Quantifying the effectiveness of early warning systems for heavy air pollution based on public responses

Fangping Wang¹,²,³, Fei Su²,³

¹ School of Electronic Engineering, Beijing University of Post and Telecommunication, Beijing 100876, People’s Republic of China;
² China Transport Telecommunications & Information Center, Beijing 100011, People’s Republic of China;
³ National Engineering Laboratory of Transportation Safety & Emergency Informatics, Beijing 100011, People’s Republic of China

E-mail address: wangfangping@cttic.cn.

Abstract. Air pollution is a major environmental and public health issue in China. Air pollution warnings are issued with the aim of allowing individuals to take protective measures and mitigate risks. Because these warnings are only reminders and not mandatory instructions, public responses play a vital role in the effectiveness of Early Warning Systems (EWSs) for heavy air pollution. However, public responses have never been considered in the evaluation of EWS effectiveness. To address this knowledge gap, a method is proposed to incorporate public responses in the assessment of the effectiveness of EWSs. Warning effectiveness was based upon costs associated with public responses and non-responses, and the minimization of total costs. Health harm was assessed based on an exposure-response relationship, and health effect terms were used to determine the cost of non-responses. In addition, willingness-to-pay values for health protection measures that reduce the risk of dying or getting sick from air pollution were used to determine response investment costs. A Monte Carlo simulation model was then designed to simulate the uncertainty of the warning issuance and public behavior. In addition, numerical experiments were performed to evaluate the model. Experimental parameters were based on the air quality index and warning response surveys from individuals in Beijing, and the effects of air pollution warning issuance were evaluated using model parameters based on several specific scenarios. The results indicated that the current warning threshold used in China is acceptable for optimizing public response. The results also suggested that positive actions taken by people to reduce health risks can improve the effectiveness of EWSs. The model proposed herein can be used by policy makers and governments to monitor and improve air pollution EWSs. In addition, the model and the results presented here are of use for investigating the improvement of global air quality EWSs.

1. Introduction
China has experienced rapid economic development, urbanization, urban population growth, and concomitant growth in vehicle usage over the past three decades, which has been accompanied by increasing air pollution, especially in mega-cities[1]. In Beijing, the capital city of China, particulate matter with an aerodynamic diameter less than 2.5 μm (PM2.5) is the main air pollutant [2] and has become a serious health issue[3]. Epidemiological studies have determined that exposure to PM2.5 can result in emergency hospital visits and even mortality due to cardiovascular, respiratory, and...
cardiopulmonary diseases [4-5]. Air pollution is unlikely to be entirely eliminated in the foreseeable future, and thus individual-level mitigation and intervention are necessary to increase the protection of human health. Air pollution early warnings are used to provide timely information for future or ongoing air pollution events that allow the public to take protective measures and avoid or minimize economic costs and health risks caused by air pollution. However, the early warnings only serve as suggestions for personal-level health protection and are not mandatory. Consequently, the public response to air pollution warnings is self-determined by individuals taking protective measures. Therefore, the public response to air pollution warnings has become a key point of focus in the reduction of pollution health risks, and has also become an important target in assessing the effectiveness of air pollution early warning systems (EWSs).

Evaluations of EWS effectiveness to date often address the technical components of the warning system. For example, Schröter et al. (2008) suggested that the important component in the effectiveness of flash flood EWSs is the connection between forecast reliability and lead time[6]. The reliability of monitoring equipment and warning signals is used to identify the effectiveness of natural-hazard EWSs [7-9]. To increase the effectiveness of EWSs, personalized warning information services have been developed based on research on individuals’ perceptual processing of warnings and the effect of warning information on public responses [10]. In addition, Paté-Cornell modeled the performance of fire EWSs based on the response to false warnings in order to identify an optimal trade-off between the Probability of Detection (POD) and the Probability of False Alarm (PFA) [11]. In these analyses, the effectiveness of EWSs is a function of POD and PFA after incorporating the functional relationship between the probability of Compliance (POC) and PFA [12]. Even with advanced monitoring, forecasting, and dissemination technologies, EWSs will not be effective if a warning does not stimulate the execution of protective measures [13-15]. For suddenly occurring hazards with visible and fatal consequences, the public must respond to early warnings. In contrast, the consequences for gradually occurring hazards are less tangible or are time-delayed, and thus the public response to these warnings is not driven by survival instincts. For example, heterogeneity in individual responses to air pollution EWSs may arise from variation in individual characteristics [16]. Wang et al. (2019) observed that responses to these types of warnings are associated with knowledge of the warning, perception of health risks from air pollution, and respondent gender[16].

Current studies have focused on air pollution forecasting in EWSs. Algorithms have been previously developed to forecast air pollutant indices, including the PM2.5, PM10 and SO2 concentrations, among other characteristics, and uncertainty in air quality predictions has been used to evaluate the effectiveness of air pollution warning systems [17-21]. However, air pollution EWSs incorporate much more information than is used for only predicting disasters. These EWSs enable the public to prepare for pollution events by taking protective measures that may reduce risks to health and life [22] resulting from hazardous air quality conditions. Individual health-related protective measures are especially helpful for reducing personal exposure and mitigating health hazards in regions with high levels of particulate matter pollution [23]. Consequently, public responses to warnings should be considered when assessing the effectiveness of air pollution EWS.

The effectiveness of EWSs is measured by monetary values wherein the net positive value or the benefit–cost ratio must be greater than one [24]. The overall operational costs of EWSs comprise costs due to societal and economic losses owing to false alarms (e.g., losses caused by evacuations and the interruption of business activities) [12]. Meanwhile, EWS benefits are determined by societal and economic savings resulting from avoiding damage and the reduction in injury and deaths due to EWSs [25]. However, the costs and benefits of EWS may not always be explicitly measured in monetary terms, and they cannot provide scientific guidance for issuing warnings. For example, Beijing issued two red warnings on December 7 and December 19 in 2015 that required schools, factories, and construction sites to be closed and placed restrictions on driving, which paralyzed the city and incurred high economic costs [26]. To reduce such high societal costs, the Beijing government raised the threshold of red warnings on January 22, 2016 [27]. However, the red warning emergency measures were only recommended for adjustment rather than reducing the number of warnings [28].
example underscores the importance of developing a method to measure the effectiveness of warning issuances and determining a reasonable warning threshold.

To address this knowledge gap, we estimated the effectiveness of air pollution EWSs based on costs associated with public responses and non-responses, and the modeling of uncertainties. Health hazards were assessed by deriving an exposure-response relationship, and the resulting health effect costs [29] were used to determine the overall cost of non-responses. Responsive investment costs were determined via willingness-to-pay amount calculations based on the contingent valuation method (CVM) for protection measures that reduce health risks from air pollution. There are various uncertainties associated with warning issuance and public responses to warnings. Monte Carlo simulation methods were used to quantify the evaluation-associated uncertainties in order to achieve a reasonable warning threshold based on public responses. A model for assessing air pollution warning issuance is introduced in addition to a description of the Monte Carlo simulation model. In addition, several experiments are described that investigate the variation in results by modulating different model parameters.

2. Methodology

A framework to assess the effectiveness of EWSs for air pollution based on public responses is first presented (see Figure 1). The framework can be divided into three components: early warning issuance, public warning response, and the associated costs of responding. The probability of early warning issuance, the probability of public response, and the public response investment were used to model these three components. The effectiveness of air pollution EWSs were estimated based on costs associated with public responses and non-responses. Detailed model parameters are defined as follows:

\[ \text{AQI with health harm, } P_{\text{w}} \]
\[ \text{No warning issuance, } P_{\text{n}} \]
\[ \text{Warning issuance } P_{\text{w}}(i = 1, 2, 3, 4) \]
\[ \text{Accurate warning issuance } P_{\text{wi}}(q > Q_h) \]
\[ \text{False warning issuance } P_{\text{fi}}(q < Q_h) \]
\[ \text{No warning issuance } P_{\text{n}}(q < Q_w) \]
\[ \text{Missed warning } P_{\text{mi}}(q > Q_w) \]
\[ \text{Response cost } V_{\text{r}} \]
\[ \text{Non-response cost } V_{\text{nr}} \]
\[ \text{Response } P_{\text{r}} \]
\[ \text{Non-response } P_{\text{nr}} \]
\[ \text{Public response cost } V_{\text{rp}} \]
\[ \text{Non-public response cost } V_{\text{npr}} \]

2.1 Early warning issuance

A wealth of indices can be used to describe and evaluate air quality, such as the Air Pollution Index (API) [30-31] and the Air Quality Index (AQI) [32-34]. The current study uses the AQI to characterize air quality because it is recommended in the Chinese national ambient air quality standard (Ambient Air Quality Standards, GB 3095-2012). Moreover, the concentration of PM$_{2.5}$ was included in the calculation of AQI, has posed stricter standards for evaluating air quality.

The variable $q$ is first defined, which represents Air Quality Index (AQI). Figure 2 shows the condition of air pollution warning issuance. $Q_h$ is the threshold of health harm, $Q_w$ is the threshold
of warning. When $q$ reaches $Q_h$, exposure to air pollution harms humans health. The probability of healthy air quality, $P_{g_j}$, where $j$ can be $0$=healthy, $1$=unhealthy. $P_{g_0}$ is the probability of healthy air quality, and is given as $P_{g_0} = Pr(q < Q_h)$. $P_{g_1}$ is the probability of unhealthy air, and is given as $P_{g_1} = Pr(q \geq Q_h)$. An air pollution warning, $w_i$, is issued to residents when the forecast of $q$ reaches $Q_w$. $w_1$ is the blue warning level, $w_2$ is the yellow warning level, $w_3$ is the orange warning level, and $w_4$ is the red warning level that represents increased durations of severe air pollution. $w_0$ represents no warning issuance for potential harm to human health. The probability of a particular warning level given the state of the air, $P_{w_i|q}$. If $Q_h < Q_w$, $P_{w_i|q_0}$ (where $i=0, 1, 2, 3, 4$) is zero. $P_{w_i|q_j}$ is the probability that $q$ is less than $Q_w$ and larger than $Q_h$ under the condition that $q$ is larger than $Q_h$, and is given as $P_{w_i|q_j} = Pr(Q_w > q \geq Q_h \mid q \geq Q_h)$. $P_{w_i|q_j}$ (where $i=1, 2, 3, 4$) is the probability that $q$ is larger than $Q_w$ under the condition that $q$ is larger than $Q_h$, and is given as $P_{w_i|q_j} = Pr(q \geq Q_w \mid q \geq Q_h)$. However, air pollution warning signals can be inaccurate. For example, when a $w_i$ level warning signal is issued, the actual AQI may or may not conform to the $w_i$ level. Consequently, $P_{q_i|w_i}$ (where $i=0, 1, 2, 3, 4$) is the probability of a given AQI value occurring when issuing a $w_i$ level warning. When $Q_h \leq q < Q_w$, $P_{q_i|w_0}$ represents the probability of no warning, $P_{q_i|w_i}$ (where $i=1, 2, 3, 4$) represents the probability of false alarm; When $q \geq Q_w$, $P_{q_i|w_0}$ represents the probability of missed alarm, $P_{q_i|w_i}$ (where $i=1, 2, 3, 4$) represents the probability of detection.

Figure 2. The conditions of air pollution warning issuance.

2.2 Public warning response
After issuing an air pollution early warning, the public may take actions to protect themselves from the effects of air pollution. There are four primary protective measures that can voluntarily be taken by the public to respond to air pollution warnings [16]. The responses of individuals to warnings are affected by multiple factors including sociodemographic characteristics, knowledge of hazards, and subjective cognition [16, 35-37]. These factors can be obtained through questionnaire survey of warning responses. A Binary Logit Regression model could be constructed to evaluate the probability of response given a particular warning level, $P_{r_k|w_i}$, where $k=0$ for no response and $k=1$ for a response. The model is as follows:

\[
\ln \left( \frac{P_{r_k|w_i}}{P_{r_k|w_0}} \right) = \beta_0 + \beta_1 \times x_1 + \cdots + \beta_n \times x_n \quad (1)
\]

where $P_{r_k|w_i}$ is the probability of a response action to the warning, $w_i$ and $P_{r_k|w_i} + P_{r_k|w_0} = 1$. $x_n$ is the independent variable and comprises effects due to gender, age, education, incomes, risk perception, and other factors, while $\beta_n$ is the corresponding coefficient, and $\beta_0$ is the intercept.

2.3 Definition of public response and non-response costs
Costs associated with the response to warnings have two components. The first is “non-response cost
assessment,” which is determined by the monetization cost of health damage as determined by the exposure-response function and the economic value of health effect terms [29]. The second component is the “response investment”, which is evaluated by willingness to pay (WTP) for protective measures that reduce the risk of dying or getting sick from air pollution, which is determined by the contingent valuation method. The model for our calculation of response costs is shown in Figure 3.

Different costs may be incurred by the public based on the actions they take in response to a warning issuance. If the public takes action, they determine the cost as given by $V_{r_i|w_i}$, otherwise the cost is determined by $V_{w_i}$. The cost $V_{r_i|w_i}$ includes the response investment $R_i$ when a level $i$ warning is issued and the cost of harm to health is $H(q)$ when air pollution $q$ occurs. Individuals that do not take action due to the warning determine the cost of health damage as $H(q)$, where $V_{w_i} = H(q)$. Meanwhile, the portion of the public that does take action pays the response investment $R_i$ and the cost of harm to health is given by $(1 - \alpha_i) \times H(q)$, where $\alpha_i (0 \leq \alpha_i < 1)$ is the reduction ratio by which the public response investment $R_i$ can reduce the damage to health due to air pollution. Thus, $V_{r_i|w_i} = R_i + (1 - \alpha_i) \times H(q)$. Table 1 summarizes the costs associated with responses and non-responses to warnings.

| Warning level | Response | Costs |
|---------------|----------|-------|
| $w_0$         | yes      | $V_{r_i|w_i} = 0$ |
|               | no       | $V_{w_i} = H(q)$ |
| ($i=1,2,3,4$) | yes      | $V_{r_i|w_i} = R_i + (1 - \alpha_i) \times H(q)$ |
|               | no       | $V_{w_i} = H(q)$ |

2.4 The effectiveness of air pollution EWSs

According to the above definitions of early warning issuance, public response, and the associated costs, the total expected cost that is used to assess the effectiveness of air pollution warnings is calculated as follows:

$$E[V] = \sum_{i=1}^{4} \left( \sum_{j=1}^{4} P_{w_j} \times \sum_{k=1}^{4} P_{r_k} \times P_{h} \times \sum_{l=1}^{4} P_{v_l} \times V_{r_l|w_l} \right)$$

$$= P_{w} \times \left( \sum_{j=1}^{4} P_{w_j} \times \sum_{k=1}^{4} P_{r_k} \times H(q) \times \sum_{l=1}^{4} P_{v_l} \times (R_i + (1 - \alpha_i) \times H(q)) \right)$$

3. Case study

Beijing is the capital city of China with a population more than 21 million. Air pollution warning issued only when the AQI reaches a heavy level in Beijing. From 2014 to 2017, a total of 66 warnings of heavy air pollution were issued in 133 days, including 30 blue warnings in 31 days, 23 yellow warnings in 52 days, 10 orange warnings in 37 days, and 3 red warnings in 13 days. Also in these four years the average annual concentration of PM$_{2.5}$ was 85.9μg/m$^3$, 80.6μg/m$^3$, 73μg/m$^3$, and 58μg/m$^3$, respectively, which were all higher than the national air quality standard (35μg/m$^3$) [Beijing Environmental Statement, 2014-2017, Beijing Municipal Environment Protection Bureau (BJEPB)].
People living in the study area experienced a long-term frequent and severe pollution. It is very necessary to investigate the effectiveness of early warning systems for heavy air pollution based on public responses. The parameter settings are as follows:

### 3.1 The probability of an early warning

The definition of air quality levels according to the Chinese Technical Regulation on Ambient Air Quality Index (HJ 633-2012) [32] is shown in Figure 4. Individual Air Quality Indices and their corresponding concentration thresholds and related information can be found on the official website of the Ministry of Ecology and Environment of the People’s Republic of China (http://kjs.mep.gov.cn/hjbhbz/bzwb/jcffbz/201203/t20120302_224166.shtml) [32].

\[
Q_{w} = 201 \quad (Q_{w} = \text{Threshold of early warning})
\]

![Figure 4. Air quality definitions.](image)

The air pollution early warning levels in Beijing’s heavy air pollution emergency plan are divided into four levels: blue, yellow, orange, and red. The warning issuance standard is as follows:

- **Blue**: forecast of heavy air pollution that is sustained for one day (24 h);
- **Yellow**: forecast of heavy air pollution that is sustained for two days (48 h);
- **Orange**: forecast of heavy air pollution that is sustained for three days (72 h);
- **Red**: forecast of heavy air pollution that is sustained for more than three days (>72 h).

Assuming that \(q_{dj}\) is the forecasted AQI value of the \(j\)th day \((j = 1, 2, 3)\), the probabilities of issuing the four warning levels are calculated by the following equations.

**Blue:**

\[
P_{r_{1} \mid r_{j}} = \Pr \left\{ q_{d} > 200 \land q_{d} \leq 200 \right\}
\]

**Yellow:**

\[
P_{r_{2} \mid r_{j}} = \Pr \left\{ q_{d} > 200 \land q_{d} > 200 \land q_{d} \leq 200 \right\}
\]

**Orange:**

\[
P_{r_{3} \mid r_{j}} = \Pr \left\{ q_{d} > 200 \land q_{d} > 200 \land q_{d} > 200 \land q_{d} \leq 200 \right\}
\]

**Red:**

\[
P_{r_{4} \mid r_{j}} = \Pr \left\{ q_{d} > 200 \land q_{d} > 200 \land q_{d} > 200 \land q_{d} > 200 \right\}
\]

AQI data encompassing air quality for Beijing between January 1, 2008, and December 31, 2017, were collected from the Ministry of Ecology and Environment of the People’s Republic of China Data Center (http://datacenter.mep.gov.cn/websjzx/queryIndex.vm). The probability of healthy air quality, \(P_{gj}\), (where \(j\) can be 0=healthy, 1=unhealthy) and the probability of a particular warning level given the state of the air, \(P_{w_{ij} \mid r_{i}}\), (where \(i=0, 1, 2, 3, 4\)) can be obtained from the AQI sample data.

### 3.2 Probability of public response

To estimate the probabilities of a public response, \(P_{r_{j} \mid w_{i}}\) and \(P_{r_{j} \mid w_{j}}\), and the investment cost of responding, \(R_{i}\), a questionnaire survey was conducted by individual interview in Beijing, China [16]. Detailed analysis and discussion of questionnaires and survey data can be found in [16]. The parameters specifying the probability of responses were set as follows:

**Model of public response to a blue warning:**

\[
\ln \left( \frac{P_{r_{1} \mid w_{i}}}{P_{r_{a} \mid w_{i}}} \right) = -1.83 - 0.38 \times \text{Gender} + 0.2 \times \text{age} - 0.18 \times \text{Education} + 0.31 \times \text{AQI} + 0.27 \times \text{HEP}
\]

\(P_{r_{1} \mid w_{i}} + P_{r_{a} \mid w_{i}} = 1\)

**Model of public response to a yellow warning:**
\[
\begin{align*}
\ln \frac{P_{\text{rw}}}{P_{\text{nr}}(\text{rw})} &= -0.17 - 0.33 \times \text{Gender} + 0.18 \times \text{age} - 0.2 \times \text{Income} + 0.27 \times \text{AQI} + 0.27 \times \text{HEP} \\
\frac{P_{\text{rw}}}{P_{\text{nr}}(\text{rw})} + \frac{P_{\text{nr}}(\text{rw})}{P_{\text{nr}}(\text{rw})} &= 1
\end{align*}
\] (8)

Model of public response to an orange warning:
\[
\ln \frac{P_{\text{o}}}{P_{\text{no}}(\text{o})} = 0.67 - 0.66 \times \text{Gender} - 0.13 \times \text{Income} + 0.44 \times \text{AQI} + 0.45 \times \text{HEP} \\
\frac{P_{\text{o}}}{P_{\text{no}}(\text{o})} + \frac{P_{\text{no}}(\text{o})}{P_{\text{no}}(\text{o})} = 1
\] (9)

Model of public response to a red warning:
\[
\ln \frac{P_{\text{r}}}{P_{\text{nr}}(\text{r})} = 0.89 - 0.64 \times \text{Gender} + 0.48 \times \text{AQI} + 0.39 \times \text{HEP} \\
\frac{P_{\text{r}}}{P_{\text{nr}}(\text{r})} + \frac{P_{\text{nr}}(\text{r})}{P_{\text{nr}}(\text{r})} = 1
\] (10)

where \(P_{\text{rw}}\) is the probability of responding to a specific warning level, \(w_i=\text{blue warning}; w_2=\text{yellow warning}; w_3=\text{orange warning}; w_4=\text{red warning}\), and \(P_{\text{nr}}\) is the probability of not responding to a specific warning level, \(w_i\). Significant variables included the respondents’ gender (1=male, 0=female), age (1= less than 20y, 2=20-29y, 3=30-39y, 4=40-49y, 5=50-60y, 6= larger than 60y), education level (1=compulsory education, 2=senior high school, 3=technical qualification, 4=undergraduate, 5=graduate), income (1=less than ¥3000, 2=¥3001-6000, 3=¥6001-9000, 4=¥9001-12000, 5=more than ¥12001), awareness of the AQI (1=yes, 0=no), and the respondent’s perception of the health effects from air pollution (HEP) (1=not affected at all, 2=somewhat affected, 3=strongly affected).

3.3 Air pollution warning response and non-response cost

3.3.1 Response investment

The response investment, \(R_i\) can be obtained from the willingness-to-pay (WTP) (CNY) survey. The WTP of individuals, as measured by the survey, is used to estimate the cost of public response in taking measures to avoid becoming ill under different air quality warning levels. The distributions of the response investments for each of the four air pollution warning levels are presented in Table 2.

| Air pollution warning level | Distribution of WTP |
|-----------------------------|----------------------|
| Blue warning                | 82+54×betarnd(3.22,3.2,1,1) |
| Yellow warning              | 118 + exprnd(41.6,1,1) |
| Orange warning              | 84.6 + 0.3×betarnd(0.463,1.24,1,1) |
| Red warning                 | 262+gamrnd(113,2.11,1,1) |

3.3.2 Reduction ratio of costs due to health hazards

There is no quantitative study on the role of protective measures taken by residents in reducing health hazards. We assumed that when the cost of response increases, the ratio of reduction in public health harm, \(\alpha_i\), increases accordingly, there are three possible ordered scenarios (Table 3).
3.3.3 Assessing the cost of non-responses
Several studies have characterized health effects from exposure to air pollution and the associated economic costs [29, 38]. In the present study, the economic cost of health effects due to particulate air pollution, \( H[C(q)] \), is based on the exposure–response relationship and unit losses of pollution-related health effects. The cost is calculated as:

\[
H[C(q)] = \sum_{i=1}^{5} \left( \exp^{\beta_i q (C - C_0)} - 1 \right) \times E_i \times iHC_i \tag{11}
\]

where \( \beta_i \) is the exposure-response coefficient that corresponds to the incidence change of the health endpoint \( i \) per \( \mu g/m^3 \) PM\(_{2.5}\) increment, \( E_i \) is the incidence of the health endpoint \( i \), \( C \) is the PM\(_{2.5}\) concentration level (\( \mu g/m^3 \)) in Beijing air and the function of \( q \). \( C_0 \) is the PM\(_{2.5}\) baseline concentration below which health effects are ignored, and \( iHC_i \) is the unit of value for various endpoints in Beijing (CNY). The parameters used in Eq. 11 were taken from previously published reports [38] and are provided in Table 4.

Table 4. Parameters for determining the economic costs of air-pollution associated health effects.

| Health endpoints                           | \( \beta_i \) | \( E_i \)   | \( iHC_i \)       |
|-------------------------------------------|---------------|------------|-------------------|
| Mortality                                 | 0.0043        | 0.01013    | $135,397 (¥1,120,816) |
| Cardiovascular hospital admission         | 0.0007        | 0.0109     | $1626 (¥13460.03)  |
| Asthma                                    | 0.0039        | 0.0561     | $6 (¥49.668)       |
| Respiratory hospital admission            | 0.0012        | 0.0058     | $803 (¥6647.234)   |
| Acute bronchitis                          | 0.0055        | 0.0372     | $8 (¥66.224)       |

The PM\(_{2.5}\) concentration and AQI value \( q \) are correlated according to the Chinese Technical Regulation on Ambient Air Quality Index (on trial) (HJ 633-2012) [32]. Consequently,

\[
C(q) = \begin{cases} 
0.7 \times q, & 0 < q \leq 50 \\
0.8 \times q - 5.5, & 5.5 < q \leq 150 \\
0.7 \times q + 10, & 150 < q \leq 200 \\
q - 50, & 200 < q \leq 400 \\
1.5 \times q - 250, & 250 < q \leq 500 
\end{cases} \tag{12}
\]

3.4 Modeling uncertainty and sensitivity analysis
A Monte Carlo simulation can be used to estimate the probability distribution of model outputs by combining their probability distribution with several input variables [39]. To identify the primary factors influencing the effectiveness of air pollution EWSs, the Monte-Carlo simulation method was used to model the early warning-response process of air heavy pollution, and the sensitivity analysis of relevant input parameters was carried out. These parameters included warning thresholds, the probability of response, the response investment cost, the reduction ratio of health damage by the response investment cost, and the baseline concentration of the exposure-response function.
Uncertainties were assessed by running a Monte Carlo simulation with a simulation term \( D \) (days) of 3,650 days and a sample capacity \( N \) (residents) of 10,000 people. In addition to uncertainty analysis, sensitivity analyses were performed to identify the critical input parameters for calculating the expected costs. The sensitivities of the model inputs were assessed by calculating the average change in expected target parameter values after each change in an input variable, thereby accounting for different ranges of input variables. The simulation model was conducted using the MATLAB R2012b computing platform.

4. Results

When calculating non-response costs, baseline concentrations must be first selected. In this study, four baseline concentrations were used corresponding to 1) the daily 24 h PM\(_{2.5}\) where \( C_o = 0 \) \( \mu g/m^3 \); 2) \( C_o = 25 \) \( \mu g/m^3 \), which is recommended by the World Health Organization (WHO) Air Quality Guidelines; 3) a concentration limit of \( C_o = 35 \) \( \mu g/m^3 \) as suggested as the US Environmental Protection Agency daily ambient standard; and 4) \( C_o = 75 \) \( \mu g/m^3 \) which is suggested by China’s Environmental Protection Ministry (Ambient Air Quality Standards, GB 3095-2012). The Chinese, US, and WHO guidelines for PM\(_{2.5}\) thresholds were used to compare estimates of expected costs. The expected costs for the three specified scenarios using a 75 \( \mu g/m^3 \) baseline concentration and warning thresholds between 60 and 500 are shown in Figure 5.

A decreasing trend was observed between expected costs coinciding with an improvement in the ratio of public health harm reduction (Figure 5). The results also suggest that regardless of how much health hazards are reduced, warning thresholds that are too high or too low result in warning cost increases. Under the three scenarios, the expected warning cost is lowest when the threshold is between 190 and 230. According to the Technical Regulation on Ambient Air Quality Index (on trial) (HJ 633-2012), the AQI warning threshold is 200, which is consistent with the simulation results reported here. Thus, the current Chinese warning threshold is appropriate for the public.

Standard deviation of the costs also increased with decreasing harm to health (Figure 5). To further investigate individual variation, nine groups of results were analyzed. Statistical measurements (mean, variance, skewness, and kurtosis) of the costs under these three ordered scenarios are shown in Table 5 and the cost distributions are shown in Figure 6. As the threshold and the reduction ratio of harm to health costs increases, population differentiation increases. These results indicate that the threshold is too high and results in a reduced number of warnings and a decrease in the proportion of public that responds. Meanwhile, an increase in the reduction ratio of health hazard costs may result in different costs for those who respond to warnings compared to those that do not.

Of the three proposed scenarios, scenario two represents moderate effects from the investment of the public. Therefore, scenario two was used in sensitivity analysis of the probability of public response and the response investment.

| Warning threshold | Scenario 1 | Scenario 2 | Scenario 3 |
|-------------------|------------|------------|------------|
|                   | Mean       | Variance   | Skewness   | Kurtosis   | Mean       | Variance   | Skewness   | Kurtosis   | Mean       | Variance   | Skewness   | Kurtosis   |
| 100               | 25.2726    | 3.44945    | -0.2214    | 2.7920     | 21.9059    | 6.03643    | -0.0592    | 3.0596     | 18.7554    | 9.83105    | 0.0601     | 3.2055     |
| 200               | 19.43680   | 3.16582    | -0.2174    | 2.8579     | 16.61634   | 6.15670    | 0.0112     | 2.9561     | 13.77692   | 11.18197   | 0.1127     | 2.9445     |
| 300               | 19.76236   | 3.26381    | -0.4470    | 2.9494     | 17.88509   | 6.90306    | -0.2916    | 2.9437     | 16.10586   | 12.42077   | -0.1817    | 2.8673     |

Public response can change due to the perception of air pollution. To investigate the effect of the response probability on the warning cost, four response probability conditions were used in the simulations. The actual response probability, half and double the actual response probabilities were used in addition to a fourth probability condition that reflects a definite response.

The four different probability condition results under scenario 2 are shown in Figure 7. These results indicate that mean costs decrease with increasing response probability. The minimum costs appear at the same threshold for the response conditions 1-3, but costs continue to decrease until the response probability reaches 100%. Thus, these results suggest that beyond a certain range of response
probabilities, the warning system may lose its effectiveness. This conclusion is further supported by
the variance approaching zero for the fourth probability condition.

Figure 5. Expected costs for the three different scenarios (a, b, and c correspond to scenarios 1, 2, and
3, respectively) using the 75 μg/m³ baseline concentration and a warning threshold between 60 and
500.

Figure 6. Distribution of expected costs using the 75 μg/m³ baseline concentration under the three
scenarios and different warning thresholds. a) Scenario 1 at the 100 threshold; b) Scenario 2 at the 100
threshold; c) Scenario 3 at the 100 threshold; d) Scenario 1 at the 200 threshold; e) Scenario 2 at the
200 threshold; f) Scenario 3 at the 200 threshold; g) Scenario 1 at the 300 threshold; h) Scenario 2 at
the 300 threshold; i) Scenario 3 at the 300 threshold.
Figure 7. Sensitivity analysis of the expected costs under scenario two using the different response probabilities of conditions a) half the actual response probabilities, b) the actual response probability, c) double the actual response probabilities, and d) definite response.

Figure 8. Sensitivity analysis of expected costs under different investment costs under scenario 2 corresponding to (a) half of actual investment cost, (b) actual investment cost, and (c) double the actual investment cost

The public has recently begun to take air pollution more seriously and has increased its investment in preventing air pollution exposure. To compare the effects of different response investments, we designed scenarios representing half or double the actual investment values (Figure 8). However, increasing or decreasing investments does not change the optimal threshold range. When the threshold is less than 150, the expected cost is more sensitive to the threshold when investment increases. Meanwhile, when the threshold is higher than 300, the expected cost is not influenced by changes in the threshold.

5. Discussion

There are few studies on the effectiveness of air pollution EWSs because most air pollution studies have exclusively focused on evaluating the accuracy of air quality forecasting [17-21]. However, air pollution EWSs incorporate much more information than is just used to predict air pollution events. Individuals in the public are the recipients and ultimate practitioners of early warnings, so the response of the public to early warnings should also be considered. Even with advanced monitoring, forecasting, and dissemination technologies, EWSs will not be effective if a warning does not stimulate the execution of protective measures [13-15].

This study is the first to propose a methodology to evaluate the effectiveness of air pollution EWSs based on public responses. A number of factors contribute to the public response to a warning and the measures that are taken to deal with air pollution, as discussed in detail previously [16]. Herein, a
model to evaluate the effectiveness of air pollution EWSs based on public responses and non-responses was presented. Major factors of uncertainty were quantified for the model, including warning issuance probability, public response probability, and response cost distribution. Further, numerical experiments based on Monte Carlo simulations were designed to evaluate these uncertainty factors and concomitant public responses in Beijing. Based on these Monte Carlo simulations, different scenarios for air pollution EWS effectiveness were compared. The results indicated that the public response to early warning systems and the positive actions that people take to reduce mortality and morbidity can improve the effectiveness of EWSs. Consequently, it is very important to educate the public about air pollution warnings. In addition, the establishment of an information platform based on air pollution EWSs that would inform the public about pollution source emissions near local environments would help guide the public to take appropriate actions and enhance the practicality of EWSs.

The modeling described here provides a foundation to build on for future research. First, several parameter values, including those for the reduction ratio of public health harm and those for health endpoints, should be refined. Second, the adaptive learning behavior of the public should be modeled more accurately since behaviors can change and are affected by a number of factors. For example, differences between perceived air quality and measured air quality may influence public trust in the warning information, thus resulting in behavioral changes. Finally, the economic cost of health effects and disease burden may not be aligned, the effectiveness of air pollution EWSs should be measured by more than just expected costs and other factors of uncertainty, and risks coming from the warning-response process should be considered. Thus, the method for assessing the effectiveness of air pollution EWS requires further discussion and refinement. Regardless of these potential limitations, the modeling described here represents the first attempt to quantify the effectiveness of air pollution EWSs by considering public response, which makes up for the bias involved in measuring effectiveness only by predictive accuracy. Further, the model provides a new perspective on evaluating the effectiveness of early warning systems.

6. Conclusions

A probability model is presented here to evaluate the effectiveness of air pollution EWSs based on public responses. The model evaluates the probability and costs of public responses, thereby allowing for the determination of an optimum warning threshold. Sensitivity analyses were performed to identify the primary factors that influenced the effectiveness of air pollution EWSs. Specifically, five parameters were analyzed, including the warning threshold, probability of response, response investment cost, reduction ratio of health damage by the response investment cost, and baseline concentration of the exposure-response function. The experimental results indicated that warning threshold and public response were vital determinants of the effectiveness of air pollution EWSs. The model also confirmed that the warning threshold system currently used in China is appropriate. The response of the public to warnings can be integrated into the existing air pollution EWS via this model, which will then result in more personalized warning information for the public, promote the development of air pollution EWS, and improve the effectiveness of air pollution EWS. These improvements will then reduce morbidity and mortality from air-pollution-related diseases, including bronchitis, asthma, respiratory diseases, cardiovascular diseases, and cardiopulmonary diseases. Moreover, although Chinese air quality was evaluated here, the model is universally applicable in assessing the effectiveness of air pollution EWSs.

Funding

This work was financially supported by the People's Insurance Company (Group) of China Limited (PICC) disaster research fund project in 2019 (YF191205) and the National Key Research and Development Program of China (Grant No.2017YFC0803900).
References

[1] Fu, B. J. (2008). Blue skies for China. Science, 321(5889), 611.

[2] Guo, S., Hu, M., Zamora, M.L., Peng, J.F., Shang, D.J., Zheng, J., Du, Z.F., Wu, Z.J., Shao, M., Zeng, L.M., Molina, M.J., and Zhang, R.Y. (2014). Elucidating severe urban haze formation in China. Proc. Natl Acad. Sci. USA., 111(49), 17373–8.

[3] Zhang, A., Qi, Q.W., Jiang, L.L., Zhou, F., Wang, J.F. (2013). Population Exposure to PM$_{2.5}$ in the Urban Area of Beijing. Plos One., 8(5), e63486.

[4] Halonen, J.I., Lanki, T., Yli-Tuomi, T., Tiittanen, P., Kulmala, M., and Pekkanen, J. (2009). Particulate air pollution and acute cardiorespiratory hospital admissions and mortality among the elderly. Epidemiology., 20, 143–53.

[5] Yang, Y., Li, R.K., Li, W.J., Wang, M., Cao, Y., Wu, Z.L., and Xu, Q. (2013). The Association between Ambient Air Pollution and Daily Mortality in Beijing after the 2008 Olympics: A Time Series Study. Plos One., 8(10), e76759.

[6] Schröter, K., Velasco, C., Torres, D., Nachtnebel, H-P., Kahl, B., Beyene, M., Rubin, C., and Gocht, M. (2008). Effectiveness and efficiency of early warning systems for flash-floods. CRUE Research Report No 1-5.

[7] Huggel, C., Khabarov, N., Obersteiner, M., and Ramirez, J.M. (2010). Implementation and integrated numerical modeling of a landslide early warning system: A pilot study in Colombia. Nat Hazards., 52, 501–18.

[8] Alfieri, L., Thielen, J., and Pappenberger, F. (2012). Ensemble hydro-meteorological simulation for flash flood early detection in southern Switzerland. J Hydrol., 424, 143–53.

[9] Rheinberger, C.M. (2013). Learning from the past: statistical performance measures for avalanche warning services. Nat Hazards, 65, 1519–33.

[10] Huang, S.K., Lindell, M.K., and Prater, C.S. (2015). Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies. Environ and Behavior., 48(8), 991-1029.

[11] Paté-Cornell, M.E. (1986). Warning systems in risk management. Risk Anal., 6, 223–34.

[12] Sättele, M., Bründl, M., and Straub, D. (2016) Quantifying the effectiveness of early warning systems for natural hazards. Nat. Hazard. Earth. Sys., 16 (1), 149-66.

[13] Baudoin, M., Henly-Shepard, S., Fernando, N., Sitati, A., and Zommers, Z. (2014). Early warning systems and livelihood resilience: exploring opportunities for community participation. UNU-EHS Working Paper Series, No.1. United Nations University Institute of Environment and Human Security (UNU-EHS), Bonn.

[14] UNEP. (2012). Early Warning Systems: A State of the Art Analysis and Future Directions. United Nations Environment Programme (UNEP), Nairobi, Kenya.

[15] UNISDR. (2015). Making development sustainable: the future of disaster risk management. Global Assessment Report on Disaster Risk Reduction. United Nations Office for Disaster Risk Reduction (UNISDR), Geneva, Switzerland.

[16] Wang, F.P., Zhao, H.P., Zhang, X.X., Niu, C.C., and Ma, J.F. (2019). Understanding individual-level protective responses to air pollution warning: A case study of Beijing, China. Hum. Ecol. Risk Assess., 25(6), 1473-1487.

[17] Birant, D. (2011). Comparison of decision tree algorithms for predicting potential air pollutant emissions with data mining models. J. Environ. Inf., 17(1), 46-53.

[18] Xu, Y., Du, P., Wang, J. (2017a). Research and application of a hybrid model based on dynamic fuzzy synthetic evaluation for establishing air quality forecasting and early warning system: A case study in China. Environ Pollution, 223, 435–48.

[19] Xu, Y., Yang, W., Wang, J. (2017c). Air quality early-warning system for cities in China. Atmos Environ, 148, 239–57.

[20] Wang, J. Z., Zhang, X. B., Guo, Z. H., and Lu, H.Y. (2017). Developing an early-warning system for air quality prediction and assessment of cities in China. Expert Systems With Applications., 84, 102–16.
[21] Yang, Z.S., and Wang, J. (2017). A new air quality monitoring and early warning system: Air quality assessment and air pollutant concentration prediction. *Environ Res.*, 158, 105–17.

[22] Yang, Y., Cao, Y., Li, W.J., Li, R.K., Wang, M., Wu, Z.L., Xu, K. (2015). Multi-site time series analysis of acute effects of multiple air pollutants on respiratory mortality: A population-based study in Beijing, China. *Sci Total Environ.*, 508, 178–87.

[23] Morishita, M., Thompson, K.C., Brook, R.D. (2015). Understanding air pollution and cardiovascular diseases: is it preventable? *Curr Cardiovasc Risk Rep.*, 9(6), 1–9.

[24] Armstrong, H., and Taylor, J. (2000). Regional Economics and Policy. Phillip Alan Publishers Ltd. Londres.

[25] Cropper, M.L., Sahin, S. (2009). Valuing mortality in the context of disaster risks. Background paper for the world bank. UN assessment on the economics of disaster risk reduction.

[26] The New York Times. (2016). Beijing to raise threshold on red alerts for smog. http://www.qqenglish.com/bn/17000.htm (accessed Feb 24, 2016).

[27] Ministry of Environmental Protection of the People’s Republic of China (MEPC). (2016). JingJinJi area will be unified air heavy pollution warning grading standards. http://www.mep.gov.cn/xxgk/hjyw/201602/t20160205_329901.shtml. (in Chinese) (accessed Feb 5, 2016).

[28] Zhao, H.P., Wang, F.P., Niu, C.C., Wang, H., Zhang, X.X. (2018). Red warning for air pollution in China: Exploring residents’ perceptions of the first two red warnings in Beijing. *Environ Res.*, 161, 540–5.

[29] Kan, H., Chen, B. (2004). Particulate air pollution in urban areas of Shanghai, China: Health-based economic assessment. *Sci Total Environ.*, 322, 71–9.

[30] Cairncross, E.K., John, J., Zunckel, M. (2007). A novel air pollution index based on the relative risk of daily mortality associated with short-term exposure to common air pollutants. *Atmos. Environ.*, 41, 8442–54.

[31] Wang, L.T., Zhang, P., Tan, S. B., Zhao, X. J., Cheng, D. D., Wei, W., Su, J., Pan, X. M. (2013). Assessment of urban air quality in China using air pollution indices (APIs). *J. Air Waste Manage.*, 63, 170–178.

[32] Ministry of Environmental Protection of the People’s Republic of China (MEPC). (2012). Technical Regulation on Ambient Air Quality Index. HJ 633-2012. Beijing: China Environmental Science Press.

[33] U.S. Environmental Protection Agency (USEPA). (2013). Air quality index reporting [EB/OL]. Washington: USEPA, 1999 (1999-8-4). http://www.Epa.gov/ttn/ctaa/t1/fr_notices/airqual.pdf. (accessed June 11, 2013)

[34] Plaia, A., Ruggieri, M. (2011). Air quality indices: a review. *Rev Environ Sci Biotechnol.*, 10 (2), 165–79.

[35] Abercrombie, G.F. (1953). December fog in London and the Emergency Bed Service. *Lancet*, i: 234–5. PMID: 13012036.

[36] Oliveira, M.S., Leon, A.P., Mattos, I.E., and Koifman, S. (2011). Differential susceptibility according to gender in the association between air pollution and mortality from respiratory diseases. *Cad Saude Publica*, 27, 1827–36.

[37] Semenza, J.C., Wilson, D.J., Parra, J., Bontempo, B.D., Hart, M., Sailor, D.J., George, L.A. (2008). Public perception and behavior change in relationship to hot weather and air pollution. *Environ Res.*, 107(3), 401–11.

[38] Zhang, M.S., Song, Y., Cai, X.H. (2007). A health-based assessment of particulate air pollution in urban areas of Beijing in 2000–2004. *Sci. Total Environ.*, 376, 100–8.

[39] Burmaster, D. E., Anderson, P.D. (1994). Principles of good practice for the use of Monte Carlo techniques in human health and ecological risk assessments. *Risk Anal.*, 14, 477-81.