CrossMark

ORIGINAL PAPER

Analysis of PM2.5 concentrations in Heilongjiang Province associated with forest cover and other factors

Yu Zheng[1] · San Li[1] · Chuanshan Zou[2] · Xiaojian Ma[1] · Guocai Zhang[2]

Abstract Atmospheric particulate matter (PM2.5) seriously influences air quality. It is considered one of the main environmental triggers for lung and heart diseases. Air pollutants can be adsorbed by forest. In this study we investigated the effect of forest cover on urban PM2.5 concentrations in 12 cities in Heilongjiang Province, China. The forest cover in each city was constant throughout the study period. The average daily concentration of PM2.5 in 12 cities was below 75 μg/m^3 during the non-heating period but exceeded this level during heating period. Furthermore, there were more moderate pollution days in six cities. This indicated that forests had the ability to reduce the concentration of PM2.5 but the main cause of air pollution was excessive human interference and artificial heating in winter. We classified the 12 cities according to the average PM2.5 concentrations. The relationship between PM2.5 concentrations and forest cover was obtained by integrating forest cover, land area, heated areas and number of vehicles in cities. Finally, considering the complexity of PM2.5 formation and based on the theory of random forestry, we selected six cities and analyzed their meteorological and air pollutant data. The main factors affecting PM2.5 concentrations were PM10, NO_2, CO and SO_2 in air pollutants while meteorological factors were secondary.

Keywords Forest cover · Heilongjiang Province · Influencing factor · PM2.5 concentrations · Random forest

The online version is available at http://www.springerlink.com

Corresponding editor: Hu Yanbo.

✉ Xiaojian Ma
mxjzy@nefu.edu.cn

Guocai Zhang
zhang640308@126.com

1 College of Science, Northeast Forestry University, Harbin 150040, People's Republic of China

2 School of Forestry, Northeast Forestry University, Harbin 150040, People's Republic of China

Introduction

PM2.5 are tiny suspended particulates with an aerodynamic diameter of less than or equal to 2.5 μm. These generally comprise both poisonous and harmful substances and are difficult to filter. Therefore PM2.5 particles have the ability to stay in the atmosphere for a long period of time and can be transmitted over large distances (Chung et al. 2014; Hossain and Easa 2012). Once inhaled, PM2.5 may cause significant harm to human health, and are one of the major precipitants that both trigger and exacerbate lung and heart diseases in cities across the world (Abbey et al. 1995; Boldo et al. 2006; Che et al. 2015; Fan et al. 2009; Franklin et al. 2007).

In previous studies, factors influencing the concentration of PM2.5 have been generally divided into two categories: natural factors, e.g., weather conditions (Hsu and Cheng 2016; Wang et al. 2013), and human factors. Examples of the latter include the emissions of PM2.5 into the atmosphere through coal-fired power plants and vehicle exhaust pipes. PM2.5 emissions is a particularly serious issue in some densely populated cities since there tend to be both a large number of motor vehicles and significant combustion of coal and other fuels for heating homes in winter (Baker

🖄 Springer

and Scheff 2007; Caggiano et al. 2011; Kulshrestha et al. 2009; Tan et al. 2015; Wang et al. 2012). In response to this situation, the mode of central heating was altered from traditional boiler-type rooms per district to co-generation of heat and power in some cities or industrial parks. Such changes have resulted in simultaneous provision of electricity and heat energy, which not only saves energy but also greatly reduces emissions of PM2.5.

Besides the aforementioned influencing factors, studies have shown that PM2.5 concentrations can be affected by forests through the physical blockage of atmospheric particulates and the absorption of particulate matter through stomata and lenticels of stems and branches. Furthermore, forests can positively affect air temperatures, relative humidity and wind speeds directly or indirectly and other meteorological conditions of the flora microclimate (Becker et al. 2000; Escobedo and Nowak 2009; Escobedo et al. 2008).

Forests play a valuable role in both reducing PM2.5 concentrations in cities and improving urban air quality. Thus, forest cover could be associated with changes in PM2.5 concentrations, and there may be a relationship between PM2.5 concentrations and other factors. Currently, PM2.5 studies mainly focus on the physical and chemical composition of these small particulates (Baker and Scheff 2007; Dan et al. 2004; Khan et al. 2016; Perrone et al. 2012; Sun et al. 2016), or on the impact of basic meteorological factors, other air pollutants, and automobile exhaust emissions on the concentrations of PM2.5. The latter has mainly been analyzed by assessing variation of the PM2.5 concentration in a city or a region where atmospheric pollution is considered to be serious, such as the Jing-Jin-Ji (Beijing, Tianjin and Hebei) region, China, southeast Queensland, Australia, and the northeast and Midwest of the USA as well as San Francisco Bay. A previous study showed that the concentration of PM2.5 in these areas varied by season and geography, and that these regions were characterized by dense populations, high energy consumption, and serious air pollution (Beaver et al. 2010; Ding et al. 2008; Wegesser et al. 2009; Yeganeh et al. 2017). In addition, many studies have demonstrated that the meteorological environment is very complex (Zhang et al. 2015). Meteorological conditions can largely diffuse or accumulate air pollutants (Tai et al. 2010; Yang et al. 2011), which makes the relationship between each meteorological factor and PM2.5 concentration complicated. In fact, Yin et al. (2016) emphasized that the relationship between wind speed and PM concentration was not a simple positive or negative correlation. Indeed, they found in a Beijing study PM2.5 concentrations and daily maximum wind speed exhibited a U-shaped relationship, while concentrations had a nonlinear relationship with PM10 and average air humidity. Analysis of

meteorological data for Nagasaki, Japan showed that precipitation was negatively correlated with PM2.5, while temperature was positively correlated (Wang and Ogawa 2015). Studies have also confirmed that PM2.5 concentration and average wind speed have a nonlinear relationship, but there were linear relationships with single related factors such as CO (carbon monoxide) or NO_2 (nitrogen dioxide) (Ni et al. 2017). In summary, no studies to date have reported a relationship between forest cover and PM2.5, and the main factors that can affect PM2.5 concentrations. Previous studies have been limited by an analysis of only one city, or have only studied the relationship between one factor and PM 2.5. The objectives of this study were (1) to identify the distribution characteristics of PM2.5 concentrations in Heilongjiang Province; (2) to confirm the relationship between forest cover and PM2.5 concentrations; and, (3) to identify the main factors which affect PM2.5 concentrations in Heilongjiang Province.

Materials and method

Study area

The study was conducted in Heilongjiang Province (E121°11′–135°05′, N43°26′–53°33′), the northernmost province of China and covers 12 cities and the Greater Khingan Mountains area (Fig. 1). It has a forest cover of 46.1%. The main climate characteristics of this Province are dry springs of low temperatures, prolonged cold

Fig. 1 Distribution of sampled cities in Heilongjiang Province, China

winters, a short frost-free period. In cold periods the people mainly heat with coal.

Data

For this study, 8760 measurements of the daily average PM2.5 concentrations were obtained from Heilongjiang Environmental Protection Bureau from January 1, 2015 to December 31, 2016. A further 1065 averaged measurements of other air pollutants (PM10, SO_2, CO and NO_2 and O_3) were also collected for a total of 9825 measurements. Daily average data for average wind speeds, sunshine duration, average atmospheric pressures, mean temperatures, and average relative humidity were collected in 12 cities from October 1, 2015 to April 30, 2016 from http://data.cma.cn and 1065 values were obtained. We also gathered data on populations, land areas, meteorological conditions, heated areas and motor vehicle numbers in each city from the Annals of Statistics of Heilongjiang Province.

Air quality rating standard

According to the *State Environmental Protection Standards of the People's Republic of China: Technical Regulation on Ambient Air Quality Index* (*HJ633-2012*), the relationships between daily average PM2.5 concentration and air quality levels are shown in Table 1.

Results and discussion

Analysis of daily average PM2.5 concentrations

PM2.5 concentrations are influenced by many factors and high concentrations mainly develop in winter and spring. According to the climate characteristics of Heilongjiang Province, a cycle is defined by a non-heating period May 1st to September 30th and a period when artificial heating is used October 1st to April 30th. The daily average PM2.5 concentrations during heating and non-heating periods in these 12 cities in 2015 and 2016 as of December 31st, 2016 are shown in Fig. 2.

For the two non-heating periods, Fig. 2 shows that the daily average concentrations of PM2.5 in Jiamusi, Mudanjiang, Qitaihe, Suihua, Yichun, Jixi, Qiqihar, and Shuangyashan were less than 75 μg/m³. Figure 2a shows that Harbin had 4 days in 2015 when the daily average PM2.5 concentrations slightly exceeded 75 μg/m³ and PM2.5 concentrations of this city were less than 75 μg/m³ in 2016. Figure 2i shows that there were 2 days in May of both years in Heihe when daily average PM2.5 concentrations exceeded 75 μg/m³. Figure 2b shows that daily average PM2.5 concentrations in Daqing were higher than 75 μg/m³ in both years (2 and 3 days, respectively). Finally, Fig. 2g indicates that the daily average PM2.5 concentrations in Hegang did not affect air quality except 3 days.

Figure 2 also demonstrates that increasing fossil fuel consumption by heating led to increases in pollution sources, especially after November when it became cold. The increasing heating demand and large amounts of coal burning led to a daily average concentration of PM2.5 in 12 cities that sometimes exceeded 75 μg/m³, though specific levels differed by city. In March and April, when the weather turned warmer and heating demand decreased, PM2.5 concentrations concomitantly declined on a gradual basis. Data pertaining to the daily average PM2.5 concentrations in the heating period of 2015 were collected and summarized in Fig. 3. These are in accord with specified standards of the daily average PM2.5 concentration (done by converting the daily average concentration standard of air quality index to PM2.5 daily average concentration standards) in the *State Environmental Protection Standards of the People's Republic of China: Technical Regulation on Ambient Air Quality Index* (*HJ633-2012*). Figure 3 shows that a large proportion of Harbin's daily average PM2.5 concentrations were at light and medium levels, while heavy pollution also accounted for a large share. Harbin was followed by Mudanjiang, Qiqihar, Qitaihe, Daqing and Suihua with respect to pollution levels.

We obtained the following results from the analysis: (1) during the non-heating period, 4 of the 12 cities had daily average PM2.5 concentrations that exceeded 75 μg/m³ but only for a period of 1–4 days. Almost all the other daily

Table 1 Corresponding air quality levels of daily average PM2.5 concentrations

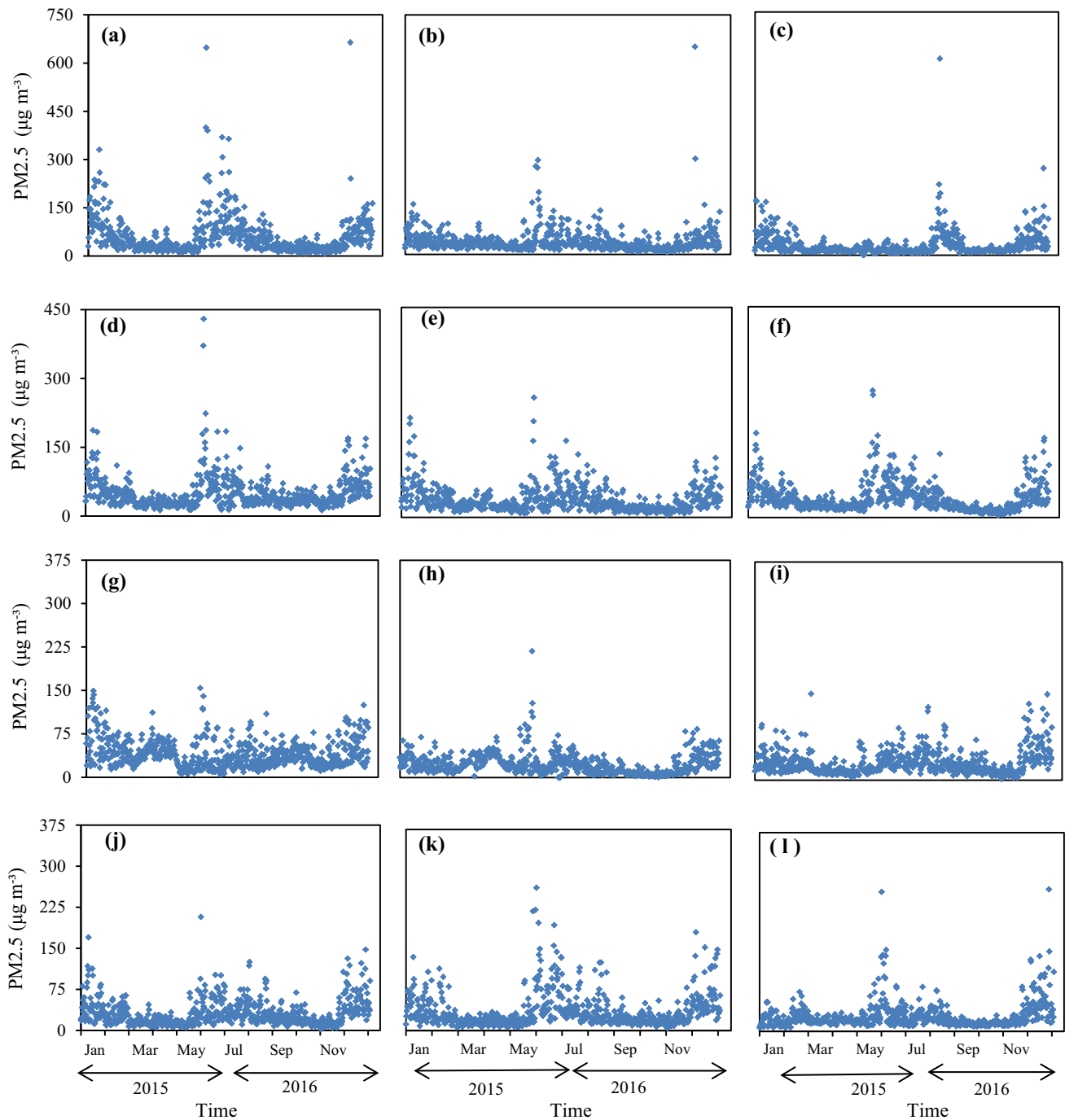| Air quality level	Daily average PM2.5 concentration range (μg/m³)
Excellent	0–35
Good	35–75
Light pollution	75–115
Medium pollution	115–150
Heavy pollution	150–250
Severe pollution	250–500

Fig. 2 Daily average concentrations of PM2.5 in the 12 cities, which are Harbin (**a**), Daqing (**b**), Suihua (**c**), Qitaihe (**d**), Shuangyashan (**e**), Mudanjiang (**f**), Hegang (**g**), Yichun (**h**), Heihe (**i**), Jiamusi (**j**), Qiqihar (**k**), and Jixi (**l**)

average concentrations were considered to be good or excellent. Therefore, we concluded that variables associated with human activities did not increase the daily average PM2.5 concentrations during the non-heating period or affected pollution levels. (2) During the heating period, demand increased significantly which is attributable to human activities and the daily average

PM2.5 concentrations often reached a standard of pollution.

Analysis of the relationship between forestry cover and PM2.5 concentrations

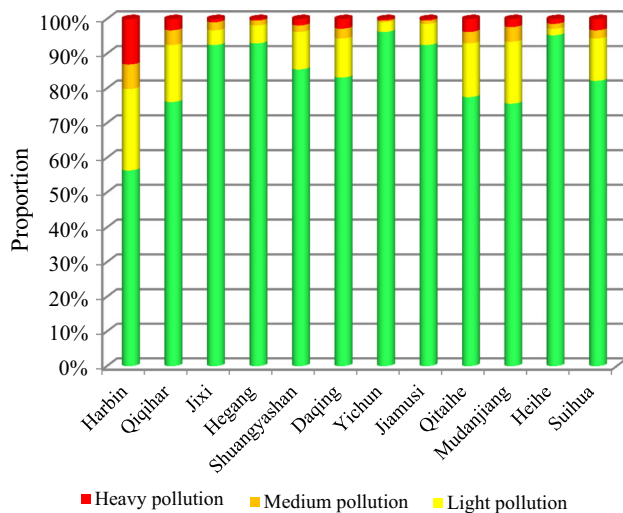Previous studies have confirmed that air quality of many cities and regions (Los Angeles, Beijing, and Santiago

Metropolitan Region) can be improved by urban forest cover through eliminating air pollutants and changing microclimates (Escobedo and Nowak 2009; Powe and Willis 2004; Yang et al. 2005). However, little research has focused on the relationship between urban air quality and forests of Heilongjiang province, which has the largest area of forest cover in China at approximately 46.1%. Differences in populations, land area, meteorological conditions, heated areas and motor vehicle levels in different cities cause PM2.5 concentration levels to vary (Hsu and Cheng 2016; Majumdar et al. 2015; Palencia et al. 2016). In the present study, according to forestry cover, relative heating areas, motor vehicle levels (Table 2) and heating method, the 12 cities, can be divided into four groups based on the

Table 2 Forestry coverage rate, relative heating area, and motor vehicle population in 12 cities

Cities	Forestry coverage rate (%)	Relative heating area (heating area/land area)	Motor vehicle population (taxi, bus, private cars)
Harbin	46	0.416380267	385,650.00
Qiqihar	11.70	0.112459	69,301.00
Jixi	28	0.07472944	49,013.00
Hegang	58	0.131798071	16,246.00
Shuangyashan	38.40	0.098896076	8396.00
Daqing	12.80	0.415848889	106,997.00
Yichun	82.20	0.065747909	16,276.00
Jiamusi	15.40	0.08931326	26,221.00
Qitaihe	48.60	0.223356845	41,151.00
Mudanjiang	62.30	0.08795382	37,647.00
Heihe	47.30	0.01390926	10,393.00
Suihua	13.20	0.050402	21,297.00

monthly average PM2.5 concentration data from May 1st 2015 to April 30th 2016 (Table 2; Fig. 4).

Cities in the first group include Yichun, Heihe, and Hegang and all had a high forest cover. There were relatively small heating areas in Yichun and Heihe, while Hegang did not have large motor vehicle numbers and therefore there were fewer air pollutants due to human factors. Consequently, the average PM2.5 concentration in these cities in one 12-month period was low and the air considered to be of good or excellent quality. Cities in the second group included Qiqihar, Daqing, and Suihua with the lowest forest cover in the Province (Suihua > Daqing > Qiqihar). Daqing and Qiqihar had relatively large heating areas during the heating period while Qiqihar and Suihua had large motor vehicle levels. Consequently, due to more air pollutants caused by human behavior, the monthly average PM2.5 concentrations in November in Daqing and Suihua were within light pollution levels, and Qiqihar was also lightly polluted in November and December (pollution levels were ranked as Qiqihar > Daqing > Suihua). The third group included Harbin, Mudanjiang, and Qitaihe. Although their forest cover was high (Mudanjiang > Qitaihe > Harbin), Harbin and Qitaihe had relatively large heated areas and all three cities had large motor vehicle numbers. Consequently, due to pollutants caused by human activities, the three cities were moderately polluted in November and December (Harbin > Qitaihe > Mudanjiang, which was in contrast to forest cover ranking). However, the PM2.5 concentration data for Harbin was considered to be approaching heavily polluted levels. The fourth group of cities included Jiamusi, Jixi, and Shuangyashan and had low forest cover, at least below the provincial average. However, the heating area in these three cities was relatively small, while thermoelectric networking was used for heating (http://www.xinhuanet. com) in both Jiamusi and Jixi. However, the population of Shuangyashan did not have a large number of motor vehicles and the monthly average PM2.5 concentration was within the scope of being good to excellent in one 12-month cycle.

We can draw the following conclusions from the analysis. A higher forest cover was associated with lower concentrations of PM2.5. However, if society was to discharge pollutants into the atmosphere without any limits, this would result in an increase in PM2.5 concentrations that would reach medium or even heavy pollution levels. In such instances, forest cover would have a limited role in mitigating such high levels of PM2.5. However, our data did suggest that higher forest cover resulted in lower PM2.5 concentrations. In contrast, a low forest cover and significant human activities usually results in high PM2.5 concentrations that reach appreciable pollution levels. When forest cover is low, it may be possible to restrain
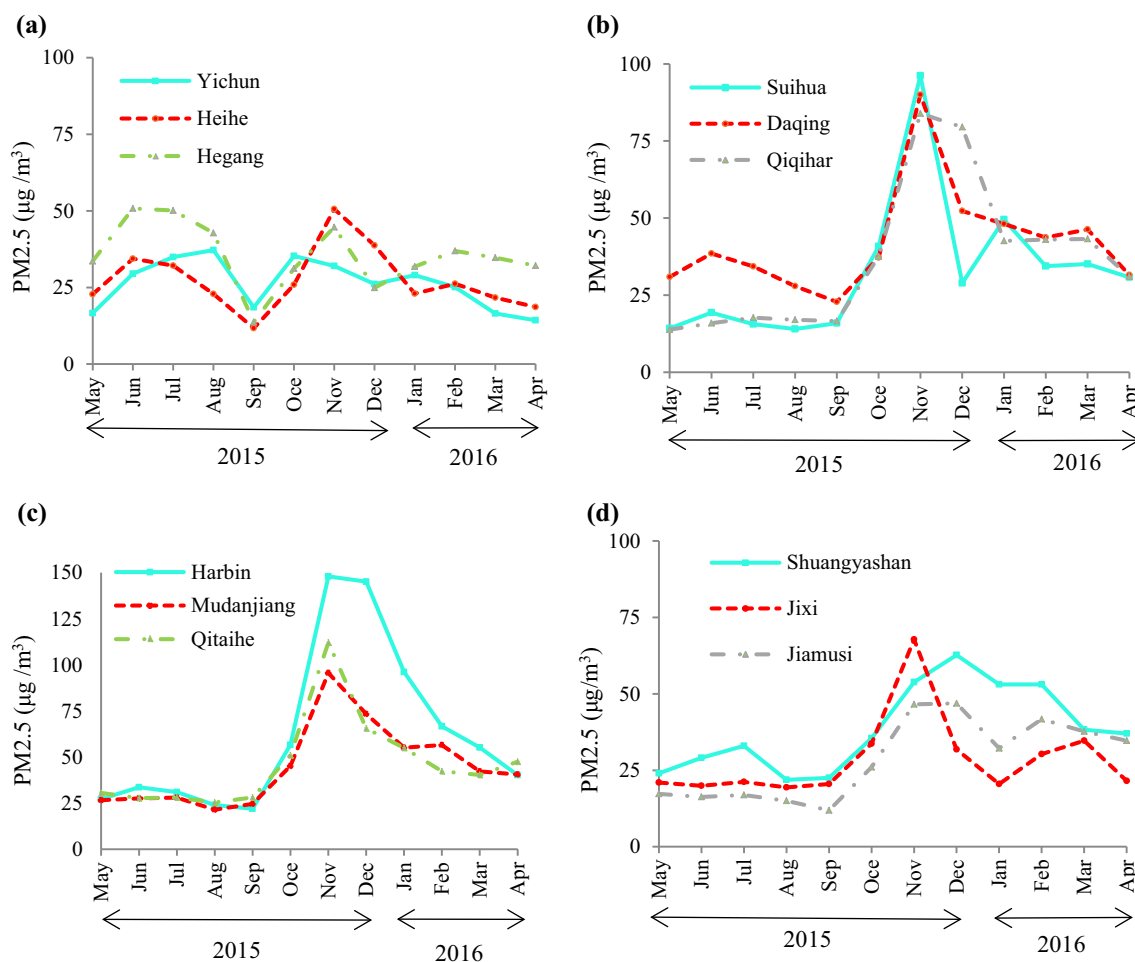
Fig. 4 The monthly average PM2.5 concentration of four groups from May 1st 2015 to April 30th 2016

human discharge of pollutants into the atmosphere which can help control PM2.5 increases.

Determination of the factors affecting PM2.5 concentrations

The formation of PM2.5 is a complex process and previous studies have only focused on PM2.5 concentrations and their association with a single factor, with data lacking on the multi-factorial analysis of PM2.5 concentrations. Furthermore, it is not possible using this type of approach to determine which factor is the most important in influencing PM2.5 concentrations. Traditional classifications and regression statistical models have been used to select the importance of indirect assessment variables through statistical significance and Akaike information criterion (AIC), which resulted in some important variables being incorrectly deleted. As a modern regression method, the Random Forest (RF) methodology has been applied to the complex situation of high-dimensional variables where there are complex relationships. The importance of this

method can be extended to each variable where important variables can be identified and be prevented from being deleted (Baccini et al. 2008; Cutler et al. 2007; Prasad et al. 2006; Xie et al. 2009). In this study, based on the theory and merits of a Random Forest model, forest cover, land area, heating area and the number of vehicles were regarded as a constant during the period of 2015. We then determined the important variables affecting the concentration of PM2.5 by data analysis for meteorological factors and air pollutants from the heating periods in 2015. Since both meteorological factors and air pollutants can affect PM2.5 concentrations, and these factors also interact with each other in a complex relationship, it is difficult to employ classical regression to confirm the main factors that are most important in determining PM2.5 levels. This paper adopted the modern regression method of RF and assessed forest cover, land area, heating area and motor vehicle levels which were considered to be constant in one 12-month cycle of 2015. Table 3 shows important variable values from high to low (two decimal fractions were used) in which X_1 to X_{10} represents average wind speed (X_1),

Table 3 Importance rank of air pollutants and meteorological factors in 6 cities (10 factors in total)

Cities	1	2	3	4	5	6	7	8	9	10
Harbin	X_6	X_9	X_8	X_7	X_1	X_2	X_5	X_4	X_3	X_{10}
	45.38	36.11	25.66	17.63	17.60	17.54	16.86	15.74	15.61	15.01
Mudanjiang	X_6	X_8	X_9	X_7	X_1	X_4	X_2	X_3	X_5	X_{10}
	21.90	15.94	13.86	10.67	8.84	8.70	7.91	7.84	7.23	7.08
Qitaihe	X_6	X_9	X_8	X_{10}	X_7	X_3	X_5	X_1	X_4	X_2
	29.81	22.52	19.24	16.60	14.91	14.69	13.85	13.82	13.81	12.76
Daqing	X_6	X_8	X_9	X_7	X_5	X_2	X_3	X_4	X_1	X_{10}
	26.17	21.82	16.36	12.46	11.68	11.37	10.31	10.12	9.24	8.87
Qiqihar	X_6	X_9	X_8	X_7	X_5	X_4	X_2	X_3	X_1	X_{10}
	27.15	20.90	17.60	15.20	15.04	14.29	14.11	13.75	11.43	9.83
Suihua	X_6	X_9	X_8	X_{10}	X_7	X_4	X_1	X_3	X_2	X_5
	28.48	19.12	15.06	13.56	11.85	11.77	10.63	9.86	9.07	8.41

Average wind speed (X1), sunshine duration (X2), average atmospheric pressure (X3), average temperature (X4), average relative humidity (X5), PM10 (X6), SO$_2$ (X7), CO (X8), NO$_2$ (X9) and O$_3$ (X10)

sunshine duration (X_2), average atmospheric pressure (X_3), average temperature (X_4), average relative humidity (X_5), PM$_{10}$ (X_6), SO$_2$ (X_7), CO (X_8), NO$_2$ (X_9) and O$_3$ (X_{10}), respectively. During the cooler months in 2015, cities with high PM2.5 concentrations, such as Harbin, Mudanjiang, Qiqihar, Qitaihe, Daqing, and Suihua, were significantly influenced by several factors that affected PM2.5 concentrations. These air pollutants were PM10, SO$_2$, NO$_2$, and CO and all meteorological factors were ranked after these four pollutants. Although different for each city, the average wind speeds and relative humidity were relatively important. We conclude that the air pollutants PM10, SO$_2$, NO$_2$, and CO were the main influencing factors for changes to PM2.5 concentration levels, and any increase in these pollutants was strongly associated with PM2.5 increases. If forest cover remains unchanged, it is imperative that there is control of population-driven pollution so that there is a concomitant reduction in PM2.5 concentrations in the atmosphere.

Conclusions

The daily average PM2.5 concentration of 75 μg/m^3 was a critical value in Heilongjiang Province. Human activities did not result in concentrations that exceeded 75 μg/m^3 during the warm months. However, the daily average PM2.5 concentrations during the cooler months (heating periods) were significantly affected by human activities. Concentrations of PM2.5 were unaffected when cities had high forest cover and PM2.5 levels were always at lower concentrations. Forests play a positive role in decreasing the concentration of PM2.5. Fine particulate matter (PM10), sulfur dioxide, nitrogen dioxide and carbon monoxide were the main factors affecting PM2.5 concentrations, while meteorological factors and O$_3$ levels were secondary. To reduce PM2.5 concentrations, it is necessary to control the discharge of pollutants, especially during the cooler months (heating period).

References

Abbey DE, Ostro BE, Petersen F, Burchette RJ (1995) Chronic respiratory symptoms associated with estimated long-term ambient concentrations of fine particulates less-than 2.5 microns in aerodynamic diameter (PM2.5) and other air-pollutants. J Expo Anal Environ Epidemiol 5(2):137–159

Baccini A, Laporte N, Goetz SJ, Sun M, Dong H (2008) A first map of tropical Africa's above-ground biomass derived from satellite imagery. Environ Res Lett 3(4):2272–2280

Baker K, Scheff P (2007) Photochemical model performance for PM2.5 sulfate, nitrate, ammonium, and precursor species SO$_2$, HNO$_3$, and NH$_3$ at background monitor locations in the central and eastern United States. Atmos Environ 41(29):6185–6195

Beaver S, Palazoglu A, Singh A, Soong ST, Tanrikulu S (2010) Identification of weather patterns impacting 24-h average fine particulate matter pollution. Atmos Environ 44(14):1761–1771

Becker JS, Bellis D, Staton I, McLeod CW, Dombovari J, Becker JS (2000) Determination of trace elements including platinum in tree bark by ICP mass spectrometry. Fresenius' J Anal Chem 368(5):490–495

Boldo E, Medina S, LeTertre A, Hurley F, Muecke HG, Ballester F, Aguilera I, Eilstein D, Apheis G (2006) Apheis: health impact assessment of long-term exposure to PM2.5 in 23 European cities. Eur J Epidemiol 21(6):449–458

Caggiano R, Fiore S, Lettino A, Macchiato M, Sabia S, Trippetta S (2011) PM2.5 measurements in a Mediterranean site: two typical cases. Atmos Res 102(1–2):157–166

Che H, Xia X, Zhu J, Wang H, Wang Y, Sun J, Zhang X, Shi G (2015) Aerosol optical properties under the condition of heavy haze over an urban site of Beijing, China. Environ Sci Pollut Res 22(2):1043–1053

Chung YS, Kim HS, Chun Y (2014) On large-scale transport of dust storms and anthropogenic dust-falls over east Asia observed in central Korea in 2009. Asia Pac J Atmos Sci 50(3):345–354

Cutler DR Jr, Edwards TC, Beard KH, Cutler A, Hess KT (2007) Random forests for classification in ecology. Ecology 88(11):2783–2792

Dan M, Zhuang GS, Li XX, Tao HR, Zhuang YH (2004) The characteristics of carbonaceous species and their sources in PM2.5 in Beijing. Atmos Environ 38(21):3443–3452

Ding AJ, Wang T, Thouret V, Cammas JP, Nedelec P (2008) Tropospheric ozone climatology over Beijing: analysis of aircraft data from the MOZAIC program. Atmos Chem Phys 8(1):1–13

Escobedo FJ, Nowak DJ (2009) Spatial heterogeneity and air pollution removal by an urban forest. Lands Urban Plan 90(3–4):102–110

Escobedo PJ, Wagner JE, Nowak DJ, De la Maza CL, Rodriguez M, Crane DE (2008) Analyzing the cost effectiveness of Santiago, Chile's policy of using urban forests to improve air quality. J Environ Manag 86(1):148–157

Fan Z, Meng Q, Weisel C, Laumbach R, Ohman-Strickland P, Shalat S, Hernandez MZ, Black K (2009) Acute exposure to elevated PM2.5 generated by traffic and cardiopulmonary health effects in healthy older adults. J Expo Sci Environ Epidemiol 19(5):525–533

Franklin M, Zeka A, Schwartz J (2007) Association between PM2.5 and all-cause and specific-cause mortality in 27 US communities. J Expo Sci Environ Epidemiol 17(3):279–287

Hossain KMA, Easa SM (2012) Pollutant dispersion characteristics in Dhaka city, Bangladesh. Asia Pac J Atmos Sci 48(1):35–41

Hsu CH, Cheng FY (2016) Classification of weather patterns to study the influence of meteorological characteristics on PM2.5 concentrations in Yunlin County, Taiwan. Atmos Environ 144:397–408

Khan MB, Masiol M, Formenton G, Di Gilio A, de Gennaro G, Agostinelli C, Pavoni B (2016) Carbonaceous PM2.5 and secondary organic aerosol across the Veneto region (NE Italy). Sci Total Environ 542:172–181

Kulshrestha A, Bisht DS, Masih J, Massey D, Tiwari S, Taneja A (2009) Chemical characterization of water-soluble aerosols in different residential environments of semi aridregion of India. J Atmos Chem 62(2):121–138

Majumdar D, Majhi BK, Dutta A, Mandal R, Jash T (2015) Study on possible economic and environmental impacts of electric vehicle infrastructure in public road transport in Kolkata. Clean Technol Environ Policy 17(4):1093–1101

Ni XY, Huang H, Du WP (2017) Relevance analysis and short-term prediction of PM2.5 concentrations in Beijing based on multi-source data. Atmos Environ 150:146–161

Palencia JCG, Araki M, Shiga S (2016) Energy, environmental and economic impact of mini-sized and zero-emission vehicle diffusion on a light-duty vehicle fleet. Appl Energy 181:96–109

Perrone MG, Larsen BR, Ferrero L, Sangiorgi G, De Gennaro G, Udisti R, Zangrando R, Gambaro A, Bolzacchini E (2012) Sources of high PM2.5 concentrations in Milan, Northern Italy: molecular marker data and CMB modelling. Sci Total Environ 414:343–355

Powe NA, Willis KG (2004) Mortality and morbidity benefits of air pollution (SO2 and PM10) absorption attributable to woodland in Britain. J Environ Manag 70(2):119–128

Prasad AM, Iverson LR, Liaw A (2006) Newer classification and regression tree techniques: bagging and random forests for ecological prediction. Ecosystems 9(2):181–199

Sun F, Lun X, Liu X, Mo L, Li R, Zhang H, Chen J, Cao Y, Shi F, Yu X (2016) Analysis of organic and elemental carbon in heating and non-heating periods in four locations of Beijing. Environ Technol 37(1):121–128

Tai APK, Mickley LJ, Jacob DJ (2010) Correlations between fine particulate matter (PM2.5) and meteorological variables in the United States: implications for the sensitivity of PM2.5 to climate change. Atmos Environ 44(32):3976–3984

Tan CH, Zhao TL, Cui CG, Luo BL, Zhang L, Bai YQ (2015) Characterization of haze pollution over Central China during the past 50 years. China Environ Sci 35(8):2272–2280

Wang J, Ogawa S (2015) Effects of Meteorological Conditions on PM2.5 Concentrations in Nagasaki, Japan. Int J Environ Res Public Health 12(8):9089–9101

Wang T, Jiang F, Deng J, Shen Y, Fu Q, Wang Q, Fu Y, Xu J, Zhang D (2012) Urban air quality and regional haze weather forecast for Yangtze River Delta region. Atmos Environ 58:70–83

Wang J, Wang Y, Liu H, Yang Y, Zhang X, Li Y, Zhang Y, Deng G (2013) Diagnostic identification of the impact of meteorological conditions on PM2.5 concentrations in Beijing. Atmos Environ 81:158–165

Wegesser TC, Pinkerton KE, Last JA (2009) California wildfires of 2008: coarse and fine particulate matter toxicity. Environ Health Perspect 117(6):893–897

Xie Y, Li X, Ngai EWT, Ying W (2009) Customer churn prediction using improved balanced random forests. Expert Syst Appl 36(3):5445–5449

Yang J, McBride J, Zhou J, Sun Z (2005) The urban forest in Beijing and its role in air pollution reduction. Urban For Urban Green 3(2):65–78

Yang L, Wu Y, Davis JM, Hao J (2011) Estimating the effects of meteorology on PM2.5 reduction during the 2008 Summer Olympic Games in Beijing, China. Front Environ Sci Eng China 5(3):331–341

Yeganeh B, Hewson MG, Clifford S, Knibbs LD, Morawska L (2017) A satellite-based model for estimating PM2.5 concentration in a sparsely populated environment using soft computing techniques. Environ Model Softw 88:84–92

Yin Q, Wang JF, Hu MG, Wong HT (2016) Estimation of daily PM2.5 concentration and its relationship with meteorological conditions in Beijing. J Environ Sci 48:161–168

Zhang C, Ni Z, Ni L (2015) Multifractal detrended cross-correlation analysis between PM2.5 and meteorological factors. Phys A Stat Mech Appl 438:114–123