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Measuring the impact of air pollution on respiratory infection risk in China☆

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A B S T R A C T

China is now experiencing major public health challenges caused by air pollution. Few studies have quantified the dynamics of air pollution and its impact on the risk of respiratory infection. We conducted an integrated data analysis to quantify the association among air quality index (AQI), meteorological variables and respiratory infection risk in Shaanxi province of China in the period of November 15th, 2010 to November 14th, 2016. Our analysis illustrated a statistically significantly positive correlation between the number of influenza-like illness (ILI) cases and AQI, and the respiratory infection risk has increased progressively with increased AQI with a time lag of 0–3 days. We also developed mathematical models for the AQI trend and respiratory infection dynamics, incorporating AQI-dependent incidence and AQI-based behaviour change interventions. Our combined data and modelling analysis estimated the basic reproduction number for the respiratory infection during the studying period to be 2.4076, higher than the basic reproduction number of the 2009 pandemic influenza in the same province. Our modelling-based simulations concluded that, in terms of respiratory infection risk reduction, the persistent control of emission in the China's blue-sky programme is much more effective than substantial social-economic interventions implemented only during the smog days.

1. Introduction

With uninterrupted rapid economic development for nearly 30 years, China is now experiencing major public health challenges due to environmental changes (Xu et al., 2013; Editoral, 2014; Feng et al., 2016). A particular issue is air pollution (Gao et al., 2015; Van Donkelaar et al., 2015) and its impact on health. Since the 'pollution shock' when heavy smog struck northern China in 2013, both the severe intensity of air pollution and the number of days with polluted air (air quality index (AQI), AQI > 100) have been exhibiting clearly increasing trends (IAQ, 2015).

Emerging toxicological and epidemiological studies provide evidence to show that, in addition to adverse effects on visibility and global climate (Menon et al., 2002; So and Wang, 2003), long-term exposure to outdoor air pollution is associated with a number of adverse health outcomes ranging from cardiovascular diseases (Polichetti et al., 2009; Maté et al., 2010) to chronic/acute respiratory illnesses (Chauhan and Johnston, 2003; Schikowski et al., 2005; Strak et al., 2010; Wong et al., 2009). The work of Zhang et al. (2014) illustrates that short-term exposures to haze and air pollution are associated with hospital admissions in Guangzhou. Additional research also demonstrates the significant association of ambient PM2.5 concentrations with monthly influenza cases in Hong Kong (Wong et al., 2009), and with influenza-like illness (ILI) risk in Beijing during an influenza season (Feng et al., 2016). Since influenza and other respiratory infectious illnesses are known to be strongly influenced by meteorological conditions, a quantitative description of the association between respiratory risk and AQI with seasonally varying meteorological conditions remains unclear,

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and falls within the scope of this study.

We develop a framework towards this quantitative analysis, with data from various sources relevant to Xi'an, a metropolitan in northwest China, lying on the Guanzhong plain (Xi'an). Xi'an has been suffering almost every year from smog and hazes. Fig. 1 provides the relevant data about ILI cases (and their stratification by demographic ages), AQI and temperature, humidity and pressure during the period 2010–2016.

Our goal is to examine the relative respiratory infection risk changes with observed AQI and predicted trend, along with meteorological information. Both the statistical generalized additive model and dynamic models for AQI evolution are to be used to provide the parameters and analytic formulation of the force-of-infection for the epidemiological models for respiratory infectious disease transmission to assess the impact of air pollution intervention on respiratory infection dynamics in Xi'an.

2. Models and data

2.1. The generalized additive model (GAM) linking ILI cases to AQI and meteorological conditions

The model selection is based on the high value of R^2_{adj} (Mittlbock and Waldhor, 2000), smaller Akaike's Information Criterion (AIC) (Akaike, 1974), and generalized cross validation (GCV) (Shahraray and Anderson, 1989). The following selected log-linear generalized additive model (GAM) model reads

$$\begin{aligned} & Y_t \sim Gamma(\mu_t, \nu); \\ & Log\mu_t = \alpha + \beta X_{t,l} + ns(t, df = 12) + ns\left(Temp_{t,l}, df = 2\right) \\ & +ns(Humi_{t,l}, df = 2) + ns(Pres_{t,l}, df = 2). \end{aligned} \tag{1}$$

where Y_t is the observed daily ILI cases (at day t), following Gamma distribution with mean μ_t and dispersion parameter $1/\nu$ (here ν can be obtained by maximum likelihood estimation), α is the intercept, β is the log-relative rate of ILI cases related to per unit increase of air pollutants. $X_{t,l}$ represents the AQI at day t with lag l ranging from 0 to 14 days (Gasparrinia et al., 2010). ns is the non-parametric smooth B-spline function of calendar time (t), temperature ($Temp_{t,l}$), humidity ($Humi_{t,l}$), and pressure ($Pres_{t,l}$). This basic model, incorporating the linear function of air pollution variable (AQI) and the smoothed B-spline functions of time and weather conditions, offers a framework to characterize non-linear and non-monotonic links between daily ILI cases and meteorological conditions (Dominici et al., 2002). The selection results are listed in Table A2 and the model check is showed in Fig. A2 (see details in SI (supporting information) section A).

2.2. Dynamical model of AQI

The dynamics of AQI is given by the following linear differential equation

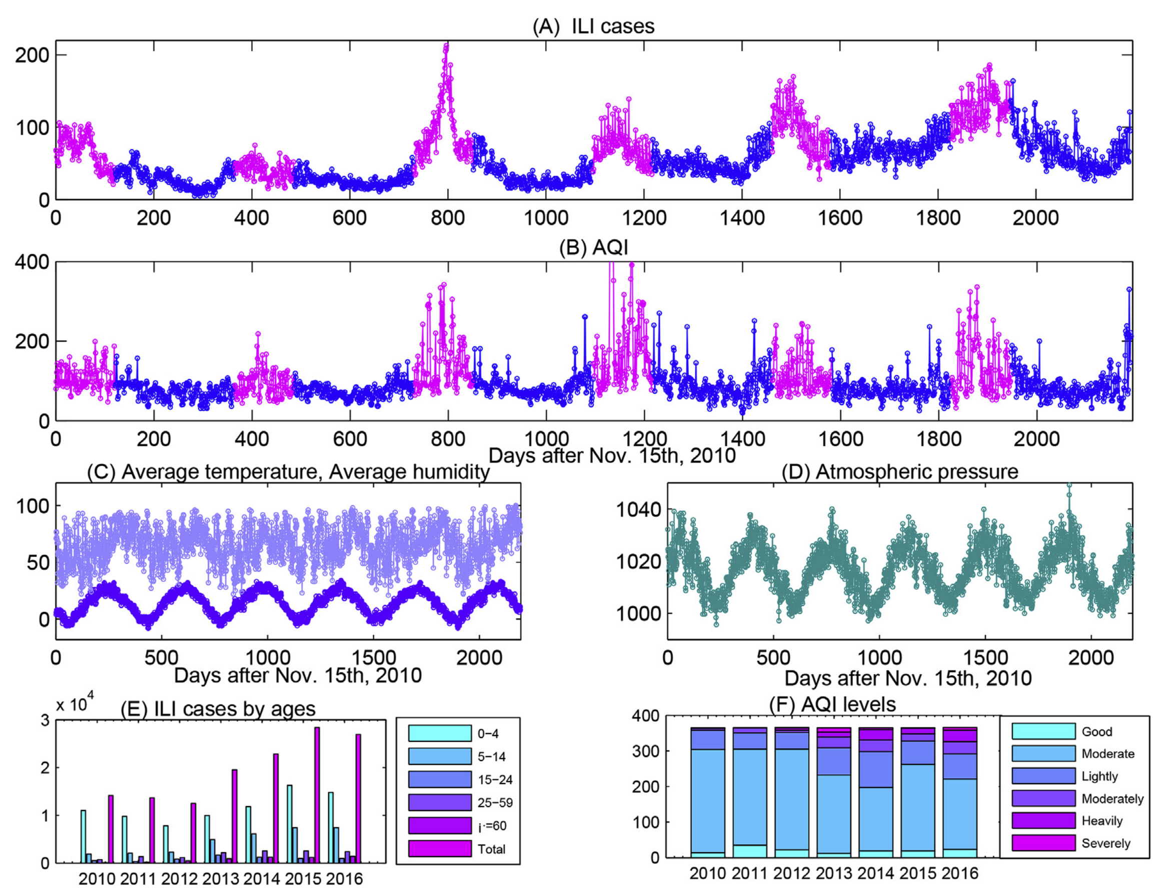

Fig. 1. The Data. (A) The newly reported ILI cases of sentinel surveillance from seven hospitals of Shaanxi province from Nov.15th, 2010 to Nov.14th, 2016; (B) Realtime Air Quality Index (AQI) for Shaanxi province; (C–D) Average temperature, humidity and pressure along time; (E) The distribution of numbers of reported ILI cases by ages and (F) the number of days at each air pollution level from the year 2010–2016. The pink curves in (A) and (B) plots correspond to the time duration from Nov.15th to Mar.15th of the following year. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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