Temporal variability of visibility and its parameterizations in Ningbo, China

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ABSTRACT

Simultaneous and continuous measurements of visibility, meteorological parameters and air pollutants were carried out at a suburban site in Ningbo from June 1, 2013 to May 31, 2015. The characteristics of visibility and their relationships with air pollutants and meteorological factors were investigated using multiple statistical methods. Daily visibility ranged from 0.6 to 34.1 km, with a mean value of 11.8 km. During the 2-year experiment, 43.4% of daily visibility was found to be less than 10.0 km and only 9.2% was greater than 20.0 km. Visibility was lower in winter with a frequency of 53.4% in the range of 0.0–5.0 km.

Annual visibility had an obvious diurnal variation, with the lowest and highest visibility being 7.5 km at approximately 06:00 local time and 15.6 km at approximately 14:00 local time, respectively. Multiple correspondence analysis (MCA) indicated that the different ranges of visibility were significantly affected by different levels of pollutants and meteorological conditions. Based on the analyses, visibility was found to be an exponential function of PM2.5 concentrations within a certain range of relative humidity. Thus, non-linear models combining multiple linear regressions with exponential regression were subsequently developed using the data collected from June 2014 to May 2015, and the data from June 2013 to May 2014 was used to evaluate the performance of the model. It was demonstrated that the derived models can quantitatively describe the relationships between visibility, air quality and meteorological parameters in Ningbo.

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**Introduction**

Horizontal visibility is defined as the greatest distance at which a black object can be visually identified with unaided eyesight against a light sky (Wark et al., 1998; Watson, 2002). The reduction of atmospheric visibility is an important indicator of deteriorating ambient air quality in the absence of unusual weather. Visibility degradation has become a serious environmental issue of public concern in populated cities and has been reported to have adverse effects on human health, crop growth and traffic safety (Che et al., 2006). It has been widely confirmed that the impairment of visibility is mainly due to the scattering and absorption of visible light by suspended particles (Chan et al., 1999; Horvath, 1995).

Atmospheric particulate matter (PM) is associated with both anthropogenic and natural emissions that consist of minuscule particles of solid or liquid matter, with diameters ranging from 0.01 to 100 μm. Atmospheric particles can affect the climate by both direct and indirect radiative forcing (Charlson et al., 1992; Xu et al., 2002), especially fine aerosols with aerodynamic diameters of 2.5 μm or less (PM2.5). Particles of decreasing size will remain suspended in the atmosphere for longer and subsequently impact the environment over greater distances. PM2.5, which comprise sulfates, nitrates, organic and elemental carbon, could effectively scatter or absorb visible light and thus reduce visibility (Zhang et al., 2012; Kim et al., 2006; Tan et al., 2009a, 2009b). All these airborne particles, together with other gaseous pollutants such as sulfur dioxide (SO2) and nitrogen dioxides (NO2), could contribute to the increase of haze and lead to a low visual range (<10 km). Specifically, the heterogeneous aqueous transformation from SO2 and NO2 is enhanced during haze episodes, which probably leads to the remarkable secondary formation of sulfate and nitrate in fine particles, further impairing visibility (Wang et al., 2006). In addition to air pollutants, many meteorological parameters such as relative humidity (RH), wind speed (WS), wind direction (WD), temperature (T), pressure and precipitation can also contribute to light extinction and degrade air quality (Zhao et al., 2011; Yang et al., 2007). In haze events, the rapid increase of PM concentrations, high RH, and low WS, can adversely impact atmospheric visibility (Tsai 2005; Zhang et al., 2010; Deng et al., 2011). As RH increases, hygroscopic particles progressively absorb more moisture, which will increase the scattering cross section of aerosols and proportionately reduce visibility. Therefore, RH could directly affect the particles that contribute to visibility reduction. While other meteorological variables such as WS, temperature, and pressure have indirect effects on visibility, they may also affect the concentration of atmospheric particles due to thermal and mechanical turbulence (Du et al., 2013). The accumulation and transport of particles are closely related to the synoptic systems and atmospheric circulations. Some studies have identified that high atmospheric pressure, low WS, high RH and low mixing layer height could significantly reduce visibility in Taiwan and Nanjing (Tsai, 2005; Deng et al., 2011).

The forecasting and early warning of visibility is not only important to environment and public health, but also to traffic control and even military actions. A number of models were previously developed to describe the correlations between visibility and air pollution, and continuous efforts have been made to improve the models based on the monitoring results of visibility measurements. Multiple linear regression equations have been established to investigate the effect of air pollutants and meteorological conditions on visibility in Taiwan (Wen and Yeh, 2010). In addition, different empirical regression models were developed for visibility in Beijing, Shanghai and Guangzhou, with a logarithm of coarse particle concentration used in the regression analyses (Lin et al., 2012; Tsai, 2005). Additionally, several studies have suggested that visibility is a linear response to the exponential function of PM2.5 concentrations under a certain RH range (Cao et al., 2012; Yu et al., 2016; Shen et al., 2016). All these studies suggested that the impacts of air quality and other variables on visibility are more complicated than linearity. However, there is still a lack of research on the characteristics of visibility in the Ningbo area, and its relationship with air pollutants and meteorological conditions. Ningbo, the second largest city of Zhejiang Province, and has experienced a severe loss of visibility in recent decades (Zhang et al., 2012). In this study, visibility was monitored from June 2013 to May 2015, with the potential relationships between visibility, air pollutants, and meteorological variables being investigated. The objectives of this study were (1) to characterize the temporal variations of visibility in the suburb of Ningbo; (2) to identify the relationships between classified visibility and other parameters using multiple correspondence analysis (MCA); (3) to provide new knowledge for improving visibility prediction in the Ningbo region.

1. **Material and methods**

1.1 Study area and data source

Ningbo (28°51′–30°33′ N, 120°55′–122°16′ E) is a coastal city of the Zhejiang Province in Eastern China. The city lies in the south of Hangzhou Bay and faces the East China Sea with an area of 9816 km². The climate conditions of Ningbo are governed by the sub-tropical monsoon, with prevailing northwest and southeast winds in winter and summer, respectively. The annual mean air temperature and precipitation are 16.4 °C and 1480 mm, respectively. Annual mean air temperature reaches its maximum (28.0 °C) in July and minimum (4.7 °C) in January. During the whole year, approximately 60% of the annual mean precipitation occurs from May to September. The annual mean WS is 2–3 m/sec in urban areas and > 5 m/sec in coastal areas.

Ningbo is one of the most highly urbanized and industrialized cities in the Yangtze River Delta (YRD) region and had a population of 7.87 million people and a vehicle fleet of 1.98 million in September 2016. With a rapid urbanization and an increase in motor vehicle numbers, energy consumption in Ningbo has increased substantially and haze events have been frequently observed in recent years (He et al., 2016; Cheng et al., 2014; Hua et al., 2015). Air pollutant concentrations and meteorological data from June 1, 2013 to May 31, 2015 at the Dongqian Lake (DQL) Monitoring Station (29°45′N, 121°37′E) were collected in this study. The monitoring station is 12 km away from the city centre of Ningbo and 1.3 km from the largest...
freshwater lake (Dongqian Lake, 22 km² in area) in the Zhejiang Province. There are several hills nearby to the west and east. Many small villages are distributed at the foot of the mountain less than 2 km to DQL site. There is a provincial road close to this site with small factories involved in mechanical processing built alongside. In recent years, the number of tourists visiting near the DQL site have also increased.

The DQL station is a part of the national air quality monitoring network of China, which is under the supervision of the national Ministry of Environmental Protection (MEP). Visibility is measured by trained operators using easily identifiable structures and objects, such as tall buildings, towers, and mountain ridges, at predetermined distances. The routine monitoring of air quality using six criteria air pollutants, i.e. SO₂, NO₂, carbon monoxide (CO), ozone (O₃), particulate matter with aerodynamic diameters of 10 µm or less (PM₁₀), PM₂.₅ at DQL station began in 2012 when the latest ambient air quality standards of China (GB 3095–2012) were established. Commercial instruments from Thermo-Fisher Scientific Inc. (USA) are used to measure gaseous pollutants, such as O₃ (Model 49i), NO₂ (Model 42i), CO (Model 48i) and SO₂ (Model 43i). PM₂.₅ and PM₁₀ are measured using a tapered-element oscillating microbalance sampler (R&P TEOM, 1400). The TEOM sampler is calibrated regularly using filters with measured masses. Zero and span checks are made weekly. Hourly averaged data were used for all analyses in this study and described by local time (UTC + 8). Meteorological variables including RH, WS, temperature, and atmospheric pressure are measured by automatic weather station (WS5000-UMB, Lufft, Germany) at the DQL site.

The Air Quality Index (AQI) has been developed to provide daily air quality information to the public in China (Zheng et al., 2014). On February 29, 2012, the MEP of the People’s Republic of China (PRC) approved the technical regulation on ambient air quality index (GB 3095–2012), which released PM₂.₅ values and calculated the AQI instead of the Air Pollution Index (API). A sub-index is calculated for each pollutant from a segmented linear function that transforms ambient concentrations onto a scale from 0 to 500. AQI is calculated as the sub-index maximum (China’s Environmental Protection Standards, HJ 633–2012). Daily AQI is defined as:

\[
AQI = \max (AQI_{PM10}, AQI_{PM2.5}, AQI_{SO2}, AQI_{NO2}, AQI_{CO}, AQI_{O3}) (1)
\]

where \(AQI_{PM10}\), \(AQI_{PM2.5}\), \(AQI_{SO2}\), \(AQI_{NO2}\), \(AQI_{CO}\) and \(AQI_{O3}\) are the partial index of air pollutants PM₁₀, PM₂.₅, SO₂, NO₂, CO and O₃, respectively.

\[
AQI_p = \frac{[AQI_{p,ph} - AQI_{p,pl}]}{C_{high} - C_{low}} \times (C_p - C_{low}) + AQI_{p,pl} (2)
\]

where \(AQI_{p,ph}\) is the partial index of air pollutant \(p\), \(C_p\) is the daily average concentration of air pollutant \(p\), and \(C_{high}\) and \(C_{low}\) are the threshold concentrations of \(p\) at air quality grade. Corresponding to \(C_{high}\) and \(C_{low}\), AQI_{p,ph} and AQI_{p,pl} are the threshold partial indexes of air pollutant \(p\) at air quality grade, respectively.

1.2. Data analysis

MCA is a data analysis technique for categorical data, used to detect and represent the underlying structures in a data set (Hair et al., 1995; Hill and Lewicki, 2007). The results of MCA can imply that objects within the same category are plotted close to each other and objects in different categories are plotted as far apart as possible. This statistical method has been widely used in sociology, economic statistics, medical science, but is still limited in environmental science (Van Stan et al., 2016; Sourial et al., 2010). In addition, all air pollutants and meteorological data were carried out using a multiple linear regression (MLR) analysis incorporating a stepwise method to develop empirical models in Ningbo. The above statistical analyses were performed using SPSS software (Version 22.0 for Windows, IBM Inc.)

2. Results and discussion

2.1. Descriptive results

The overall statistical analysis of daily visibility, air pollutants, and meteorological variables during the two years of observations at DQL station are summarized in Table S1. Day-to-day variations of visibility, PM₂.₅ and PM₁₀ are shown in Fig. S1. From June 1, 2013 to May 31, 2015, the daily average visibility ranged from 0.6 to 34.1 km, with a mean value of 11.8 km, which was just over the defined threshold for haze (i.e. visibility <10.0 km), indicating poor air quality over the study region. The mean PM₂.₅, PM₁₀, SO₂, NO₂, CO and O₃ concentrations were 42.6, 64.6, 15.0, 28.9, 0.9 and 70.2 µg/m³, respectively. The average value of AQI, RH, temperature, WS and surface pressure were 65.6, 73.2%, 17.8 °C, 1.7 m/sec and 1013.0 hPa, respectively.

Visibility impairment mainly resulted from airborne particulate matter, particularly from PM₂.₅ (Deng et al., 2014; Sabetghadam and Ahmadi-Givi 2014). According to the air quality daily report from MEP, PM₂.₅ in the atmosphere was the primary pollutant of concern in Ningbo during the two years of monitoring (http://www.zhb.gov.cn/hjzl/zghjzkgb/lnzghjzkgb/). Therefore, the daily variations of PM₁₀ and PM₂.₅ were required for analysis during the study period in DQL station. Fig. S1 shows that the concentrations of PM₂.₅ and PM₁₀ were generally higher in winter and lower in summer, and the proportion of PM₂.₅ in PM₁₀ was relatively high. During the two years, almost all daily PM₂.₅ concentrations in winter exceeded the national ambient air quality standard Grade II (75 µg/m³) (China Environmental Protection Ministry 2012), revealing severe pollution from fine particles.

In December, 2013, extremely high levels of PM₁₀ and PM₂.₅ were observed with daily average concentrations of 511 and 389 µg/m³, respectively. At 22:00 on December 6, the hourly concentrations of PM₁₀ and PM₂.₅ reached peak values of 707 and 530 µg/m³, respectively. Visibility dramatically decreased to 0.6 km during this episode, which was the minimum value measured during the two years. This haze episode was also observed in the YRD region (Xue et al., 2015).

2.2. Seasonal and diurnal variations of visibility

Fig. 1a shows that 43.4% of the daily visibility was less than 10.0 km during the two years and only 9.2% was greater than
20.0 km, indicating bad air quality in the DQL area. The maximal frequency (33.4%) of daily visibility was observed in the range of 5.0–10.0 km. Poor visibility (<5.0 km) often occurred in winter with a frequency of 53.4%. Daily visibilities of spring and summer contributed as much as 41.8% and 38.8% to the visual range of 20.0–35.0 km, respectively.

Generally, the average value of AQI decreased with increasing visibility (Fig. 1). The mean value of AQI for the visual range of 0–5.0 km was 111.8 (>100), which indicates the occurrence of a haze episode under low visibility. The AQI values were 72.3 and 61.4 for the visual range of 5.0–10.0 km and 10.0–15.0 km, respectively. This indicates that the local air was moderately polluted. Good visibility (15.0–35.0 km) occurred simultaneously with the lowest AQI value (<50), i.e. when the air quality was good. These data confirmed that the local air quality had an obvious positive correlation with visibility (Tsai et al., 2003).

Fig. 1b depicts the diurnal patterns of annual and seasonal mean visibility in Ningbo. Visibility shows an obvious and similar diurnal variation throughout four seasons, with a sharp decrease in early morning, i.e. 06:00–08:00 local time and a peak in the afternoon, i.e. 14:00–16:00 local time. From the perspective of the annual average, the lowest and highest visibility was 7.5 and 15.6 km, respectively. The diurnal patterns during different seasons were desynchronized, which is due to differences in weather pattern (i.e. day-night length, sunrise and sunset time, monsoon etc.) and the stability of atmospheric boundary layer (ABL) in each season. For example, the lowest and highest daily levels of visibility in wintertime are nearly two hours later than in summertime,
which is mainly attributed to a later sunrise time and smaller ABL depth. It can also be seen that visibility in spring and summer was better than in autumn and winter, with winter more associated with poor visibility and bad air quality.

2.3. Monthly variations of visibility and environmental factors

Monthly variations of visibility, air pollutant concentrations and meteorological factors were investigated in this study (Fig. 2). The highest average visibility was observed in July, with a value of 16.6 km, and the lowest average visibility was observed in December with a value of 9.1 km. Different trends of monthly variations were observed between visibility and other environmental variables in the study area. It was noteworthy that the visibility greatly decreased in June, when the air pollutant concentrations stayed at low levels. It is well-known that visibility is negatively correlated with air humidity (Deng et al., 2011). The relatively high level of RH in June might account for the lower visibility due to the light scattering and absorption of water vapor.

Fig. 2 – Monthly variations of visibility and other environmental variables.
Fig. 2 shows that the PM_{10} and PM_{2.5} pollution of the study area was severe. The monthly mass concentrations of PM_{10} and PM_{2.5} were in the range of 34.7–139.3 and 23.7–94.9 μg/m³, respectively. The concentrations of PM_{10} and PM_{2.5} were higher from November to February, while lower from June to September. The temporal variations of anthropogenic emissions and weather conditions might account for the seasonal cycle of PM. The average ratio of PM_{2.5} to PM_{10} (i.e. PM_{2.5}/PM_{10}) was 66.6% with a range of 59.3%–72.1%. Remarkably, there was a negative correlation (−0.47, P < 0.001) between visibility and PM_{2.5}/PM_{10} (Table S4), especially in June, July and October. The high proportions of PM_{2.5} contained within PM_{10} in poor visibility episodes indicated that fine particles could play an important role in affecting local visibility.

The monthly variations of SO_{2}, NO_{2} and CO were consistent with PM which could also be confirmed by Pearson correlation, with higher and lower concentrations being observed in winter and summer, respectively. All three gaseous pollutants showed negative correlations with visibility (Table S4). However, the observed correlation between O_{3} and visibility can be related to the observation that O_{3} concentration is typically higher in summer, and positively associated with temperature (Fig. 2). Two monthly peaks of O_{3} were observed in May (100.3 μg/m³) and October (71.4 μg/m³) along with better visibility, while the lowest O_{3} concentration (41.4 μg/m³) occurred in December when lower visibility was observed. The winter minimum O_{3} level is commonly observed in mid-latitude locations in the Northern Hemisphere (Tu et al., 2007; Semple et al., 2012; Kumar et al., 2010), which is mainly due to the relatively weaker photochemical processes. Good visibility is often related to stronger solar radiation, which can significantly promote the photochemical generation of O_{3} (Pudasainee et al., 2006). This might account for the good correlation between O_{3} levels and visibility during warm seasons in this study.

The variation of RH displayed a summer maximum and winter minimum, with the highest (82.1%) and lowest (62.3%) values occurring in June and December, respectively. A negative correlation (−0.452) between visibility and RH was observed together with a positive correlation (0.358) between PM_{2.5}/PM_{10} and RH (Table S4). With an increase of RH, the lower O_{3} concentration (41.4 μg/m³) occurred in December when lower visibility was observed. The winter minimum O_{3} level is commonly observed in mid-latitude locations in the Northern Hemisphere (Tu et al., 2007; Semple et al., 2012; Kumar et al., 2010), which is mainly due to the relatively weaker photochemical processes. Good visibility is often related to stronger solar radiation, which can significantly promote the photochemical generation of O_{3} (Pudasainee et al., 2006). This might account for the good correlation between O_{3} levels and visibility during warm seasons in this study.

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was closely distributed with V3 rather than V4 in the correspondence map (Fig. 3), but the concentration of O₃ did not increase with visibility completely. In fact, except for the lower concentrations of O₃, the points of 2O₃ to 4O₃ were all closely placed within the third quadrants of Fig. 3, which were generally associated with a relatively higher temperature and lower WS. The relatively high WS (WS4 & WS3) in the second quadrant was unfavorable to the accumulation of O₃. These data also indicated that the production of O₃ was not only affected by visibility, other pollutants and meteorological parameters, but also factors including solar radiation, which was not included in this study (Tong et al., 2017). In addition, the effects of RH on visibility could not be ignored. The visibility was always below 15 km (V1~V3) when RH was higher than 80% (i.e. RH3 & RH4), which indicated that visibility remained at low values even with low air pollution concentrations.

2.5. Relationship between visibility and other factors

To gain a deeper insight into how relevant factors affect visibility, Pearson correlations were performed between daily visibility, air pollutants and meteorological variables (Table S4). Visibility had significantly negative correlations with PM₂.₅ (r = -0.50), CO (r = -0.51), and NO₂ (r = -0.47). The moderate relationship between visibility and PM₂.₅ was expected, given the scattering effect of aerosols, especially fine particles (Charlson et al., 1992; Xu et al., 2002). Visibility had no direct relationship with CO, but the correlation coefficient between both variables was a little higher than that between visibility and PM₂.₅. This may be because CO is generated by intensive biomass burning together with incomplete combustion from vehicle engines, during which large quantities of particles would be generated. Fine particles formed simultaneously with CO could lead to visibility reduction by scattering and absorbing light radiation (Xue et al., 2015), which might account for the negative correlation between visibility and CO. For NO₂, there was a weak direct influence on visibility. However, secondary pollutants such as nitrate, which is produced by photochemical conversions from NO₂ might play an important role in visibility reduction (Sabetghadam and Ahmadi-Givi, 2014). Nitrate is the main water-soluble constituent in PM₂.₅ and is an important factor in the increase of PM₂.₅ concentrations. A strong positive correlation between NO₂ and PM₂.₅ (r = 0.70, Table S4) was observed in this study, which might explain why NO₂ was significantly correlated with visibility in the DQL area.

In analyses examining effects of meteorological factors, visibility showed a significant positive correlation (r = 0.39) with WS and a negative correlation (r = -0.40) with RH, which was in accordance with previous research (Deng et al., 2011; Zhang et al., 2010). High wind speed would promote the dispersion of pollutants and could reduce air pollutant concentrations and increase visibility. Also, hygroscopic aerosols are greatly increased with high RH, which could cause the increase of PM concentration and extinction capability, further reducing visibility. As presented in Table S4, visibility showed a rather weak negative and positive correlation with air pressure and temperature, respectively. Air pressure and temperature are both important indicators of a weather system at a given location, and they have no direct effect on visibility. The changes of air pressure and temperature could have an impact on the diffusivity of the atmosphere, and further affect the concentration of air pollutants. The relatively high correlation between PM₂.₅ and temperature (r = -0.45), and between PM₂.₅ and pressure (r = 0.43) also confirmed this conclusion.

Scatter plots and regression functions of one-year data (Fig. 4) were applied in this study in order to examine the deep
connections between visibility and the two major factors (i.e. PM$_{2.5}$ and RH). Fig. 4 and obtained Eq. (3) show the relationships between hourly-averaged visibility and mass concentration of PM$_{2.5}$ under different RH conditions (Yu et al., 2016). RH was classified over four ranges: RH $\leq$ 60%, 60 $<$ RH $\leq$ 80%, 80 $<$ RH $\leq$ 90%, and RH $>$ 90%. The visibility decreased exponentially with increasing PM$_{2.5}$ concentrations in each RH range.

\[
\text{Visibility} = f(\text{PM}_{2.5}) = \begin{cases} 
35.65 \times \exp(-0.017 \times \text{PM}_{2.5}), & (\text{RH} \leq 60\%), \ r = 0.835 \\
28.99 \times \exp(-0.020 \times \text{PM}_{2.5}), & (60\% < \text{RH} \leq 80\%), \ r = 0.732 \\
22.84 \times \exp(-0.027 \times \text{PM}_{2.5}), & (80\% < \text{RH} \leq 90\%), \ r = 0.599 \\
9.32 \times \exp(-0.021 \times \text{PM}_{2.5}), & (\text{RH} > 90\%), \ r = 0.384 
\end{cases}
\]

Firstly, with the increase of PM$_{2.5}$ concentration, the visual range decreased sharply. Initially, the visibility decreased sharply while the PM$_{2.5}$ concentration increased; but when PM$_{2.5}$ concentrations reached a certain level (e.g. above 100 $\mu$g/m$^3$), the change in visibility was not sensitive to PM$_{2.5}$ concentrations any further. Secondly, with the increase of RH, a lower correlation coefficient between PM$_{2.5}$ and visibility was observed. This implied that visibility stayed at a very low level when RH values were very high (> 80%), even with low PM$_{2.5}$ concentrations. In this case, a large amount of water vapor could cover particle surfaces, enhancing the scattering ability of aerosol and reduce visibility significantly. Thirdly, the maximum visibility under different RH conditions was decreased with the increase of RH value (Fig. 4). Eq. (3) suggested that the maximum visibility was just 9.32 km in the case of RH $>$ 90%, and this result was consistent with MCA (Fig. 3).

Obviously, a single parameter regression such as Eq. (3) are not suitable for the forecasting of visibility at another location or in another year, which ignores the effects of other environmental variables, such as NO$_2$, CO, T, WS etc. As presented in Fig. S2, in which a year’s hourly visibility was predicted with Eq. (3), the regression lines between observed and simulated visibility significantly deviate from the 1:1 diagonal line. A larger deviation existed when RH $>$ 90%, indicating a greater contribution of other factors to visibility. Nevertheless, the above equation further confirmed the exponential relationship between visibility and PM$_{2.5}$ under different RH levels. This finding should form the basis of a forecasting model of visibility.

### 2.6. Regression model development and validation

To further develop a brief model for visibility prediction in Ningbo, it was first assumed that the apparent visibility is the final result of a combination of factors influencing air pollution together with meteorological parameters. As shown in Eq. (4),

\[
\text{Visibility} = f(\text{PM}_{2.5}) + f(\text{RH}, T, \text{NO}_2, O_3...)
\]

where $x_i$ represents any important factor for visibility, $a_i$ is a linear regression coefficient, and $\epsilon$ is the error term.

\[
\text{Visibility} - f(\text{PM}_{2.5}) = \sum_i a_i x_i + \epsilon
\]

or

\[
\text{Visibility} - \sum_i (a_i x_i) = f(\text{PM}_{2.5}) + \epsilon
\]

The obtained regression parameters in Eq. (3) were chosen as initial values of modeling fit. Multiple linear regression was conducted between the residue of prediction and other environmental parameters. Datasets with hourly resolution from June 2014 to May 2015 were used to develop the multiple nonlinear regression equations. An independent variable was added into the regression equation by a stepwise procedure based on importance. It demonstrated that for the first two RH categories, i.e. RH $\leq$ 80%, RH is the common factor in addition to particle concentration for the variation of visibility, then the regression equations for these two levels were eventually combined together. After several circles of regression and iteration, the final modeling results considering main influencing factors besides PM$_{2.5}$ and RH within three RH ranges are listed in Table 1. It showed that the main contributors to visibility under different RH are different, and the influence of all variables on visibility was additive. Specifically, the independent variables in the model are PM$_{2.5}$, and RH when RH $\leq$ 80%, while O$_3$ is the major

<table>
<thead>
<tr>
<th>Stepwise regression model</th>
<th>Correlation coefficient</th>
<th>N.</th>
</tr>
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<tbody>
<tr>
<td>$V = 23.044 + 27.835\exp(-0.04199\text{PM}_{2.5}) - 0.196\text{RH}$</td>
<td>RH $\leq$ 80%</td>
<td>0.816</td>
</tr>
<tr>
<td>$V = 56.072 + 24.44\exp(-0.07128\text{PM}_{2.5}) - 0.536\text{RH} - 0.037\text{O}_3$</td>
<td>80 $&lt;$ RH $\leq$ 90%</td>
<td>0.671</td>
</tr>
<tr>
<td>$V = 79.095 + 10.228\exp(-0.06571\text{PM}_{2.5}) - 0.822\text{RH} + 0.033\text{T}$</td>
<td>RH $&gt;$ 90%</td>
<td>0.589</td>
</tr>
</tbody>
</table>
contributor to visibility (aside from PM$_{2.5}$ and RH) within RH of 80–90%. The importance of O$_3$ in the model requires further investigation. Results presented in Table 1 also suggested that temperature can affect visibility when RH > 90%. Likely, temperature affects visibility by influencing condensation of water vapor in the atmosphere.

To further verify the validity of the non-linear models combining exponential and multiple linear regressions, hourly observed visibility data from June 2013 to May 2014 were examined. Fig. 5 presents the simulated results based on equations in Table 1 vs. the observed visibility. The newly developed multiple nonlinear model improved the visibility prediction with generally higher R values compared to those based on single parameter regression model (Eq. (3)), especially under high RH (>90%) conditions (Fig. S2). A time series of daily observed visibility and daily visibility simulated by nonlinear regression model from June 2013 to May 2014 is plotted in Fig. 6. There was a high degree of consistency between model-fitted visibility and observed visibility, indicating that the newly developed model is a suitable and practical model for simulating visibility based on air quality in DQL area.

3. Conclusions

Visibility, atmospheric pollutants and meteorological variables monitored in a suburban area (DQL) of Ningbo from June 1, 2013 to May 31, 2015 were analyzed in this study. The characteristics of visibility and its affecting factors were described in detail using multiple statistical methods.
Based on these analyses, the following conclusions can be derived:

The temporal variation of visibility in DQL during the study period demonstrated notable regional characteristics. The seasonal pattern of visibility was characterized by higher levels in spring-summer and lower levels in autumn-winter. Nearly half of all measurements of visibility were lower than 10 km, indicating poor air quality over the study region. Visibility displayed an obvious diurnal variation in each season, with the lowest and highest visibility being 7.5 km at approximately 06:00, and 15.6 km at approximately 14:00, respectively.

The results of MCA indicated that good visibility was always associated with good meteorological conditions and low levels of air pollutants, except for O₃. The results of MCA explained 66.9% necessity of the segmented studies of visibility. Based on the correlation analysis, PM₂.₅, WS and relative humidity were found to have significant impacts on visibility in Ningbo. Also, model equations between visibility, PM and RH were derived, with visibility decreasing exponentially with increasing PM₂.₅ concentrations in different RH ranges. Additionally, the non-linear models combining exponential with multiple linear regressions were developed to investigate the underlying relationships between visibility, air quality and meteorological conditions. The main factors which have the largest influences on visibility change under different RH ranges. Based on a comparative evaluation, the model prediction was found to be relatively accurate for this suburban area.

This study demonstrated that the correlations between visibility and air pollutants/meteorological parameters are relatively consistent and it is possible to predict visibility based on air pollutant concentrations and weather conditions in Ningbo. However, the coefficients and model fitting of other cities may differ from Ningbo due to variations in the pollution characteristics and weather conditions. In order to gain a more precise and generalized model and to simulate the visibility in other cities (such as in YRD region), a dataset of multiple cities will be considered in our future work.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jes.2018.09.015.

REFERENCES


Tan, J.H., Duan, J.C., He, K.B., Ma, Y.L., Duan, F.K., Chen, Y., et al., 2009b. Chemical characteristics of PM2.5 during a typical haze episode in Guangzhou. J. Environ. Sci. 21, 774–781.


Van Stan, J.T., Gay, T.E., Lewis, E.S., 2016. Use of multiple correspondence analysis (MCA) to identify interactive meteorological conditions affecting relative throughfall. J. Hydro. 533, 452–460.


