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Acute health impacts of airborne particles estimated from satellite remote sensing☆

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Abstract

Satellite-based remote sensing provides a unique opportunity to monitor air quality from space at global, continental, national and regional scales. Most current research focused on developing empirical models using ground measurements of the ambient particulate. However, the application of satellite-based exposure assessment in environmental health is still limited, especially for acute effects, because the development of satellite $PM_{2.5}$ model depends on the availability of ground measurements. We tested the hypothesis that MODIS AOD (aerosol optical depth) exposure estimates, obtained from NASA satellites, are directly associated with daily health outcomes. Three independent healthcare databases were used: unscheduled outpatient visits, hospital admissions, and mortality collected in Beijing metropolitan area, China during 2006. We use generalized linear models to compare the short-term effects of air pollution assessed by ground monitoring (PM_{10}) with adjustment of absolute humidity (AH) and AH-calibrated AOD. Across all databases we found that both AH-calibrated AOD and PM_{10} (adjusted by AH) were consistently associated with elevated daily events on the current day and/or lag days for cardiovascular diseases, ischemic heart diseases, and COPD. The relative risks estimated by AH-calibrated AOD and PM_{10} (adjusted by AH) were similar. Additionally, compared to ground PM_{10}, we found that AH-calibrated AOD had narrower confidence intervals for all models and was more robust in estimating the current day and lag day effects. Our preliminary findings suggested that, with proper adjustment of meteorological factors, satellite AOD can be used directly to estimate the acute health impacts of ambient particles without prior calibrating to the sparse ground monitoring networks.

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Appendix A. Supplementary data
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Keywords

Absolute humidity; Aerosol optical depth; Environmental health; Particulate matter; Satellite remote sensing

1. Introduction

Environmental epidemiology studies have established a robust association between acute and chronic exposure to airborne fine particulate matter with diameter <2.5 μm ($PM_{2.5}$) and adverse health effects such as increased overall mortality, as well as cause-specific mortality, cardiovascular and pulmonary diseases, asthma, and lung cancer (Dockery et al., 1993; Laden et al., 2006; Pope and Dockery, 2006). In contrast to chronic health effect studies of PM which primarily rely on spatial heterogeneity in mean PM concentrations to estimate the effects (Yanosky et al., 2008), day-to-day variations of PM levels are much more important in short-term health effect studies (Dominici et al., 2006; Samet et al., 2000). Many previous studies relied on central monitors to assign uniform exposure to population living within a certain distance to the monitor. Besides the exposure misclassification related to this approach, its application is limited to the spatial and temporal availability of ground measurements from a monitoring network. For example, most U.S. $PM_{2.5}$ monitors are operated on an every-3-day or every-6-day sampling schedule. In addition, most monitors are located in urban area with sparse or no coverage in suburban and rural areas even in the U.S. Lack of routine ground monitoring is a major factor limiting both chronic and acute $PM_{2.5}$ health effects research in developing countries.

Various modeling approaches have been explored to improve the spatial and temporal coverage of $PM_{2.5}$ concentrations. For example, land use regression models have been developed to provide spatially resolved $PM_{2.5}$ levels to support chronic health effect studies (Jerrett et al., 2005). Model simulated $PM_{2.5}$ levels have been evaluated as exposure estimates (Bravo et al., 2012). Given its broad spatial coverage, satellite-based monitoring data can greatly supplement and expand ground monitoring networks to study the spatial and temporal variations of PM, particularly in suburban and rural areas far from ground monitoring sites. Satellite-derived aerosol optical depth (AOD), retrieved at visible wavelengths such as the green bands (550 nm), is more sensitive to $PM_{2.5}$ and can be used as a quantitative measure of $PM_{2.5}$ abundance in the atmospheric column (Gupta et al., 2006; Koelemeijer et al., 2006; Liu et al., 2005; Liu et al., 2007a; Paciorek et al., 2008). Although satellite-derived AOD has been successfully used to document pollution episodes (Al-Saadi et al., 2005; Wang and Christopher, 2003), the application of satellite-based exposure assessment in environmental health is in its infant stage. Most research focuses on a pre-calibration approach of developing simple empirical models of AOD based on ground $PM_{2.5}$ measurements, and then evaluates the health effects of built models (Kloog et al., 2012). However, the success of model building is limited by temporal mismatch between 24-h average $PM_{2.5}$ and daytime (often single snapshot) AOD and various factors impacting on the measurement accuracy from ground or space. To date, there are only a few studies that have examined the relationships between pre-calibrated AOD and long-term health effect (Hu, 2009; Hu and Rao, 2009).

Considering the limited success in model building using pre-calibration approach, we tested the hypothesis that AOD is directly associated with acute and/or chronic health effects without pre-calibration, as observed using ground data, under the condition that AOD is an indicator of ground-level PM concentrations. In this exploratory study, we tested this hypothesis using a healthcare database of hospital admissions collected from the entire geographic region of Beijing in 2006, and further evaluated using two independent healthcare databases, including unscheduled outpatients visits and mortality, from sub-geographic regions of Beijing. We focused on daily health outcomes extracted from these databases to evaluate the acute effects associated with PM exposure. Our main objective was to compare air pollution-associated health effects monitored from space (by AOD) and ground (by PM), thus, ground measurement of PM_{10} particles was used as reference to evaluate the AOD application in environmental health research even though there was no $PM_{2.5}$ data available in Beijing. To our knowledge, this study was the first quantitative application of satellite aerosol remote sensing data to estimate air pollution-health effects.

2. Methods

2.1. Healthcare datasets

Three databases covering different geographic regions of Beijing (Fig. 1) were used to compare the effects of air pollution assessed using ground PM_{10} and AOD, including unscheduled outpatient visits, hospital admissions, and mortality. The daily events were extracted according to the disease categories in Table 1. Strongly influenced by weekday/weekend schedule, major national holidays, and administrative interruptions, the daily events of unscheduled outpatient visits and hospital admissions had regular patterns of weekly fluctuations (Fig. 2). The days at the weekends, holidays, and administrative interruptions had the lowest daily events, and the days immediately followed the weekends, holidays, and administrative interruptions had the highest daily events. Using a 7-day moving average, we were able to completely remove weekly fluctuations resulting in a few major gaps corresponding to holidays and administrative interruptions longer than five weekdays. In these two databases, we investigated lag effects of air pollution within one-week period by using 7-day moving average of daily events starting from the current day or the next day.

2.2. Ground air quality monitoring data and meteorological data

Air Quality Index (AQI) is a color-coded reporting system commonly used by government agencies to characterize the air quality for a number of pollutants. It is a piecewise linear function to convert air pollutant concentration into AQI, which is divided into ranges with a descriptor and a color code assigned to each range. China implemented a modified AQI system, according to the guideline issued by the US Environmental Protection Agency (http://www.epa.gov/ttn/oarpg/t1/memoranda/rg701.pdf).

Chinese AQI level is based on the levels of 5 atmospheric pollutants, including sulfur dioxide (SO_2), nitrogen dioxide (NO_2), particulates (PM_{10}), carbon monoxide (CO), and ozone (O_3). A daily AQI score is assigned to the level of each pollutant and the final daily AQI is the highest of those 5 scores. The type of pollutant is only specified for the day with AQI> 50.

Daily AQI covering Beijing area was obtained from the Beijing Environmental Protection Bureau. In 2006, PM_{10} was considered as the major air pollutant because PM_{10} had the highest concentrations among all monitored pollutants for all of the days with AQI above 50, which accounted for over 92% of the days in 2006. Daily AQI values at all 35 ground monitors in Beijing were converted to PM_{10} concentrations, and geometric means of PM_{10} were used in this study. For those days without pollutant specified (AQI<50), we treated PM_{10} as the major air pollutant. To convert from concentration to AQI the equation:

$$C=\left(C_{high}-C_{low}\right)/\left(I_{high}-I_{low}\right)*(I-I_{low})$$

was used, where: I=AQI value, C=the PM_{10} concentration, C_{low} =the lower limit of PM_{10} concentration of corresponding range of C, C_{high} = the higher limit of PM_{10} concentration of corresponding range of C, I_{low}=the lower limit of AQI corresponding to C_{low}, I_{high}=the lower limit of AQI corresponding to C_{high}.

Local meteorological parameters collected at one station located at Beijing International Airport (32 km northeast of city center) were extracted from Worldwide Surface Observations Database (DS3505, integrated surface hourly) at National Climatic Data Center. Daily averages of meteorological parameters were calculated from hourly values, including temperature, relative humidity (RH), precipitation, air pressure, wind, and visibility. Absolute humidity (AH) was calculated from RH and temperature data as described previously (Shaman and Kohn, 2009).

2.3. Satellite AOD

The Moderate Resolution Imaging Spectroradiometer (MODIS) instruments, aboard on the EOS Terra (since February 2000) and Aqua (since June 2002) satellites, cross the equator at approximately 10:30 a.m. and 1:30 p.m. local time, respectively (Remer et al., 2005). Both MODIS instruments provide AOD retrievals at a spatial resolution of 10 km every 1–2 days at mid-latitudes. AOD values of Collection 5 MODIS data in 2006 covering northern China including Beijing were downloaded from the Goddard Space Flight Center MODIS Level 1 and Atmosphere Archive and Distribution System (http://ladsweb.nascom.nasa.gov). Daily AODs were retrieved as described previously (Liu et al., 2009). Briefly, we first selected MODIS pixels whose centroids fall within Beijing city boundaries, then calculated city-average Terra MODIS AOD and Aqua MODIS AOD respectively, and finally took the average of two satellite AOD values as daily mean AOD. Given our single-city study domain and the relatively coarse resolution of MODIS AOD, satellite data in our analysis is used to improve the temporal coverage of fine particle exposure estimates only.

2.4. Statistical analysis

To relate short-term effects of air pollution to the daily health outcome, we used the time series procedures. Because daily counts of health events typically follow a Poisson distribution with large dispersion, we implemented generalized linear models (GLM) with negative binomial distribution as described previously (Dominici et al., 2000; Katsouyanni et al., 1996; Schwartz et al., 1996). The effects on the same day or lagged days of PM exposure (daily PM_{10} or AOD) were investigated for each health outcome. Since AOD is dimensionless, we used $\log_2$-transformed values in modeling to obtain uniformed comparison of the PM-related health effects assessed by ground and space monitoring. To accommodate weekly fluctuations in hospital admission and unscheduled outpatient visit, we created a categorical variable to represent weekdays or weekends/holidays, and incorporate this variable in analysis. This variable was not included in mortality analyses. Since the data structure is relatively simple, which were collected with-in one calendar year and one geographic region, we did not use smoothing function for seasonality and weather control. Instead, a parametric season variable and meteorological variables were included in the models. We also conducted several sensitivity analyses to assess the impacts of different meteorological variables. Model selection, as well as evaluation between health effect models of AOD and PM exposure, was based on likelihood test, Akaike Information Criterion, and residual predictions. In order to reduce weekly fluctuation we also used the 7-day moving average of daily health events in the analysis of hospital admission and unscheduled outpatient visit, without categorical variable representing weekdays or weekends/holidays. All statistical analyses were performed using the SAS package (version 9.1, SAS Inc., Cary, NC). Relative risks were calculated, and all statistical tests were two-sided and values of $P<0.05$ were considered significant.

3. Results

3.1. Calibration of AOD by absolute humidity

In 2006, PM_{10} daily average was 161 μg/m^3 with the 25th percentile at 94 μg/m^3 and the 75th percentile at 196 μg/m^3. There were 265 days (73%) with valid AOD measurements, and the missing days were not significantly clustered in any season (χ^2 test, p=0.082). The correlation between ground PM_{10} and AOD was low (Pearson correlation coefficient, 0.22; p=0.0003). Compared with PM_{10}, the weather condition had more effects on the AOD as there were stronger correlations between AOD and meteorological factors (Supplemental material, Table 1). In contrast to higher levels of air pollution observed normally in winter and spring, AOD tended to be higher in summer (data not shown).

AOD values can be inversely affected by atmospheric water content. Relative humidity (RH) is the most frequently used meteorological factor for measuring the atmospheric water content, contrary to that the absolute humidity (AH, absolute measure of water vapor in the air) was seldom used in previous studies. Although there was a strong correlation between the two measurements (Supplemental material, Table 1), their daily average showed significantly different patterns (Fig. 3A and B). RH tended to have large day-to-day variations and was more variable in winter, spring, and fall, because high values could be found in all seasons but low RH was seldom observed in summer. AH had much smaller day-to-day variation (mean daily changes, 1.4±1.3 g/m^3), with an annual daily average of 8.2 g/m^3 (median: 5.9 g/m^3; range, 0.4–25.9 g/m^3). Annual distribution of daily AH had a distinct bell-shaped pattern and fitted well with the seasonality (Fig. 3A). Driven by low ambient temperature, winter in Beijing had very low AH. AH started to increase gradually in the spring, peaked in the summer, decreased gradually in the fall, and returned to low levels in the next winter. Compared with AH, daily RH seemed to overestimate the atmospheric water content (Fig. 3B) and less coped with seasonal variations (Fig. 3A). Moreover, AH had a strong but non-linear correlation with daily dew point (Fig. 3C), another meteorological measure of atmospheric moisture. Furthermore, the impacts of AH on AOD was supported by a moderate positive correlation (Pearson correlation coefficient, 0.454; p<0.0001), contrary to a small negative correlation between PM_{10} and AH (Pearson correlation coefficient, −0.225; p<0.0001). Therefore, we calibrated daily AOD values by simply dividing them by corresponding daily average AH, named. The AH-calibrated AOD had an annual trend which agreed well with that of PM_{10} (Fig. 3D). The correlation coefficient between the AH-calibrated AOD and the PM_{10} was 0.323 (p<0.0001), considerably higher to that estimated for the uncalibrated AOD.

3.2. Seasonal variations of air quality and health outcomes

Certain disease categories, especially cardiovascular and respiratory diseases, demonstrated a clear seasonal trend, with summer having fewer daily events but winter having more events (Fig. 3E and Supplemental material, Fig. 1). Annual patterns of PM_{10} and AOD were similar (Fig. 3D), and aligned well with health outcomes (Fig. 3F). Thus, seasonality had clear impacts on both air pollution and health outcomes in Beijing. Major meteorological factors, such as temperature, atmospheric pressure, dew point, and humidity, were highly correlated (Supplemental material, Table 1). Except RH, all meteorological factors had seasonal variations with either bell-shaped (AH, temperature, and dew point) or inverted bell-shaped (atmospheric pressure) patterns (data not shown). Since the atmospheric water content as measured by AH is determined by both ambient temperature and pressure, and had direct effects on the AOD, we selected AH as the representative variable of seasonality in this study.

3.3. Comparison of health effects of air pollution assessed by ground and space remote monitoring

Since AH was used to calibrated AOD, we did not adjusted AH or other meteorological factor as an independent covariate of seasonality in GLM analysis as we did for PM_{10}. In the hospital admission database, both AH-calibrated AOD and PM_{10} were associated with significantly increased daily admissions of cardiovascular diseases including ischemic heart diseases and heart failure, as well as respiratory tract infections, but not associated with heart rhythm disturbances, strokes, neoplasm, and gastrointestinal disorders (Fig. 4A). AH-calibrated AOD was also significantly associated with higher daily admissions related to peripheral vascular disease, COPD, diabetes, and hypertension. Furthermore, AH-calibrated AOD was associated with decreased daily admissions caused by injury, whereas, the PM_{10} did not have significant associations with them. In GLM models, all relative risks predicted by PM_{10} had wider confidence intervals. When we examined the lag effects using 7-day moving average, AH-calibrated AOD had robust predictions on all disease categories except heart rhythm disturbances (Supplemental material, Fig. 2A). Instead of having no immediate effects, AH-calibrated AOD seemed to have significant lag effects on heart rhythm disturbances. In contrast, PM_{10} predictions on the current day effects and the lag effects were not consistent (Supplemental material, Fig. 2B).

We did not observe any immediate effects by the current day exposure in the database of daily unscheduled outpatient visits. Instead, we found significant lag effects during a 7-day period on cardiovascular diseases, ischemic heart diseases, COPD, and respiratory tract infections by both AH-calibrated AOD and PM_{10} (Fig. 5A). In contrast to the PM_{10}, AH-calibrated AOD was not significantly associated with strokes.

Because daily mortalities did not have weekly fluctuations, we could investigate lag effects on single day instead of in the 7-day period. As showed in Fig. 6, both AH-calibrated AOD and PM_{10} performed well in GLM models. The most robust associations were observed with one lag day for daily mortalities. AH-calibrated AOD appeared more sensitive in detecting lag effects.

Across all databases, we found that both AH-calibrated AOD and PM_{10} were consistently associated with the elevated daily events for cardiovascular diseases, ischemic heart diseases, and COPD. The relative risks estimated by AH-calibrated AOD and PM_{10} were similar, with the largest effects associated with COPD related outcomes. Overall, AH-calibrated AOD had narrower confidence intervals and was more sensitive in detecting adverse outcomes due to short-term exposure.

3.4. Health effects associated with AH and other meteorological factors

We also tested AH as a stand-alone risk factor for daily health outcomes (Figs. 4A, 5A, and 6). In all databases, AH demonstrated protective effects at compatible levels for all categories of cardiovascular and respiratory diseases. Additionally, it had protective effects on diabetes and hypertension, but had increased risk for injury, in the databases of hospital admissions and unscheduled outpatient visits. AH had no effects on daily events related to neoplasm. To address the question whether AH-calibrated AOD associated effects were solely driven by AH component, we further conducted the analyses using uncalibrated AOD and AH in the same GLM models, as in the analyses of PM_{10}. We observed some discrepancies between AH-calibrated AOD and uncalibrated AOD mostly among the disease categories with small number of daily events (Figs. 4B, 5B, and 6). However, we still observed that uncalibrated AOD had significant increased risks associated with cardiovascular diseases, ischemic heart diseases, and COPD. Relative risks estimated for these diseases were compatible to those from AH-calibrated AOD, as well as from PM_{10}. In an additional set of analyses, we calculated residual AOD after linear regression by AH, and applied residual AOD and AH in the same models. Since AH only accounted for a small portion of AOD variations (adjusted $R^2=0.203$, $p<0.0001$), the results of residual AOD were very similar to the results of uncalibrated AOD (data not shown).

Because of high degree of correlations, other meteorological factors were also associated with daily health outcomes in all databases (Supplemental material, Fig. 3). Further, using other meteorological factors to replace AH, we obtained similar results for PM_{10} (data not shown). Among all meteorological factors, AH always gave the best models. However, we could not substitute AH with other meteorological factors in uncalibrated AOD models.

4. Discussion

In this study, we observed that AH-calibrated AOD were consistently associated with elevated daily events on the current day and/or lag days for cardiovascular diseases, ischemic heart diseases, and COPD. The results were robust across three independent databases. The associated disease patterns and overall effects estimated by relative risks were similar to ground monitoring by PM_{10}. Additionally, compared to ground PM_{10}, we found that AH-calibrated AOD had narrower confidence intervals for all models and was more robust in estimating the current day and lag day effects. The short-term effects associated with AOD were also consistent with previous studies using ground $PM_{2.5}$ on the acute health effects of unscheduled outpatient visit, hospital admission and mortalities (Chang et al., 2005; Dominici et al., 2006; Fung et al., 2005; Ostro et al., 2006), including studies in Beijing (Xu et al., 1994, 1995b).

Water absorption can increase the size of hydrophilic particles containing sulfate, nitrate, ammonium, and certain species of organic carbon (Tang and Munkelwitz, 1994). The atmospheric water content has direct but inverse impacts on the optical measurement of PM from space, as AOD is a measure of particle light extinction (Malm and Day, 2001). Compare to RH, AH is a specific and direct measure of water vapor density, and is more relevant to the physical characteristics of the optical measurement. Thus, AH-calibrated AOD could provide a more accurate assessment of fine PM-related effects. Our findings suggest that adjusting AOD with other meteorological measures of water vapor content, such as RH and dew point, did not result in robust associations were consistent this (data not shown). We had also tried various ways to adjust AOD using AH, including square or square root of AH, cube or cube root of AH, or log transformed AH, and found that the simple dividing AOD by AH gave the best and most robust models (data not shown).

Since AOD dimensionless, we used $\log_2$-transformed values to obtain uniformed comparison of PM-related health effects assessed by ground and space monitoring. Our results can be interpreted as the levels of increased health risks when the ambient PM level is doubled. Beijing is a highly polluted megacity with PM to be the most severe air pollution issue (Okuda et al., 2004; Song et al., 2006). Besides high daily levels, Beijing also had large day-to-day PM variations, as we observed 40 occasions (~every 10 days) that daily PM_{10} increases were above 2 folds throughout 2006. In addition, the significant linear relationships between $\log_2$-transformed PM values and the adverse health effects suggested a nonlinear exposure-response with larger effects at low PM exposure, consistent with previous studies in Beijing (Xu et al., 1995a) and other regions (Pope et al., 2009).

Daily PM_{10} can be substantially reduced by occasional precipitation and strong wind, but it was less influenced by temperature and humidity. Without adjusting meteorological factor, we found PM_{10} still had significant associations with cardiovascular and respiratory diseases with similar estimated risks (data not shown). Daily averages of meteorological factors were highly correlated, and were independently associated with daily health outcomes. Similar observations were previously reported in Beijing (Xu et al., 1994), as well as in other countries (Braga et al., 2001; Morabito et al., 2005; Sharovsky et al., 2004). Among meteorological factors, AH seemed to have a robust performance in estimating weather-related health effects, attributing to its inseparable physical characters with atmospheric temperature and pressure. For most of disease categories, AH caused less than 2% changes on daily health events with one unit change (g/m^3). Mechanisms leading to the possible influence of weather are most likely multifactorial, with a complex relationship between seasons and pathophysiological exogenous and endogenous factors (Abrignani et al., 2009). Shaman et al. recently reported that AH had stronger effects than RH on influenza virus survival within aerosolized droplets (Shaman and Kohn, 2009), and was a major determinant for seasonal variations of virus transmission and associated with influenza-related mortality in the United States (Shaman et al., 2010). Furthermore, a previous study reported that influenza infection was a major cause of winter increase of all-cause and cardiovascular diseases mortality in the United States over a 40-year period (Reichert et al., 2004). Therefore, the weather-related health effects might be indirectly caused by the increased burden of infections in cold seasons.

Several factors might account for a poor correlation between PM_{10} and AOD. Firstly, they are measuring different categories of particles between PM_{10} and AOD (Engel-Cox et al., 2004; Liu et al., 2007b). One limitation of this study was the lack of ground $PM_{2.5}$ data. Secondly, the sampling periods are different with PM_{10} representing 24-h average, whereas, AOD corresponding to a snap-shot of daytime PM level. Thirdly, ground monitoring stations have insufficient coverage of PM and meteorology over the entire metropolitan area of Beijing. Finally, various factors have different impacts on the measurement accuracy from ground or space. Being aware of these potential impacts, all of previous studies focused on developing empirical models of AOD by calibrating with ground measurement and local meteorological information (Koelemeijer et al., 2006; Liu et al., 2005). This approach, depending on the available ground data, worked well for long-term average of PM over a large geographic region (Al-Saadi et al., 2005; van Donkelaar et al., 2010; Wang and Christopher, 2003). Currently, there are limited studies that adopt empirical AOD models in environmental health research. By merging AOD with ground measurements using geographically weighted regression, the standardized county-level biennial mortality rates (2003–2004) of chronic heart diseases in the United States were associated with two-year average re-calculated $PM_{2.5}$ levels (Hu, 2009), or with two-year average satellite-derived AOD raster data (Hu and Rao, 2009). It is worth to note that, in these studies, data for cold seasons (October to March) were not used in the two-year average calculation and model analysis.

The intrinsic differences of healthcare data and associated quality attributed to the variations of PM and/or weather related effects. Since the admission database covered the entire metropolitan area with large daily events and more accurate diagnosis, models for both PM_{10} and AOD performed best in this database. The mortality data was limited to eight districts of downtown Beijing with small daily events and a lower quality on diagnosis. In contrast, cohort outpatient data was collected from a small, older (mean age±SD: 60±15), and female dominant (67%) population. Although it had large daily events, the quality was affected by large amounts of regular visits for medicine refill and less accuracy on diagnosis.

5. Conclusion

To our knowledge, this is the first study of directly assessing PM-induced acute adverse health effects by satellite remote sensing, without a prior calibration using ground monitoring data. AH-calibrated AOD is an integrated measurement of satellite-based AOD and local weather conditions. By bypassing a pre-calibration step of empirical model building, it avoids the problems caused by the lack of ground monitoring networks. In contrast to ground monitoring data that often lack spatial and temporal coverage and suffer unbalanced spatial distribution, the repetitive and broad-area coverage of satellites allows atmospheric remote sensing to offer a unique opportunity to monitor air quality at global, continental, national and regional scales. Satellite-based remote sensing could help fill pervasive data gaps that impede efforts to study air pollution and protect public health. In addition, the evidence of satellite-based environmental health research supports targeting of policy interventions on high-risk regions to reduce pollution levels. Addition studies are warranted to further explore the potential health benefits of satellite remote sensing.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Abbreviations

AH	Absolute humidity
AOD	Aerosol optical depth
AQI	Air quality index
GLM	Generalized linear models
MODIS	Moderate Resolution Imaging Spectroradiometer
PM	Particulate matter
RH	Relative humidity

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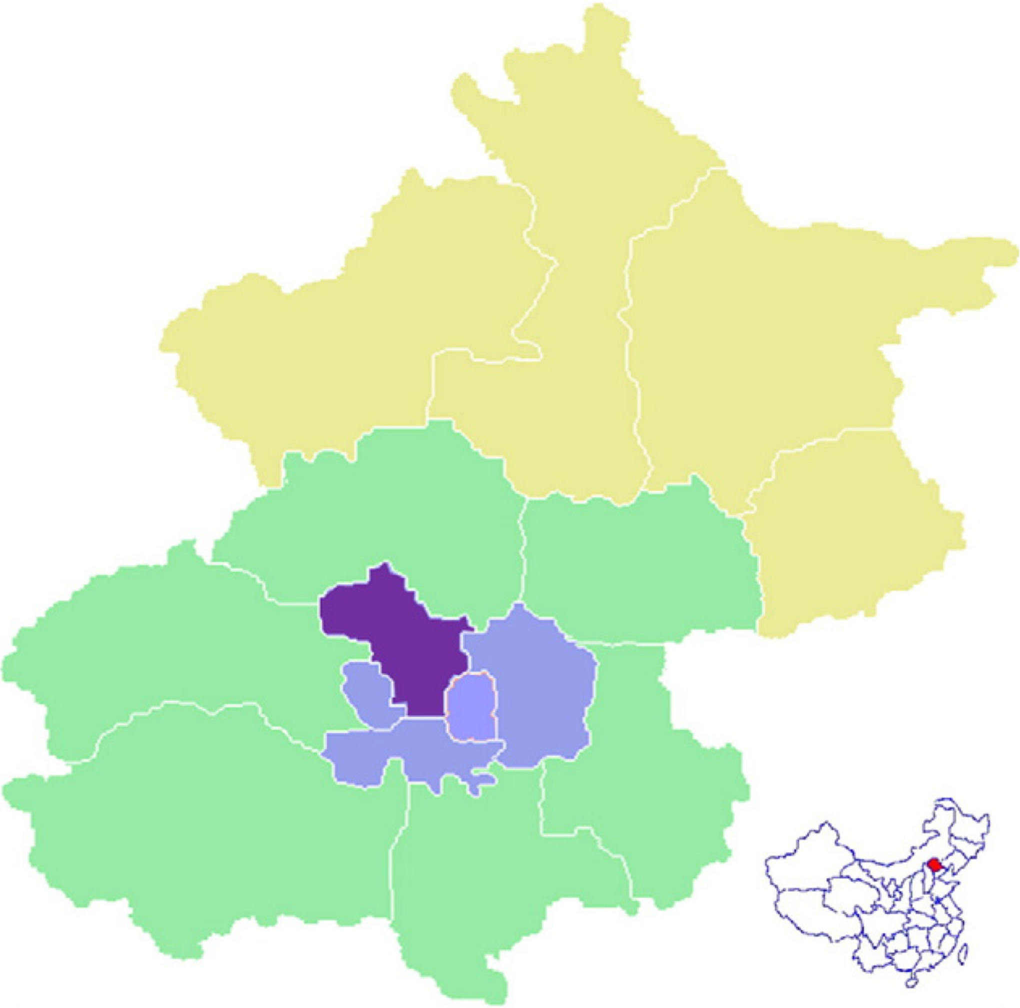

Dataset	Region	Area (km²)	Population (millions)
Outpatient	🟪	431	1.98
Hospital admission	All	16411	11.97
Mortality	🟦 🟪	1386	7.33

Fig. 1.

Population and geographic locations of the healthcare databases used in this study.

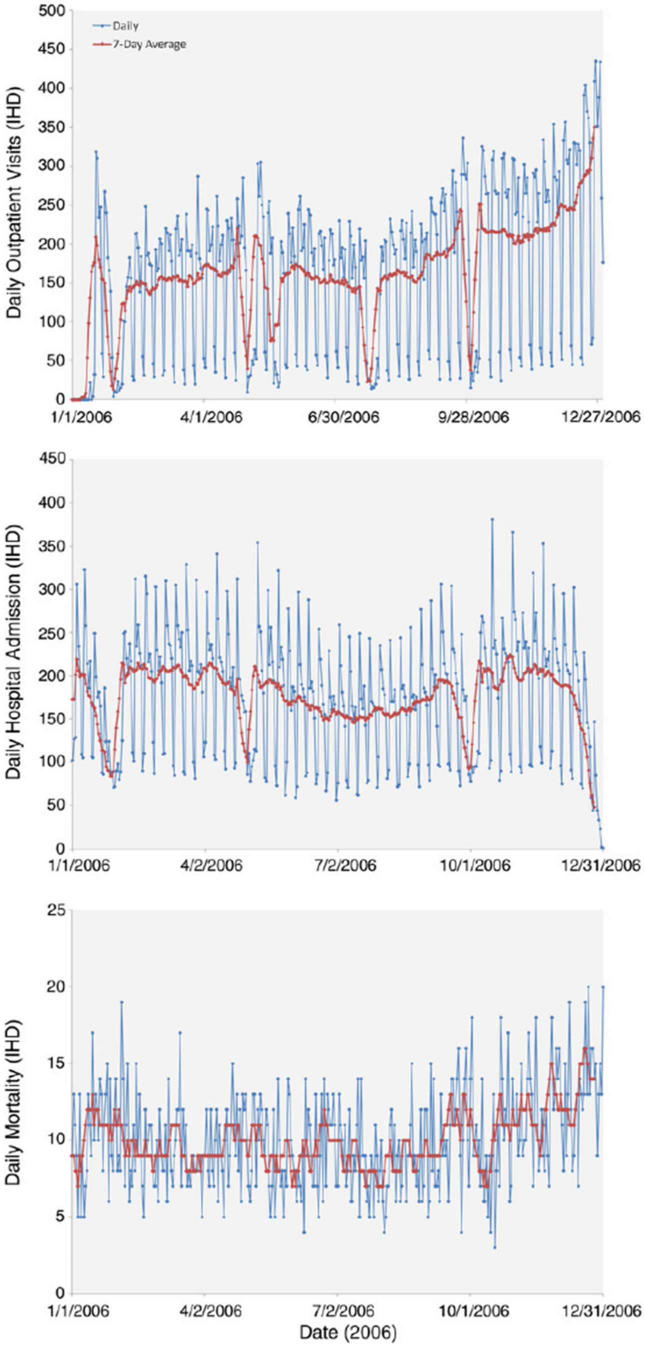

Fig. 2.

Distributions of daily and 7-day moving average for ischemic heart diseases. 7-day moving average was calculated from the current day to the 6th lag day.

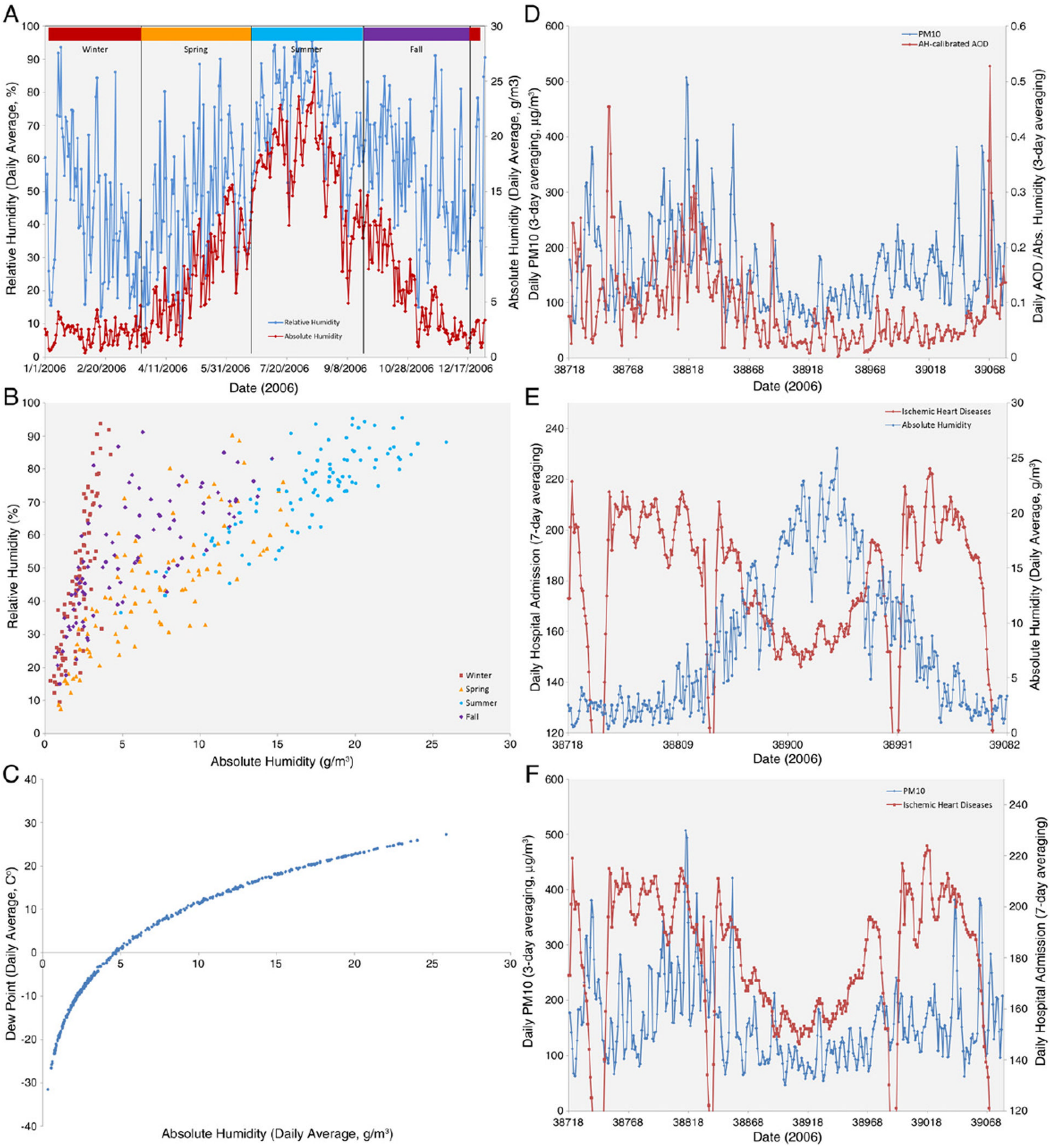

Fig. 3.

Comparison of annual trends among meteorological factors, particulate matter assessed by ground and space monitoring, and ischemic heart diseases in Beijing, China, 2006. A) Daily average of relative humidity and absolute humidity. B) Plot of daily average of relative humidity verses daily average of absolute humidity. C) Plot of daily average of dew point verses daily average of absolute humidity. D) 3-day moving average of PM_{10} and AH-calibrated 260 AOD. E) Daily average of absolute humidity and daily admission of ischemic heart diseases (7-day moving average). F) Daily average of absolute humidity and 3-day moving average of PM_{10}. We used 3-day moving average of PM_{10} and AOD for better visualizing the annual trend, which were calculated by the values of prior one day, current day, and post one day. 7-day moving average of healthcare outcome was calculated from the current day to the 6th lag day.

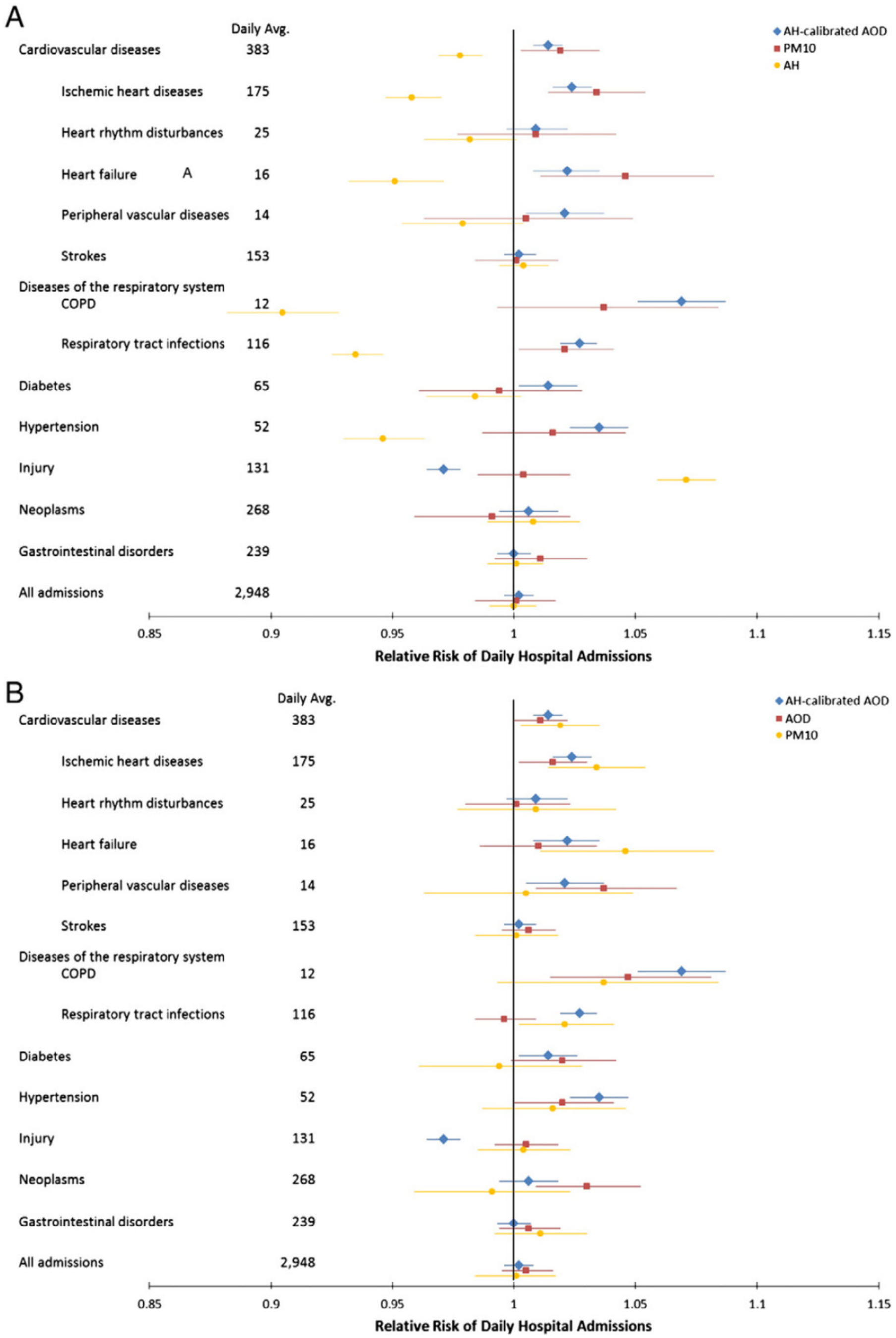

Fig. 4.

Effects of ground and satellite remote monitored air pollution and absolute humidity on daily hospital admissions. In the analyses of AH-calibrated AOD and AH, day of week was included as covariate; and in the analyses of AOD and PM_{10}, absolute humidity and day of week was used as covariates. Since there were significant drops of admission before 2007 New Year, we excluded the last week of 2006. The final hospital admission data included 257 days for AH-calibrated AOD and AOD model analyses, and 348 days for PM_{10} and AH analyses. In all analyses, AH-calibrated AOD, AOD, PM_{10}, and AH were $\log_2$-transformed for easy comparison.

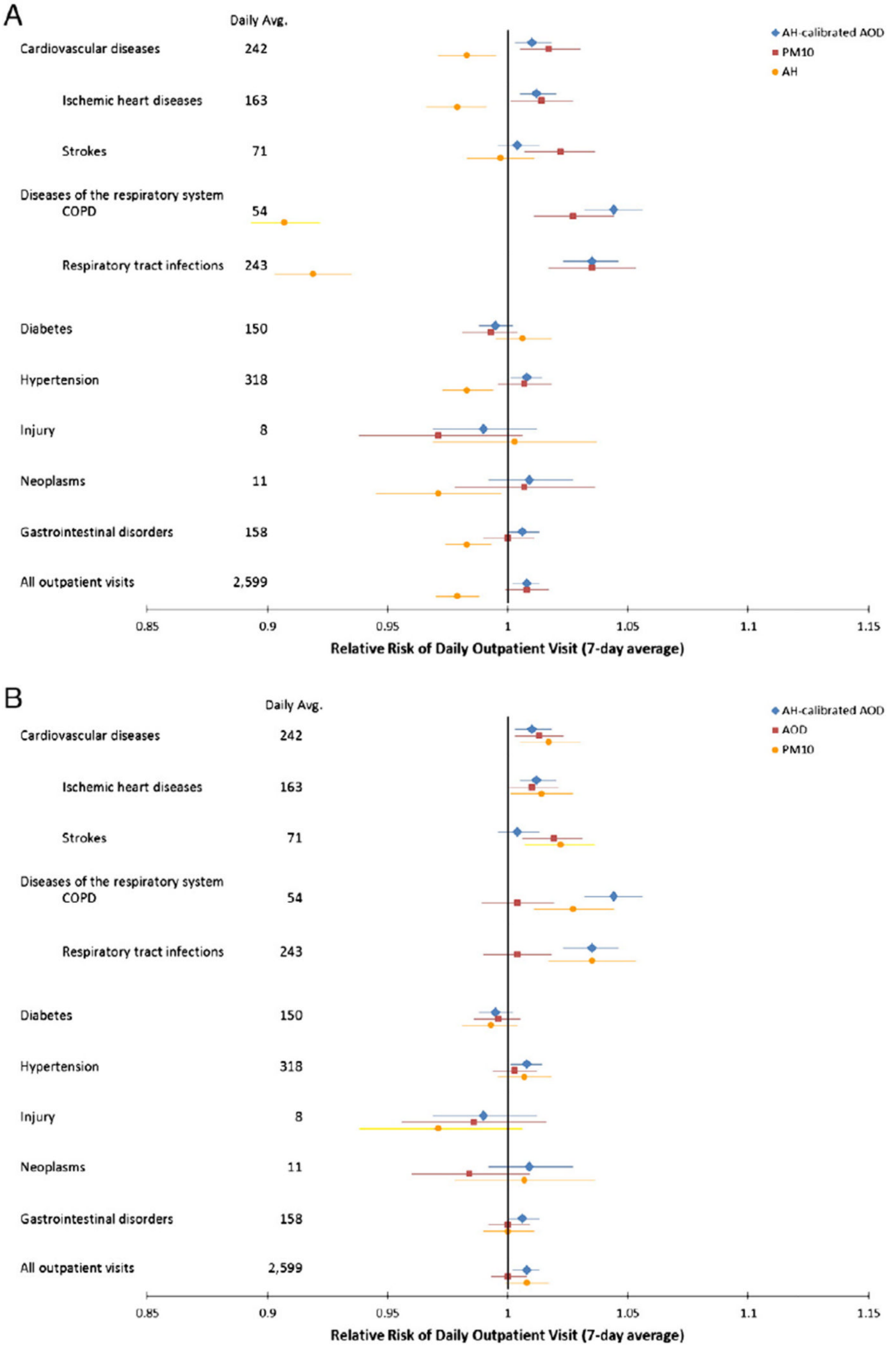

Fig. 5.

Effects of ground and satellite remote monitored air pollution and absolute humidity on daily unscheduled outpatient visits. In the analyses of AH-calibrated AOD and AH, season was used as a covariate; and in the analyses of AOD and PM_{10}, absolute humidity and season was used as covariates. The analyses were limited on non-holiday/non-administrative interruption days, with 202 days for AH-calibrated AOD and AOD model analyses, and 269 days for PM_{10} and AH analyses. Due to small number of daily events resulted in unstable statistical estimations, we did not include the results for heart failure, heart rhythm disturbances, and peripheral vascular diseases. In all analyses, AH-calibrated AOD, AOD, PM_{10}, and AH were $\log_2$-transformed for easy comparison.

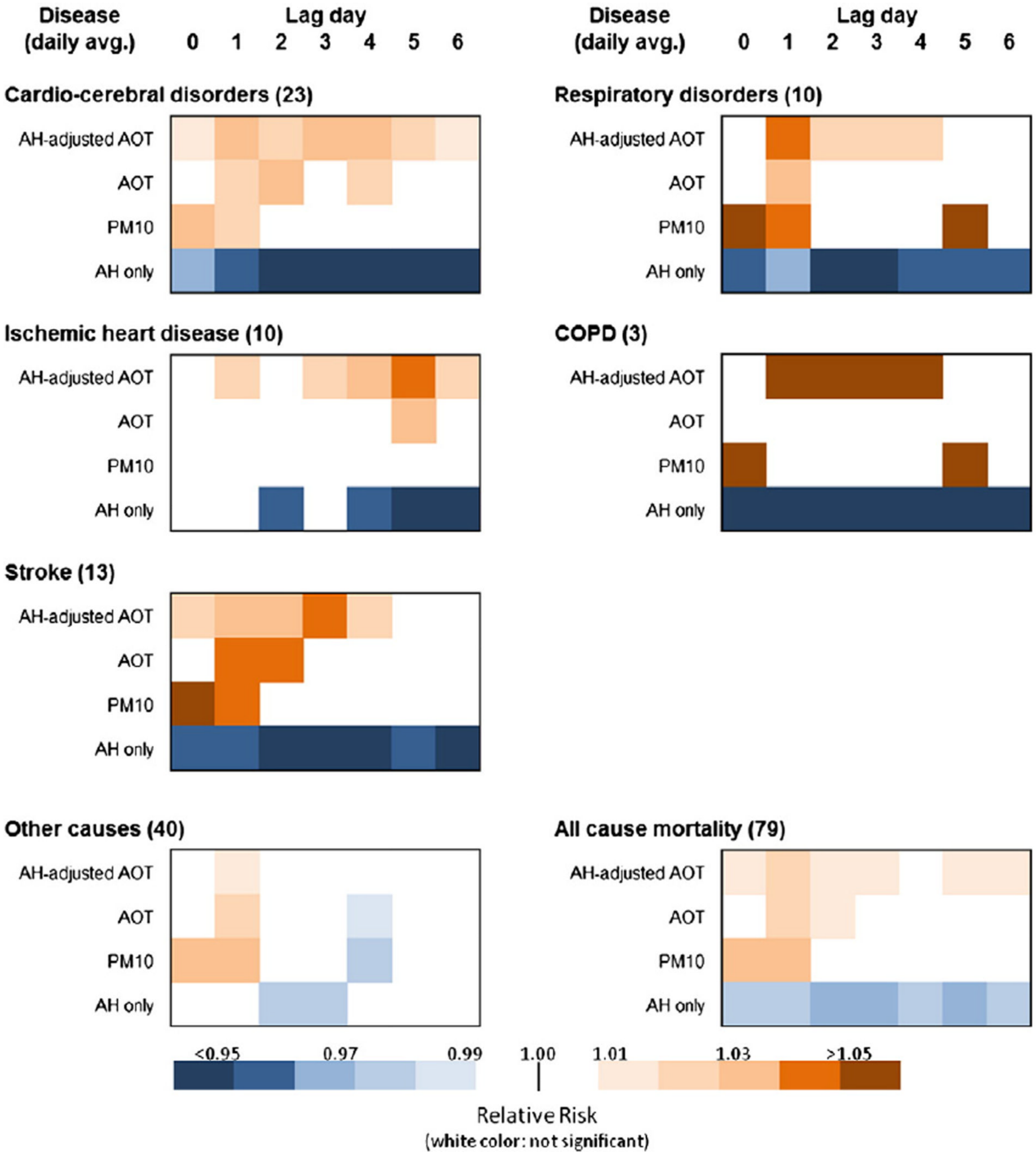

Fig. 6.

Heat maps showing the effects of ground and satellite remote monitored air pollution and absolute humidity on daily mortality. A color coded cell represented a relative risk estimated by generalized linear models, at a significant level of $p<0.05$. In the analyses of AH-calibrated AOD and AH, season was used as a covariate; and in the analyses of AOD and PM_{10}, absolute humidity and season was used as covariates. In all analyses, AH-calibrated AOD, AOD, PM_{10}, and AH were $\log_2$-transformed for easy comparison.

Table 1

Summary of healthcare databases in Beijing, China, 2006[a]

	ICD10	ICD9	Outpatient[b]		Hospital admission[c]		Mortality	
			Annual total (%)[d]	**Daily avg. ±Std**	**Annual total (%)[d]**	**Daily avg. ± Std**	**Annual total (%)[d]**	**Daily avg. ± Std**
Cardio-cerebral disorders	100–I99	390–459	88,330 (9.3)	242 ± 157	139,842 (13)	383 ± 148	8353 (29)	23 ± 5
Heart failure	150	428	285 (0)	1 ± 1	5723 (0.5)	16 ± 6	–	–
Heart rhythm disturbances	144–147, 149	426–427	2081 (0.2)	6 ± 5	9269 (0.9)	25 ± 14	–	–
Strokes	160–169	430–438	25,924 (2.7)	71 ± 46	55,845 (5.2)	153 ± 52	4684 (16.3)	13 ± 4
Ischemic heart disease	120–125, 151	410–414, 429	59,537 (6.3)	163 ± 108	63,783 (5.9)	175 ± 75	3669 (12.7)	10 ± 3
Peripheral vascular disease	170–178, M30, M31	440–448	503 (0.1)	1 ± 2	5222 (0.5)	14 ± 9	–	–
Hypertension	110–115	401–404	115,997 (12.2)	318 ± 203	19,060 (1.8)	52 ± 28	–	–
Diabetes	E09–E14	250	54,860 (5.8)	150 ± 97	23,855 (2.2)	65 ± 40	–	–
Respiratory disorders	J00–J99	460–519	–	–	–	–	3695 (12.8)	10 ± 3
COPD	J40–J43	490–492	19,540 (2.1)	54 ± 40	4207 (0.4)	12 ± 5	1110 (3.9)	3 ± 2
Respiratory tract infections	J00–J11	464–466, 480–487	88,769 (9.4)	243 ± 169	42,244 (3.9)	116 ± 32	–	–
Gastrointestinal disorders	K20–K93	530–579	57,770 (6.1)	158 ± 94	87,337 (8.1)	239 ± 101	–	–
Neoplasms	C00–D48	140–239	3901 (0.4)	11 ± 8	97,801 (9.1)	268 ± 189	–	–
Injury	S00–S99	800–849	2984 (0.3)	8 ± 6	47,770 (4.4)	131 ± 33	–	–
Accident	V01–Y98		–	–	–	–	550 (1.9)	2 ± 1
Other disorders			–	–	–	–	14,565 (50.6)	40 ± 7
Total			948,634	2599	1,075,953	2948 ± 1359	28,810	79 ± 11

[a] Databases for unscheduled outpatient visit, hospital admission, and mortality were obtained from different administrative regions of Beijing, China, as illustrated in Fig. 1.

[b] Unscheduled outpatient visits were obtained from billing claims of a healthcare insurance program covering ~61,000 individuals in Haidian District, Beijing.

[c] Hospital admissions were obtained from hospital discharge forms collected from all major hospitals in Beijing, excluding military-operated hospitals.

[d] Parenthesis is the percentage of annual total events in the database.