional logistic regression	2001–2007	$PM_{2.5}$ and PM_{10}	Significant associations with cardiorespiratory hospital admissions

Table 4 continued

References	City, nation	Model type	Years of study	Significant air pollutants	Health outcome
Frank et al. (2014)	Santiago, Chile	Conditional logistic regression	2004–2007	NO_2	The most adverse effects on CVD hospital admissions
				$PM_{2.5}$ and PM_{10}	The second most adverse effects on CVD hospital admissions
				CO	The third most adverse effects on CVD hospital admissions
Rushworth et al. (2014)	London, UK	Spatiotemporal	2003–2009	$PM_{2.5}$	1.8 % increase in the rate of respiratory hospital admissions
				CO	2.7 % increase in the rate of respiratory hospital admissions
Qiu et al. (2013)	Hong Kong	Generalized additive Poisson	1998–2007	NO_2	1.76 % increase in emergency COPD admissions
				O_3	3.43 % increase in emergency COPD admissions
				SO_2	1.99 % increase in emergency COPD admissions
Cai et al. (2014)	Shanghai, China	Over-dispersed generalized additive	2005–2011	PM_{10}	1.82 % increase in asthmatic hospitalizations
				SO_2	6.41 % increase in asthmatic hospitalizations
				NO_2	8.26 % increase in asthmatic hospitalizations

urban areas. The results of the modeling logistic regressions and ANNs confirmed the optimality of the ANNs versus logistic regressions models for detection of the best predictors of hospital admissions caused by air pollution. Further research is required to investigate the effects of seasonal variations on air pollution-related health outcomes.

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