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Original Article

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The concentration-response functions for short-term exposure to ambient air pollution

Abstract

Introduction. There are a few statistical approaches to estimate health impacts of the ambient air pollution concentrations. Air health effects are often studied in short-term exposure. In this context two main techniques are used; time-series and case-crossover (CC). This work focuses on the CC methodology. In the standard method risk is estimated using log-linear models.

Aim. This work proposes other types of the models.

Material and methods. The CC design is applied with various transformations of air pollution concentration. The mortality data are used for the period from 1987 to 2015 for Toronto, Canada. Daily concentration level of ambient ozone is considered as an exposure. The ozone concentration is transformed and used in the statistical models. The transformation is a product of two parts; a simple function such as logarithm and a logistic function as a weight. The transformed concentration is used in the CC statistical models. The models estimate the coefficient related to transformed concentration. It allows to construct the concentration-response function. The generated models are assessed using the Akaike information criterion (AIC).

Results. The relative risks (RR), reported at 75th percentile of the concentration (55 ppb) are different. The standard CC model gives RR=1.0195 with the 95% confidence interval (1.0035, 1.0358), whereas the model with the transformation gives better fit and estimates RR=1.0054 (1.0026, 1.0082).

Conclusions. The proposed methodology allows to construct an accurate approximation of the concentration-response functions. These functions provide adequate approximations and also identify a potential threshold.

Keywords: concentration, exposure, function, logistic function, mortality, risk, transformation.

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INTRODUCTION

An important research aspect in environment epidemiology is to asses the reliable association between ambient air pollution and human health. There are many approaches to obtain the quantitative estimation of the risks related to fluctuations in air pollution concentrations. Very often the goal of such studies is to determine the concentration-response function (CRF). The function allows the representation of the risks along the concentration levels. In particular, the function can determine a threshold and allow the identification of the concentration levels with higher impact on human health [1]. The shape of the concentration-response relationship is critical for estimating public health impacts [2,3].

Here, we focus on short-term exposure associations and mainly our goal is to present some methodological approaches. There are some publications related to the CRF and to ambient air pollution and short-term effects of the exposure on health and mortality but information in the literature about the shape of the CRF is limited [4,5].

The methodology proposed here is the technique to construct the CRF in the form of the parametric algebraic functions. A similar algorithm to estimate an optimal CRF was proposed for long-term exposure in the Canadian longitudinal mortality study in relation to fine particulate matter [6]. In this study daily counts of deaths in Toronto are analysed using conditional Poisson regression.

MATERIAL AND METHODS

Data

In this work, health data considered were all non-accidental mortality for Toronto, Canada. These data are part of the data used in the recently published results of a multi-city multi-country study [7]. We analyzed daily counts of mortality for the period from January 01, 1987 to December 31, 2015. In total we considered 797,650 death cases during 10,592 days with daily average 75.3 cases and with standard deviation (SD), SD=12.1 cases.

For air pollution exposure, we used the concentration of ambient ozone. The concentration was represented as daily maximum 8-hr mean. The same day and one day before death (lag01) concentrations were averaged used to represent the exposure in the constructed statistical models. The considered concentration has an average equal to 46.4 and SD=18.1 in ppb.

Two weather factors, temperature and humidity, were incorporated into the realized statistical models. Temperature

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and relative humidity were represented in the form of natural splines with three degrees of freedom. In this work, we mainly focused on the presented methodology rather than on a specific analysis of the exposure and their lags impact on health effects. Just to simplify the paper we used one exposure (lag01; an average of two days) and one design of the model.

Statistical models

Here we used a case-crossover (CC) technique as the base of our statistical approach and modelling [8]. An important aspect of the CC methodology is to determine the control periods for the case period. Among various methods to assign the controls is the time-stratified method [9]. The time-stratified case-crossover design is widely used in environmental epidemiology to analyze the short-term effects of air pollution. In the time-stratified technique the control periods are in the same days of week as the analyzed case. The time-window is restricted to one and common month for the case and control periods. In this paper we worked with daily counts. We constructed hierarchical clusters with the following structure using the calendar components: years, months, and day of week. The model is realized as a conditional Poisson regression with respect to the structural clusters of the form <year: month: day of week>, [10-13]. This construction results in 4 or 5 days in one cluster. The time effect is controlled by the applied structure. The calculations were conducted in the R statistical software (ver. 4.0; R Core Team 2020, [14]). The calculations were performed using the procedure gnm (generalized non-linear models). After identification of an optimal transformation the statistical model is re-calculated with the option "quasipoisson" [15,16].

Here we are using Z to represent the concentration of air pollutant. Thus in this work it is simple Z=ozone (O_3). We realize the transformation T of air pollution concentration before using it in the statistical models. The applied transformation is given by the following formula

T(Z)=f(Z)*L(Z),

Where the function f has a simple form such as f(Z)=Z,log(Z), or other simple functions of the concentration. Here we also analyzed the functions with an additional parameter A, such as f(Z)=Z^A,log(1+Z/A). The function L(Z) is the logistic function and it is given by the following expression

L(Z)=1/(1+e^((μ-Z)/(τ*r))).

The logistic function is applied here as a weight and allows us to construct the transformation T. The parameters control the shape of the weighting function. Here r is the concentration range of Z, μ (mu) is a location parameter, and the parameter τ (tau) controls the curvature of the weighting function. Larger values of the parameter give shapes with less curvature. For very small values of tau (such as τ<0.001) L(Z) approximates an indicator function at μ. The function L(Z) is almost linear for τ>0.5. It implies that a wide spectrum of the various shapes can be obtained and modelled [6,15].

The concentration-response function (CRF) is given by the relation

CRF(Z)=e^(β*T(Z)),

where the coefficient β is determined by the statistical model. Here this model is the CC model.

To obtain the form of the function CRF we need to have the value of the coefficient β and values of the parameters (here they are mu, tau, and A) used to construct the transformation T(Z).

The coefficient related to air pollutant, here β, is estimated by a realized statistical model. In this presentation we applied the case-crossover technique. In the standard approach we simply do not perform any transformation or we can interpret this situation as T(Z)=Z. In this situation we simply have the following relation CRF(Z)=e^(β*Z).

To apply a non-trivial transformation T(Z), we need to have the parameters of the weighting logistic function, mu and tau, and for some functions also A. Two approaches are proposed, and it depends on how many the parameters should be determined.

Approach I

This method can be easily applied when only two parameters, mu and tau, have to be determined. This approach is based on tabulation of the transformation function for various values of these parameters. It was observed that practically we can consider two values of the parameter tau; τ=0.1 and τ=0.2. Thus in practice only these two values of tau are tested. As the candidates we consider values for the parameter μ selected as percentiles of the distribution of Z. Simply, we use the proposed pair (μ,τ) and we build the function T(Z). This function was incorporated into the model. The statistical model was constructed with T(Z) values as an exposure. The Akaike information criterion (AIC) was collected for each tested pair of the parameters. The proposed pair (μ,τ) was evaluated. The quality of the approximation was measured by the AIC value. The pair which gives the lowest AIC was applied to realize the final transformation and statistical models.

Approach II

We can determine the parameters of the transformation T in an iterative process. The process can be described as follows. We define a function G which constructs statistical model and returns the coefficient β and the AIC value. The function G is used as a goal function in the minimization problem. The function nlminb in R is used here for this purpose [17]. The process starts with an initial (guess) value of the parameters describing the transformation. We have to use this approach in the case where the transformation has also the parameter A.

RESULTS

Table 1. summarizes the values of the coefficients of the analyzed models. The first line of the results corresponds to the standard CC method. This method gives the AIC value as 78707.7. The lowest AIC value is obtained as 78699.3 for three methods with transformation. The relative risk (RR) and the 95% confidence interval (95%CI) are calculated for all presented approaches at 75th percentile of Z (=55 ppb). These values were calculated after the corresponding models were identified as optimal ones using the AIC value as a criterion. The final results (RR, 95%CI) were calculated with determined transformation and the option "quasipoisson" in the gnm procedure.

TABLE 1. Fitted parameters for the constructed models. Estimated relative risks for ozone = 55 ppb. Non-accidental mortality and ambient ozone. Toronto, Canada, 1987-2015.

Beta	Error	mu	tau	A	AIC	F(Z)	RR	95% CI
0.000351	0.000147	#	#	#	78707.7	CC - #	1.0195	(1.0035, 1.0358)
0.001557	0.000413	159.967	0.201	#	78699.4	Z	1.0052	(1.0025, 1.0079)
0.051152	0.013543	161.099	0.162	#	78699.3	log (Z)	1.0064	(1.0031, 1.0097)
0.020120	0.005330	160.464	0.174	#	78699.3	sqrt (Z)	1.0059	(1.0028, 1.0090)
0.000121	0.000032	159.572	0.242	#	78699.4	Z^1.5	1.0046	(1.0022, 1.0070)
3.18E-08	8.45E-09	100.038	0.805	3.083	78699.4	Z^A	1.0032	(1.0015, 1.0048)
0.202369	0.053617	161.587	0.179	62.066	78699.3	log (1+Z/A)	1.0054	(1.0026, 1.0082)

Notes: Parameters mu and tau determine the logistic function. Two used functions f(Z) are defined by an additional parameter A, and they are: Z^A and log (1+Z/A). The first line shows the coefficient estimated by the CC method (with no a transformation). RR – relative risk, CI – confidence interval.

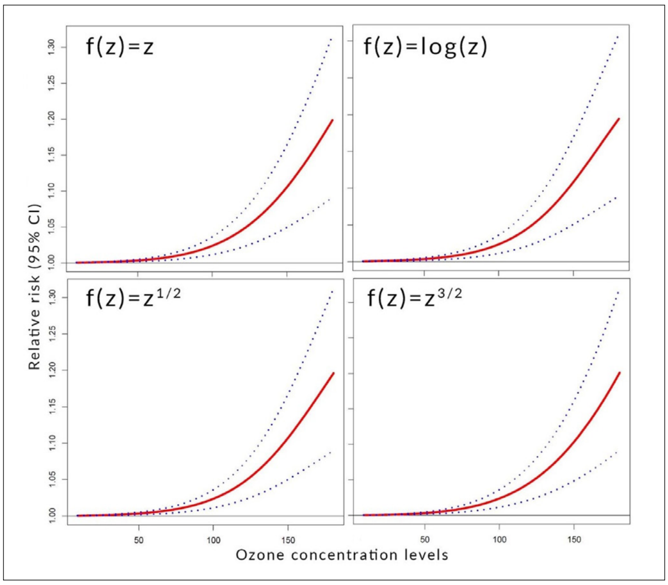

FIGURE 1. Four CRF shapes estimated with the indicated transformations (f(Z) * L(Z)).

Figure 2. illustrates the histogram of the considered concentrations. It also shows the concentration-response shapes for the CC method and two methods with the transformations, where the parameter A is present. We may assume that the transformation with f(Z)=log(1+Z/A) is preferable, as it is universal and easy to implement.

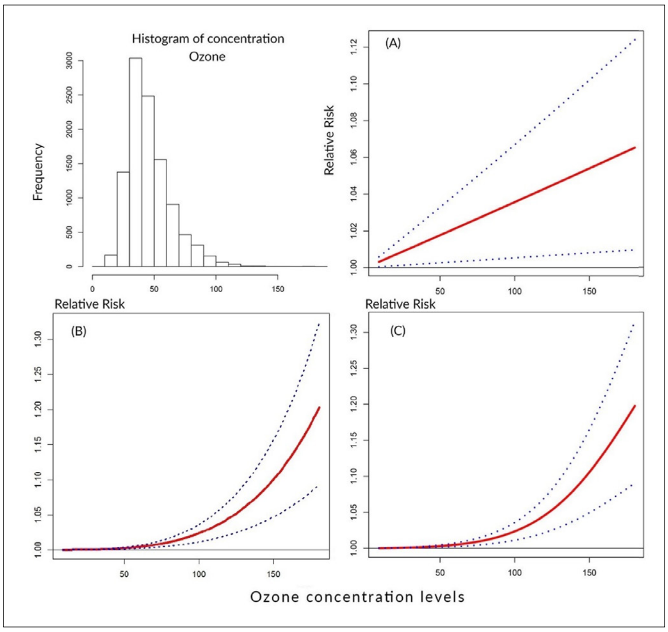

FIGURE 2. Histogram of ozone concentration. (A) The CRF shape for the CC method. (B-C) The CRF shapes for the methods with the transformations; (B) f(Z)=Z^A, (C) f(Z)=log(1+Z/A).

We should highlight that the standard case-crossover method gives the following estimations: RR=1.0195 (95% CI: 1.0035, 1.0358) and the method with f(Z)=log(1+Z/A) gives the corresponding values as RR=1.0054, (95% CI: 1.0026, 1.0082). Both the results are reported for Z=55 ppb.

DISCUSSION

According to the assumed criterion to evaluate the constructed models, in our case it is the AIC value criterion, the models with the transformations generate more accurate approximations. The estimated relative risk is smaller than in the case of the standard case-crossover approach. In the CC models the log-linear association is assumed and assessed.

As we see in Fig. 2, the histogram shows that the most frequent concentrations of ambient ozone are less than 75 ppb. The standard CC method indicates RR up to 1.025 in this range of the concentration. The models with the transformation suggest the lower risk than the CC method generates. The models with transformation even indicate almost no effect below 75 ppb concentration level. For the higher levels of the concentrations, for example, 150 ppb, the situation is opposite. The standard CC method estimates RR=1.05. The model with the transformative gives RR=1.15. These values are estimated from the CRF graphs.

We really do not know where the true value lies. The obtained estimations are the results of the statistical methods. We may try to remove some high values of the concentration to observe the behaviour of the proposed models. All techniques and statistical methods considered here estimated the associations as positive and statistically significant. The obtained CRF shapes induce a threshold. Here we have changes only in the form of the f(Z) function and as a consequence the shapes are similar. The proposed method generates various forms of the CRF shapes which are flexible to the considered health outcomes. As an example of the possible various shapes see in [6] Fig. 1.

REFERENCES

1. Ren M, Fang X, Li M, et al. Concentration-response relationship between PM2.5 and daily respiratory deaths in China: A systematic review and metaregression analysis of time-series studies. Biomed Res Int. 2017;2017:5806185.
2. Hoek G, Boogaard H, Knol A, et al. Concentration response functions for ultrafine particles and all-cause mortality and hospital admissions: results of a European expert panel elicitation. Environ Sci Technol. 2010;44(1):476-82.

3. Pope CA 3rd, Cropper M, Coggins J, Cohen A. Health benefits of air pollution abatement policy: Role of the shape of the concentration-response function. J Air Waste Manag Assoc. 2015;65(5):516-22.
4. Atkinson RW, Yu D, Armstrong BG, et al. Concentration-response function for ozone and daily mortality: results from five urban and five rural U.K. populations. Environ Health Perspect. 2012;120(10):1411-7.
5. Yan M, Wilson A, Bell ML, et al. The shape of the concentration-response association between fine particulate matter pollution and human mortality in Beijing, China, and its implications for health impact assessment. Environ Health Perspect.2019;127(6):67007.
6. Nasari MM, Szyszkowicz M, Chen H, et al. A class of non-linear exposure-response models suitable for health impact assessment applicable to large cohort studies of ambient air pollution. Air Qual Atmos Health. 2016;9:961-72.
7. Vicedo-Cabrera AM, Sera F, Liu C, et al. Short term association between ozone and mortality: global two stage time series study in 406 locations in 20 countries. BMJ. 2020;368:m108.
8. Maclure M. The case-crossover design: a method for studying transient effects on the risk of acute events. Am J Epidemiol. 1991;133(2):144-53.
9. Janes H, Sheppard L, Lumley T. Case-crossover analyses of air pollution exposure data: referent selection strategies and their implications for bias. Epidemiology. 2005;16:717-26.
10. Armstrong BG, Gasparrini A, Tobias A. Conditional Poisson models: A flexible alternative to conditional logistic case cross-over analysis. BMC Med Res Methodol. 2014;14:122.
11. Szyszkowicz M. Use of generalized linear mixed models to examine the association between air pollution and health outcomes. Int J Occup Med Environ Health. 2006;19:224-7.
12. Szyszkowicz M. Case-crossover method with a short time-window. Int J Environ Res Public Health. 2019;17(1):202.
13. Szyszkowicz M. Use of two-point models in "Model choice in time-series studies of air pollution and mortality". Air Qual Atmos Health. 2020;13:225-32.
14. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria; 2020.
15. Szyszkowicz M. Concentration-response functions for short-term exposure and air pollution health effects. Environ Epidemiol. 2018;2(2):e011.
16. Turner H, Firth D. Generalized nonlinear models in R: An overview of the gnm package. (R package version 1.1-1). 2020. [http://CRAN.R-project.org/package=gnm]
17. David M. Gay DM. Usage summary for selected optimization routines. Computing Science Technical Report 153, AT&T Bell Laboratories, Murray Hill; 1990.

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