



Published in final edited form as:

Environ Res Lett. 2015 August ; 10(8): . doi:10.1088/1748-9326/10/8/084009.

The impact of weather changes on air quality and health in the United States in 1994–2012

Iny Jhun¹, Brent A Coull², Joel Schwartz¹, Bryan Hubbell³, and Petros Koutrakis¹

Iny Jhun: iny@mail.harvard.edu

¹Department of Environmental Health, Harvard School of Public Health, 401 Park Drive, Boston, MA 02215, USA

²Department of Biostatistics, Harvard School of Public Health, 655 Huntington Avenue, Boston, MA 02115, USA

³Office of Air Quality, Planning, and Standards, US Environmental Protection Agency, 109 TW Alexander Drive, Research Triangle Park, NC27711, USA

Abstract

Air quality is heavily influenced by weather conditions. In this study, we assessed the impact of long-term weather changes on air quality and health in the US during 1994–2012. We quantified past weather-related increases, or ‘weather penalty’, in ozone (O₃) and fine particulate matter (PM_{2.5}), and thereafter estimated the associated excess deaths. Using statistical regression methods, we derived the weather penalty as the additional increases in air pollution relative to trends assuming constant weather conditions (i.e., weather-adjusted trends). During our study period, temperature increased and wind speed decreased in most US regions. Nationally, weather-related 8 h max O₃ increases were 0.18 ppb per year (95% CI: 0.06, 0.31) in the warm season (May–October) and 0.07 ppb per year (95% CI: 0.02, 0.13) in the cold season (November–April). The weather penalties on O₃ were relatively larger than PM_{2.5} weather penalties, which were 0.056 µg m⁻³ per year (95% CI: 0.016, 0.096) in warm months and 0.027 µg m⁻³ per year (95% CI: 0.010, 0.043) in cold months. Weather penalties on O₃ and PM_{2.5} were associated with 290 (95% CI: 80, 510) and 770 (95% CI: 190, 1350) excess annual deaths, respectively. Over a 19-year period, this amounts to 20 300 excess deaths (5600 from O₃, 14 700 from PM_{2.5}) attributable to the weather penalty on air quality

Keywords

air pollution; weather; trend analysis; ozone; fine particulate matter; mortality

1 Introduction

Air quality is significantly influenced by both emissions and weather conditions. Among pollutants, ozone (O₃) and fine particulate matter (PM_{2.5}) have been extensively studied, as

O₃ and PM_{2.5} exposures are associated with a wide range of adverse health outcomes, including respiratory illnesses, hospital admissions, and premature mortality (Jerrett *et al* 2009, Krewski *et al* 2009, US EPA 2010). Studies evaluating the efficacy of O₃ and PM_{2.5} mitigation efforts have utilized statistical methods to account for the effects of weather-related variations and simultaneously derived the relationships between air pollution and weather parameters (Cox and Chu 1993, Bloomfield *et al* 1996, Cox and Chu 1996, Thompson *et al* 2001, Camalier *et al* 2007, Zheng *et al* 2007). In this study, we built upon prior methods to directly quantify the impact of long-term weather conditions on air pollution changes in the US.

The influence of weather conditions on O₃ and PM_{2.5} differ substantially, which affects both the magnitude and uncertainty of the impact of long-term weather changes on these two pollutants. The effect of ground-level weather conditions on O₃ is generally more robust and better characterized than that on PM_{2.5}. O₃ primarily results from reactions between nitrogen oxides and volatile organic compounds in the presence of sunlight, and high temperature, low humidity, and low wind speed conditions favor O₃ formation (The National Academies Press 1991). Weather impacts on PM_{2.5} can be more variable, given the diversity of particle components (e.g., sulfate, nitrate, organic carbon, and elemental carbon). In general, particles are efficiently scavenged through wet deposition (Balkanski *et al* 1993), but other weather impacts can be more complex. For instance, rising temperatures can increase oxidation and production of sulfate particles (Dawson *et al* 2007b), but reduce nitrate particles through volatilization from particle to gas phase (Seinfeld and Pandis 2006).

In this study, we employed statistical regression methods to quantify the effect of ground-level weather changes, or ‘weather penalty’, on recent O₃ and PM_{2.5} trends in the US (1994–2012). We then applied mortality risk estimates from epidemiological studies to estimate the excess mortalities associated with the weather penalty on O₃ and PM_{2.5} (see figure 1 for schematic illustration). Specifically, we analyzed the impact of changes in temperature, wind speed, water vapor pressure, and precipitation frequency, as prior studies have identified these parameters to be among the most important meteorological determinants of O₃ and PM_{2.5} concentrations (Thompson *et al* 2001, Dawson *et al* 2007a, 2007b, Tai *et al* 2010).

2. Materials and methods

2.1. Air quality data collection

Hourly O₃ and daily 24 h PM_{2.5} concentrations were obtained from the US Environmental Protection Agency (EPA)’s Air Quality System and Speciation Trend Networks, and Interagency Monitoring of Protected Visual Environments network. We selected sites with at least 10 years of year-round (January–December) data in 1994–2012 and at least 14 daily measurements each month; this yielded 468 O₃ sites and 62 PM_{2.5} sites (figure 2). We chose 1994 as the starting year due to wider availability of O₃ measurements. Of note, most PM_{2.5} measurements are available starting 1998. As we ultimately assess health impacts, sites were categorized into seven regions (Industrial Midwest (IM), Northeast (NE), Northwest (NW), Southeast (SE), Southern California (SC), Southwest (SW), Upper Midwest (UM)) as defined by the National Morbidity Mortality Air Pollution Study (NMMAPS) (Samet *et al* 2000). As the national O₃ standards are based on the annual 4th highest maximum daily 8 h

average averaged over 3 years, we computed the daily 8 h max O₃ metric utilizing a 75% data capture criterion. Specifically, the 8 h max metric was estimated on days with at least 18 of 24 valid 8 h moving averages, which were calculated from at least 6 valid hourly values.

2.2. Weather data collection

Daily precipitation frequency (0/1) and hourly temperature (°C), wind speed (m s⁻¹), and water vapor pressure (hPa) were obtained from the National Oceanic Atmospheric Administration's National Climatic Data Center. Daily averages were calculated from at least 18 of 24 hourly measurements. Selected stations had all 19 years of year-round data and at least 21 daily measurements (~75%) per month; this yielded 194 stations measuring surface temperature, wind speed, and water vapor pressure, and 168 stations measuring precipitation frequency (figure S1). Air pollution data were matched to the nearest weather station's data. Data from 87 weather stations were matched to 468 O₃ stations with an average distance of 77.3 km, and data from 41 weather stations were matched to 62 PM_{2.5} stations with an average distance of 30.4 km (table S1). Matching distance between PM_{2.5} and weather stations were slightly higher (37.2 km) for precipitation frequency data.

2.3. Weather penalty calculation

For each region and season (cold and warm), weather associated changes in O₃ and PM_{2.5} were quantified by estimating: (1) the magnitude of the unadjusted and weather-adjusted pollution trends using generalized additive models (GAMs), (2) the magnitude of the trend differences (i.e., the weather-related penalty), and (3) the standard error of the trend differences through bootstrap methods (see figure S2 for schematic overview). To estimate national averages, region-specific trends and penalties were meta-analyzed accounting for within- and between-region variability (Berkey *et al* 1998).

2.3.1. Regional air pollution trends—First, regional-level GAMs were applied to estimate the long-term trends of daily PM_{2.5} and O₃ concentrations, with and without adjusting for weather parameters. Many trend analysis studies have employed GAMs to adjust for inter-annual meteorological variation using smoothing spline functions (Camalier *et al* 2007, Zheng *et al* 2007, Pearce *et al* 2011). We stratified the trend analysis into warm (May–October) and cold (November–April) months, as O₃ exhibited dichotomous trends (figure S3). For each of the seven regions and season (cold/warm), the unadjusted and weather-adjusted trends were calculated from the following GAMs, using the R statistical package (R Development Core Team 2011):

$$(O_3)_{ij} = \beta_0 + \beta_{1, \text{unadjusted}} \text{year}_{ij} + \gamma \text{month}_{ij} + \delta \text{weekday}_{ij} + \varepsilon_{ij}, \quad (1)$$

$$(O_3)_{ij} = \beta_0 + \beta_{1,\text{adjusted}} \text{year}_{ij} + \gamma \text{month}_{ij} + \delta \text{weekday}_{ij} + s_1(\text{tmp}) + s_2(\text{ws}) + s_3(\text{wvp}) + \varepsilon_{ij},$$

(2)

$$(PM_{2.5})_{ij} = \beta_0 + \beta_{1,\text{unadjusted}} \text{year}_{ij} + \gamma \text{month}_{ij} + \delta \text{weekday}_{ij} + \varepsilon_{ij}, \quad (3)$$

$$(PM_{2.5})_{ij} = \beta_0 + \beta_{1,\text{adjusted}} \text{year}_{ij} + \gamma \text{month}_{ij} + \delta \text{weekday}_{ij} + s_1(\text{tmp}) + s_2(\text{ws}) + s_3(\text{wvp}) + s_4(\text{prcp}) + \varepsilon_{ij},$$

(4)

where, $(O_3)_{ij}$ and $(PM_{2.5})_{ij}$ represent daily 8 h max O_3 or daily $PM_{2.5}$ concentrations, respectively, at site i and on date j and; β_0 is the intercept and $\beta_{1,\text{unadjusted}}$ and $\beta_{1,\text{adjusted}}$ estimate the linear unadjusted and weather adjusted pollutant trends (ppb per year or $\mu\text{g m}^{-3}$ per year) in 1994–2012 for a specific region and season. The smoothing spline function, denoted by $s()$, characterizes and adjusts for the nonlinear relationships between weather parameters and daily O_3 or $PM_{2.5}$ concentrations. The weather-adjusted O_3 trends adjusted for temperature (tmp), wind speed (ws), and water vapor pressure (wvp), and the weather-adjusted $PM_{2.5}$ trends additionally adjusted for precipitation frequency (prcp). γ and δ are vectors of coefficients that represent monthly and weekday variability, respectively.

2.3.2. Regional weather penalty on air pollution—The adjustment of weather parameters in models (2) and (4) removes the impact of inter-annual weather variation on air pollution trends; in other words, the weather-adjusted trends represent trends that assume weather parameters remained constant during the study period. In comparison, the weather impact is incorporated into the unadjusted trends. Therefore, any differences between the unadjusted and weather adjusted trends are entirely attributable to the impact of long-term weather changes. We obtained the trend differences for each region and season, and refer to them as the weather ‘penalty’:

$$\text{Penalty} \left(\text{ppb year}^{-1} \text{ or } \mu\text{gm}^{-3} \text{ year}^{-1} \right) = \beta_{1,\text{unadjusted}} - \beta_{1,\text{adjusted}}. \quad (5)$$

A positive penalty ($\beta_{1,\text{unadjusted}} > \beta_{1,\text{adjusted}}$) indicates that an increase in air pollution was associated with long-term weather changes during the study period.

2.3.3. Standard error of regional weather penalty—The standard errors for the trend differences (penalties) were derived by utilizing a block bootstrap procedure (Politis 2003) as the penalties are estimated from two related regression models applied to the same data.

Briefly, we created randomized subsets of the actual data (i.e., pseudo-datasets) that accounted for serial correlation structures among O₃ or PM_{2.5} observations. We utilized a block size of 20 days to create 100 pseudo-datasets for each region and season (1400 pseudo-datasets total for each pollutant). Then, the unadjusted trends, weather-adjusted trends, and penalty were iteratively estimated from each pseudo-dataset. The standard deviations of the distribution of 100 estimates of the unadjusted trend, weather-adjusted trend, and penalty obtained from 100 pseudo-datasets were estimated as the corresponding standard errors.

2.4. Weather trends

For each region and season, a general linear regression model was applied to estimate trends of temperature and wind speed, adjusting for monthly variability within a season. Region-specific trends were meta-analyzed to estimate national average trends (Berkey *et al* 1998). Unlike temperature and wind speed, water vapor pressure and precipitation frequency trends were not linear during our study period and exhibited a shift in trends during the latter half of the study period. We estimated trends of water vapor pressure and precipitation frequency during 1994–2003 (10 years) and 2004–2012 (9 years). A binomial regression model was utilized to estimate precipitation frequency trends.

2.5. Mortality impact estimation

Mortality calculations were conducted using EPA's Environmental Benefits Mapping and Analysis Program (BenMAP) ver.4.0.66 (Abt Associates Inc. 2011). For each NMMAPS region, we estimated three different annual mortality counts: mortality averted by observed improvements in air quality (applying unadjusted pollution trends), mortality that would have been averted if weather conditions remained constant (applying weather-adjusted pollution trends), and the excess mortality resulting from the weather penalty. To estimate mortality associated with unadjusted and weather-adjusted pollution trends and the weather penalty, we applied the following health impact function for each region and season:

$$\Delta\text{Mortality} = y_0 \times (1 - e^{-\beta \times \delta}) \times \text{Pop}, \quad (6)$$

where, β is the mortality risk coefficient, δ is the regional air quality change of interest (unadjusted trend, weather-adjusted trend, or weather penalties), Pop is the exposed population size, and y_0 is the baseline mortality incidence rate. We utilized BenMAP's library of county-level population and mortality incidence data for 2010. The county-level mortality estimates were aggregated to the regional level. We applied national risk coefficients from epidemiological cohort studies on chronic O₃-related respiratory mortality (Jerrett *et al* 2009) and PM_{2.5}-related chronic mortality from cardiopulmonary disease and lung cancer (Krewski *et al* 2009) in adults (> 30 years). These studies reported a 3.9% increase (95% CI: 1.0%, 6.7%) in mortality risk per 10 ppb increase in O₃ and a 5.8% increase (95% CI: 3.8%, 7.8%) in risk per 10 $\mu\text{g m}^{-3}$ increase in PM_{2.5}. The risk coefficients selected for this analysis are consistent with those used by the US EPA in recent regulatory analyses (US EPA 2006, 2008) as well as other papers (Tagaris *et al* 2009, Anenberg *et al* 2010). National mortality risk estimates were used to estimate regional mortality changes

associated with regional air quality changes, due to high uncertainty of regional mortality risk estimates reported by epidemiological studies compared to the pooled national risk estimate.

To be consistent with air pollution metrics utilized in these studies, we re-estimated trends and weather penalties using year-round (January–December) PM_{2.5} and warm season (April–September) 1 h max O₃ metrics. To obtain the uncertainty around mortality estimates, we accounted for standard errors of both the health risk coefficients and air quality change of interest (unadjusted trend, weather-adjusted trend, or weather penalty) using the multivariate delta method (Agresti 2012):

$$\text{Variance} = (\partial f / \partial \beta)^2 \times \text{Variance}(\beta) + (\partial f / \partial \delta)^2 \times \text{Variance}(\delta), \quad (7)$$

where, f represents the partial derivative of equation (6) with respect to either β or δ . The variances of β and δ are derived from epidemiological studies and the bootstrap procedure, respectively.

3. Results and discussion

3.1. Raw monthly average time series of O₃ and PM_{2.5}

To assess the air quality measurement data from selected monitoring sites (468 O₃ and 62 PM_{2.5} sites), we estimated the raw national monthly averages of PM_{2.5} and 8 h max O₃, as well as cold (November–April) and warm (May–October) season averages in 1994–2012. During our study period, significant PM_{2.5} decreases were observed, while there was only a modest change in 8 h max O₃ (figure 3). Trends derived from regression analyses are discussed in subsequent sections. Most PM_{2.5} measurements were available starting 1998 and showed considerable decreases in both warm and cold months from 16.2 to 9.7 $\mu\text{g m}^{-3}$ and 14.1 to 9.6 $\mu\text{g m}^{-3}$ in 1998–2012, respectively. These drastic PM_{2.5} decreases were consistent with the national PM_{2.5} trends and concentrations reported by the US EPA (US EPA 2014b). In contrast, the cold season average of daily 8 h max O₃ increased from 34.3 to 38.0 ppb in 1994–2012, while warm season 8 h max O₃ decreased from 48.0 to 44.4 ppb in 1994–2009 then increased slightly there-after. Recent warm season O₃ increases are also reported by the US EPA (US EPA 2014a). These time series reflect the raw air pollution concentrations resulting from a combination of emissions and weather conditions. In the following sections, we estimated the proportion of changes in air pollution attributable to changes in weather conditions.

3.2. Trends of weather parameters

To investigate the weather-associated changes in air quality, we analyzed data on temperature, water vapor pressure, wind speed, and precipitation frequency from over 200 weather stations (figure S1); prior observational and model perturbation studies identified these four parameters to be among the most important meteorological determinants of O₃ and PM_{2.5} concentrations (Dawson *et al* 2007a, 2007b, Jacob and Winner 2009, Fiore *et al*

2012). We assessed the raw time series and trends of each weather variable, and summarized the trends in table 1.

3.2.1. Temperature trends—During the study period (1994–2012), temperature increases were observed year-round in most regions (figure 4). A national meta-analysis of regional temperature trends yielded a statistically significant increase by 0.035 °C (0.64%) per year in the cold months and 0.036 °C (0.18%) per year in the warm months. Percent changes are relative to national average temperatures. The temperature increases during our study period were in agreement with those reported in the literature (Isaac and van Wijngaarden 2012). The greatest temperature increases were observed during the cold season in the Northern regions (e.g., UM, IM, NE). The West Coast regions (NW and SC) exhibited the least or no temperature change.

3.2.2. Wind speed trends—Decreases in ground level wind speed were observed in all regions except in the SW (figure 4). Meta-analysis of regional wind speed trends yielded a national decrease in wind speed by 0.021 m s⁻¹ (0.49%) per year in the cold season and 0.021 m s⁻¹ (0.57%) per year in the warm season. The magnitude of wind speed declines during our study period were in agreement with those reported in the literature (Pryor *et al* 2009). In addition, wind speed is expected to continue to decline, as frequency and duration of stagnation episodes increase in the future climate (Mickley 2004).

3.2.3. Water vapor pressure trends—Trends of water vapor pressure and precipitation frequency were not linear in many regions during our study period. We estimated regional and national water vapor pressure trends during 1994–2003 (10 years) and 2004–2012 (9 years) (table S2). Nationally, cold season water vapor pressure increased by 0.023 hPa (0.32%) per year in 1994 to 2003 and by 0.008 hPa (0.11%) per year in 2004 to 2012. In contrast, warm season water vapor pressure did not exhibit statistically significant changes in 1994–2003 and decreased by 0.047 hPa (0.30%) per year in 2004–2012. These water vapor pressure trends were in general agreement with those reported in the literature (Isaac and van Wijngaarden 2012). During the cold season, water vapor pressure increased in areas where temperature increased (IM, NE, UM, SE) and decreased in areas where temperature decreased (NW, SC). In contrast, warm season water vapor pressure decreased in 2004–2012 in most regions (NW, UM, IM, SE, SW) while temperature increased.

3.2.4. Precipitation frequency trends—As precipitation provides a main sink for PM_{2.5}, we accounted for changes in precipitation frequency in subsequent analyses to estimate the weather penalty on PM_{2.5}, but not for O₃ given the weak evidence on its correlation with precipitation (Dawson *et al* 2007a). Specifically, precipitation frequency is a more relevant metric than the intensity or amount of rainfall (Jacob and Winner 2009, Tai *et al* 2012), as particles are efficiently scavenged through wet deposition (Balkanski *et al* 1993).

During the cold season, precipitation frequency increased in 1994–2003 in all regions (by 1.3% per year on average) and decreased in 2004–2012 in most regions except NW and NE (by 0.35% per year on average). During the warm season, precipitation frequency increased

in 1994–2003 in all regions except SC (by 2.6% per year on average) and increased in 2004–2012 in most regions except NW, SC, and UM (by 0.44% per year on average).

3.3. Weather penalty on air quality

Weather changes during our study period (1994–2012) were associated with significant increases in daily 8 h max O₃ and daily PM_{2.5} during both cold and warm seasons, particularly in the Eastern US (NE, SE, and IM) (figure 5). The unadjusted O₃ and PM_{2.5} trends in each region and season reflect the trends resulting from a combination of weather changes and emission changes. The weather-adjusted trends remove the influence of inter-annual changes in temperature, wind speed, and water vapor pressure (and precipitation frequency as well for PM_{2.5}) on air quality. Finally, the differences between unadjusted trends and weather-adjusted trends reflect the impact of long-term weather changes on air pollutant trends (i.e., weather penalty). The weather penalty we estimate includes direct effects of weather conditions (e.g., photochemical reactions), indirect effects (e.g., more heating use on cold days), and effects of other meteorological phenomena with ground-level weather manifestations (e.g., transport of cold, dry air mass).

3.3.1. Ozone trends and weather penalty—Nationally, the cold season daily 8 h max O₃ increased by 0.22 ppb (or 0.64%) per year, and all regions exhibited cold season O₃ increases. If temperature, wind speed, and water vapor pressure had not changed during our study period, the cold season O₃ would have increased by 0.15 ppb per year instead. In other words, weather changes led to additional O₃ increases by 0.07 ppb per year (95% CI: 0.02, 0.13). During the warm season, O₃ decreased by 0.15 ppb (0.31%) per year nationally, and decreased in most regions except the NW. If weather conditions had remained constant, warm season-O₃ would have decreased even more (0.33 ppb per year), reflecting a weather-associated penalty of 0.18 ppb per year (95% CI: 0.06, 0.31). Over 19 years, these amount to a total weather-related increase in daily 8 h max O₃ of 1.5 ppb in the cold season and 3.4 ppb in the warm season.

Water vapor pressure and temperature were the most important determinants of the absolute O₃ concentrations and trends in all regions and in both warm and cold seasons. O₃ is strongly correlated with temperature, as the presence of sunlight increases O₃ formation. During the warm season, weather penalties were greatest in the Eastern US (SE, NE, and IM), where temperature increases were also greatest. We conducted additional modeling analyses including different permutations of the weather parameters in model (2), which showed that the combination of changes in temperature and water vapor pressure made up the majority of weather penalty on O₃. Therefore, the nonlinear changes in water vapor pressure during our study period, together with the increases in temperature, resulted in a significant net increase in O₃ concentrations. Of note, our results were robust to the use of relative humidity instead of water vapor pressure (table S3, figure S4). This combined effect of water vapor pressure and temperature changes was particularly important in the SE, where the highest O₃ penalties were observed.

Water vapor has competing effects on O₃ concentrations by facilitating hydroxyl radical production from O₃ photolysis, which can collectively yield a net O₃ loss (via photolysis) or

net O₃ production (via hydroxyl radical chemistry). Very dry conditions, however, can cause drought stress and suppress stomatal O₃ uptake and contribute to the high warm season O₃ (Vautard *et al* 2005, Solberg *et al* 2008). Therefore, drier and hotter conditions in recent years (2004–2012) may have increased warm season O₃ concentrations.

Decreases in wind speed were consistently associated with O₃ increases in the warm season. Low wind speed and high ambient temperature are conditions characteristic of stagnation leading to favorable conditions for O₃ formation during the summertime (Banta *et al* 1998). In fact, additional analyses showed that the combined effect of wind and temperature were important during the warm season and yielded a statistically significant weather-associated penalty, whereas little or no significant impacts were observed during the cold season.

In summary, much of the weather penalty on O₃ can be attributed to changes in temperature and water vapor pressure, but the significant decline in wind speeds also contributed to the warm season O₃ penalty.

3.3.2. PM_{2.5} trends and weather penalty—The weather penalty on PM_{2.5} was relatively smaller than that of O₃, but statistically significant nonetheless. Nationally, daily PM_{2.5} decreased by 0.37 μg m⁻³ (2.6%) per year during the cold season. Without weather changes, PM_{2.5} would have decreased by 0.39 μg m⁻³ per year, reflecting a weather penalty of 0.03 μg m⁻³ per year (95% CI: 0.01, 0.04). During the warm season, PM_{2.5} decreased by 0.35 μg m⁻³ (2.3%) per year nationally, and would have decreased by 0.40 μg m⁻³ per year without weather changes. This reflects a warm season weather penalty of 0.06 μg m⁻³ (95% CI: 0.02, 0.10) per year. Over a 19-year period, the weather penalty on PM_{2.5} would have been approximately 0.5 μg m⁻³ during the cold season and 1.1 μg m⁻³ during the warm season.

Temperature and wind speed were the most important determinants of PM_{2.5} concentrations and trends in most regions. Most regions (except UM and SC) exhibited statistically significant weather-related PM_{2.5} increases during both seasons. Weather penalties on PM_{2.5} were highest during the warm season in the Eastern US regions (NE, SE, and IM), where warm season temperature increases were also greatest. Temperature increases can have opposing effects on PM_{2.5} by increasing sulfate concentrations through increased oxidation and decreasing nitrate levels due to ammonium nitrate volatilization (Seinfeld and Pandis 2006, Dawson *et al* 2007b). Therefore, the net effect depends by the relative abundance of nitrate and sulfate. Sulfate typically makes up a significant proportion (30–60%) of the PM_{2.5} mass composition in the Eastern US regions due to high sulfate emissions from coal-fired power plants (Hand *et al* 2012). Therefore, this is consistent with temperature-related PM_{2.5} increases in the Eastern US, especially as peaks in sulfate concentrations are more common in the warm season. During the cold season, the weather penalty on PM_{2.5} was lower than the warm season penalty despite greater cold season temperature increases.

In contrast, the association between wind speed and PM_{2.5} was more consistently negative in all regions in both warm and cold seasons. Studies have shown that high wind speed is generally correlated with low pollutant levels due to enhanced advection and deposition (Dawson *et al* 2007b). Therefore, a decline in wind speed can contribute to a more favorable

condition for particle formation. Nonetheless, the overall weather penalty on $PM_{2.5}$ was relatively smaller than O_3 , which is likely attributable to nonlinear effects as well as competing effects of weather parameters on different $PM_{2.5}$ components.

3.4. Mortality impact of weather penalty

In order to characterize the health consequences of weather-associated increases in O_3 and $PM_{2.5}$, we applied national risk estimates reported by two epidemiological studies on O_3 and $PM_{2.5}$ associated mortality (Krewski *et al* 2009, Jerrett *et al* 2009). As we analyzed long-term air quality changes, we chose mortality risk estimates from chronic (rather than acute) air pollution health effects studies. We re-estimated regional air pollution trends and penalties using air pollution exposure metrics consistent with those of the epidemiological studies (figure S5).

The magnitude of the regional mortality estimates depends on both regional air quality changes and size of population exposed. As such, weather-related penalty on air quality had the greatest mortality impacts in the Eastern US (NE, SE, and IM), where both population size and weather penalties were highest (figure 6). Nationally, 6100 (95% CI: 4100–8100) deaths were averted annually because of air quality improvements during our study period. However, if weather conditions (i.e., temperature, wind speed, water vapor pressure) had not changed, even more deaths, totaling 7200 (95% CI: 4900–9400) annually, would have been avoided. Therefore, weather-related increases in O_3 and $PM_{2.5}$ were associated with 1100 (95% CI: 300–1900) excess deaths annually. Over a 19-year period, this would amount to approximately 20 300 excess deaths attributable to the weather penalty on air quality.

The weather penalty was associated with 290 annual deaths related to O_3 and 770 annual deaths related to $PM_{2.5}$. Even though the weather penalty on O_3 was relatively greater, weather-related $PM_{2.5}$ increases yielded 160% more excess deaths, as $PM_{2.5}$ exposure has a greater mortality effect per unit than O_3 exposure. While this suggests that weather-associated increases in $PM_{2.5}$ -related mortality may continue to be greater, projections for $PM_{2.5}$ and consequently its future health impacts are much more uncertain than those of O_3 .

3.5. Limitations

There are several important limitations to our study that affect the magnitude of the weather penalty and mortality estimates. First, in effort to maximize the completeness of weather data to minimize air quality data loss, the weather stations and air pollution monitors were often not co-located. As we aimed to estimate the impact of long-term changes of weather conditions, we assumed that long-term weather trends are similar within the range of distances of our matched sites. A larger distance between air pollution and weather stations is more likely to yield a weaker association, and subsequently an underestimation of the weather penalty.

To further minimize air quality data loss, we also applied a 75% data capture criterion for creating daily O_3 metrics. While this is the EPA's minimum data completeness requirement, a non-random pattern of missing hourly values may be a source of bias. In our prior work, we estimated O_3 trends by hour of the day and season within each region, and found very consistent diurnal and seasonal pattern of trends across all regions (Jhun *et al* 2015). This

robust pattern of hourly trends across all seven regions reflect that missing hourly values did not substantially affect the estimation of trends. Furthermore, the effect of missing values on estimating the weather impact on trends (i.e. penalty) is likely even less. Other limitations discussed below are much more likely to be important.

Second, we estimated linear air pollution trends and trend differences. Ideally, we would estimate non-linear trends and trend differences; however, we were limited by computational capacity necessary for estimating non-linear trend differences and their uncertainty via the bootstrap method. As linear trends are more sensitive to outliers, we re-estimated trends and penalties excluding data from the year 2012, as temperature was unusually high that year. We did not observe any statistically significant difference for O₃ and PM_{2.5} trend differences (i.e., penalty). PM_{2.5} was more sensitive to the exclusion, but any difference was within the 95% confidence interval as we reported above.

Third, due to computational limitations, we estimated trends and trend differences at a regional, rather than site-level scale. Site-to-site heterogeneity is reflected in the confidence interval of the regional trends and trend differences (i.e., weather penalty) we report. On a regional scale, confidence intervals of weather penalties were much smaller than those of trends. This suggests that while site-to-site variation of air pollution trends may be larger, the impacts of weather changes on trends are less variable between sites, and subsequently, between regions. Since our primary aim was to estimate the weather penalty, the regional-level analyses were appropriate and adequate. Another limitation to regional-level analyses, however, is the differences in the number of sites in each region. While there were large site-to-site differences in actual pollution trends, our results show much less heterogeneity in the weather penalty. Nonetheless, the regional weather penalty we estimate (particularly for regions with only a few PM_{2.5} sites) may not be representative of the entire region due to a limited number of selected sites.

Fourth, we only assessed the impact of three or four weather parameters on air pollution trends. We applied a limited set of weather parameters to maximize completeness of the weather data and feasibility of a national analysis. After reviewing the literature, temperature, wind speed, and water vapor pressure (and precipitation frequency for PM_{2.5}) were identified as the most important determinants of O₃ and PM_{2.5} concentrations. As such, the majority of weather-associated penalty on O₃ and PM_{2.5} are likely accounted for by these variables. However, there are certainly other weather parameters that could have been included such as cloud cover, transport direction/ distance, and atmospheric mixing height. Many of these additional weather parameters may be strongly correlated with the weather variables already included in our models. The incremental value of accounting for other weather parameters may be minimal, given that our models already explain 30–60% of the daily variability in O₃ and PM_{2.5} concentrations.

Lastly, regional excess mortality associated with weather penalties has important sources of uncertainty. First, we apply a national mortality risk estimate in the health impact function to estimate the mortality impact of regional air quality changes. The regional risk estimates reported by epidemiological studies were highly variable with wide confidence intervals. Second, the O₃ mortality estimates only account for mortality in April to September of each

year, and may be an underestimate to the extent that there are O₃-related deaths in October through March. Finally, the baseline population data from 2010 were utilized to estimate annual weather-associated excess mortality. Population size changes during our study period, however, represent a very small fraction of the uncertainty of mortality risk estimates and air quality changes.

4. Conclusions

In this study, we quantified past weather impacts on air quality and health using long-term observational data. The weather penalty we estimate includes direct effects of weather conditions (e.g., photochemical reactions), indirect effects (e.g., more heating use on cold days), and effects of other meteorological phenomena with ground-level weather manifestations (e.g., transport of cold, dry air mass). Within the recent two decades, historical changes in weather conditions have had significant impacts on air quality and health. Temperature has increased and wind speed has decreased in most US regions. Weather-associated increases in O₃ were driven primarily by changes in temperature and water vapor pressure, and weather-associated increases in PM_{2.5} were driven by temperature and wind speed. These weather penalties had significant mortality impacts, with approximately 1100 excess deaths per year attributable to the weather penalty on air quality. Excess mortality related to weather-related pollution increases were particularly pronounced in the Eastern US, and were greater for PM_{2.5} even though the weather penalty on O₃ concentrations was relatively higher. As climate models predict temperature increases, higher frequency of heat waves, and more stagnation episodes, weather-related increases in both O₃ and PM_{2.5}-related mortalities will likely persist in the future. Changes in weather conditions will continue to modify the benefits of emission controls, and this may require additional emissions reductions as more areas exceed air quality standards in the future climate.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The Harvard School of Public Health Scholarship and the US EPA grant RD-834798-01 made this work possible. Its contents are solely the responsibility of the grantee and do not necessarily represent the official views of the US EPA. Further, the US EPA does not endorse the purchase of any commercial products or services mentioned in the publication. We thank Choong-Min Kang for his assistance with creating the air pollution and weather dataset, and Marianthi Kioumourtzoglou for her help with the bootstrap method development. We also thank Neal Fann and Charles Fulcher for their technical support for BenMAP.

References

- Abt Associates Inc. Environmental Benefits and Mapping Program (Version 4.0). 2011. (www.epa.gov/air/benmap)
- Agresti, A. Categorical Data Analysis. New York: Wiley; 2012. 16.1 Delta method; p. 587-591.
- Anenberg SC, Horowitz LW, Tong DQ, West JJ. An estimate of the global burden of anthropogenic ozone and fine particulate matter on premature human mortality using atmospheric modeling. *Environ. Health Perspect.* 2010; 118:1189–1195. [PubMed: 20382579]

- Balkanski YJ, Jacob DJ, Gardner GM, Graustein WC, Turekian KK. Transport and residence times of tropospheric aerosols inferred from a global three-dimensional simulation of 210Pb. *J. Geophys. Res.* 1993; 98:20573.
- Banta RM, et al. Daytime buildup and nighttime transport of urban ozone in the boundary layer during a stagnation episode. *J. Geophys. Res.* 1998; 103:22519.
- Berkey CS, Hoaglin DC, Antczak-Bouckoms A, Mosteller F, Colditz GA. Meta-analysis of multiple outcomes by regression with random effects. *Stat. Med.* 1998; 17:2537–2550. [PubMed: 9839346]
- Bloomfield P, Royle JA, Steinberg LJ, Yang Q. Accounting for meteorological effects in measuring urban ozone levels and trends. *Atmos. Environ.* 1996; 30:3067–3077.
- Camalier L, Cox W, Dolwick P. The effects of meteorology on ozone in urban areas and their use in assessing ozone trends. *Atmos. Environ.* 2007; 41:7127–7137.
- Cox WM, Chu S-H. Meteorologically adjusted ozone trends in urban areas: a probabilistic approach. *Atmos. Environ.* 1993; 27:425–434.
- Cox WM, Chu S-H. Assessment of interannual ozone variation in urban areas from a climatological perspective. *Atmos. Environ.* 1996; 30:2615–2625.
- Dawson JP, Adams PJ, Pandis SN. Sensitivity of ozone to summertime climate in the eastern USA: a modeling case study. *Atmos. Environ.* 2007a; 41:1494–1511.
- Dawson JP, Adams PJ, Pandis SN. Sensitivity of PM_{2.5} to climate in the Eastern US: a modeling case study. *Atmos. Chem. Phys.* 2007b; 7:4295–4309.
- Fiore AM, et al. Global air quality and climate. *Chem. Soc. Rev.* 2012; 41:6663–6683. [PubMed: 22868337]
- Hand JL, Schichtel BA, Pitchford M, Malm WC, Frank NH. Seasonal composition of remote and urban fine particulate matter in the United States. *J. Geophys. Res.* 2012; 117:D05209.
- Isaac V, van Wijngaarden WA. Surface water vapor pressure and temperature trends in North America during 1948–2010. *J. Clim.* 2012; 25:3599–3609.
- Jacob DJ, Winner DA. Effect of climate change on air quality. *Atmos. Environ.* 2009; 43:51–63.
- Jerrett M, Burnett RT, Pope CA, Ito K, Thurston G, Krewski D, Shi Y, Calle E, Thun M. Long-term ozone exposure and mortality. *New Engl. J. Med.* 2009; 360:1085–1095. [PubMed: 19279340]
- Jhun I, Coull Ba, Zanobetti A, Koutrakis P. The impact of nitrogen oxides concentration decreases on ozone trends in the USA. *Air Qual. Atmos. Health.* 2015; 8:283–292.
- Krewski, D., et al. *Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality.* Boston, MA: Health Effects Institute; 2009.
- Mickley LJ. Effects of future climate change on regional air pollution episodes in the United States. *Geophys. Res. Lett.* 2004; 31:L24103.
- Pearce JL, Beringer J, Nicholls N, Hyndman RJ, Tapper NJ. Quantifying the influence of local meteorology on air quality using generalized additive models. *Atmos. Environ.* 2011; 45:1328–1336.
- Politis DN. The impact of bootstrap methods on time series analysis. *Stat. Sci.* 2003; 18:219–230.
- Pryor SC, Barthelme RJ, Young DT, Takle ES, Arritt RW, Flory D, Gutowski WJ, Nunes A, Roads J. Wind speed trends over the contiguous United States. *J. Geophys. Res.* 2009; 114:D14105.
- R Development Core Team. *R: A Language and Environment for Statistical Computing.* 2011 (www.r-project.org).
- Samet, JM.; Zeger, SL.; Dominici, F.; Curriero, F.; Coursac, I.; Dockery, DW. *Morbidity and Mortality from Air Pollution in the United States.* Cambridge, MA: Health Effects Institute; 2000. The national morbidity, mortality, and air pollution study: II.
- Seinfeld, J.; Pandis, S. *Atmospheric Chemistry and Physics: From Air Pollution to Climate Change.* New York: Wiley; 2006.
- Solberg S, Hov Ø, Søvde A, Isaksen ISA, Coddeville P, De Backer H, Forster C, Orsolini Y, Uhse K. European surface ozone in the extreme summer 2003. *J. Geophys. Res.* 2008; 113:D07307.
- Tagaris E, Liao K-J, Delucia AJ, Deck L, Amar P, Russell AG. Potential impact of climate change on air pollution-related human health effects. *Environ. Sci. Technol.* 2009; 43:4979–4988. [PubMed: 19673295]

- Tai APK, Mickley LJ, Jacob DJ. Correlations between fine particulate matter (PM_{2.5}) and meteorological variables in the United States: implications for the sensitivity of PM_{2.5} to climate change. *Atmos. Environ.* 2010; 44:3976–3984.
- Tai APK, Mickley LJ, Jacob DJ, Leibensperger EM, Zhang L, Fisher JA, Pye HOT. Meteorological modes of variability for fine particulate matter (PM_{2.5}) air quality in the United States: implications for PM_{2.5} sensitivity to climate change. *Atmos. Chem. Phys.* 2012; 12:3131–3145.
- The National Academies Press. *Rethinking the Ozone Problem in Urban and Regional Air Pollution*. Washington, DC: The National Academies Press; 1991.
- Thompson ML, Reynolds J, Cox LH, Guttorp P, Sampson PD. A review of statistical methods for the meteorological adjustment of tropospheric ozone. *Atmos. Environ.* 2001; 35:617–630.
- US EPA. Final Regulatory Impact Analysis: PM_{2.5} NAAQS. 2006. (www.epa.gov/ttn/ecas/ria.html)
- US EPA. Final Ozone NAAQS Regulatory Impact Analysis. 2008. (www.epa.gov/ttn/ecas/ria.html)
- US EPA. *Our Nation's Air: Status and Trends Through 2008*. Research Triangle Park, NC: 2010.
- US EPA. National Trends in Ozone Levels. 2014a. (www.epa.gov/airtrends/ozone.html)
- US EPA. National Trends in Particulate Matter Levels. 2014b. (www.epa.gov/airtrends/pm.html)
- Vautard R, Honore C, Beekman M, Rouil L. Simulation of ozone during the August 2003 heat wave and emission control scenarios. *Atmos. Environ.* 2005; 39:2957–2967.
- Zheng J, Swall JL, Cox WM, Davis JM. Interannual variation in meteorologically adjusted ozone levels in the eastern United States: a comparison of two approaches. *Atmos. Environ.* 2007; 41:705–716.

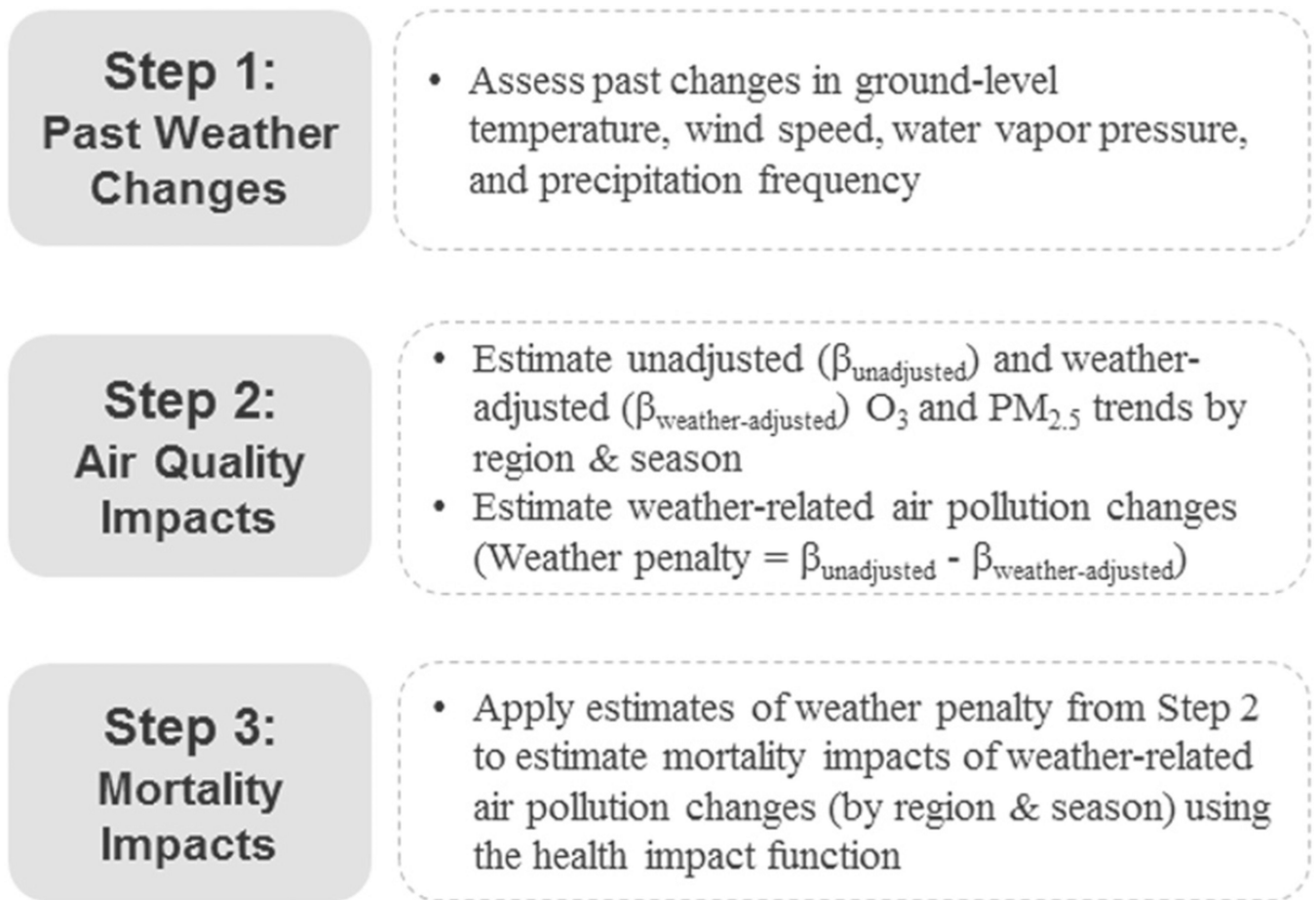


Figure 1.
Schematic illustration of stages of analyses.

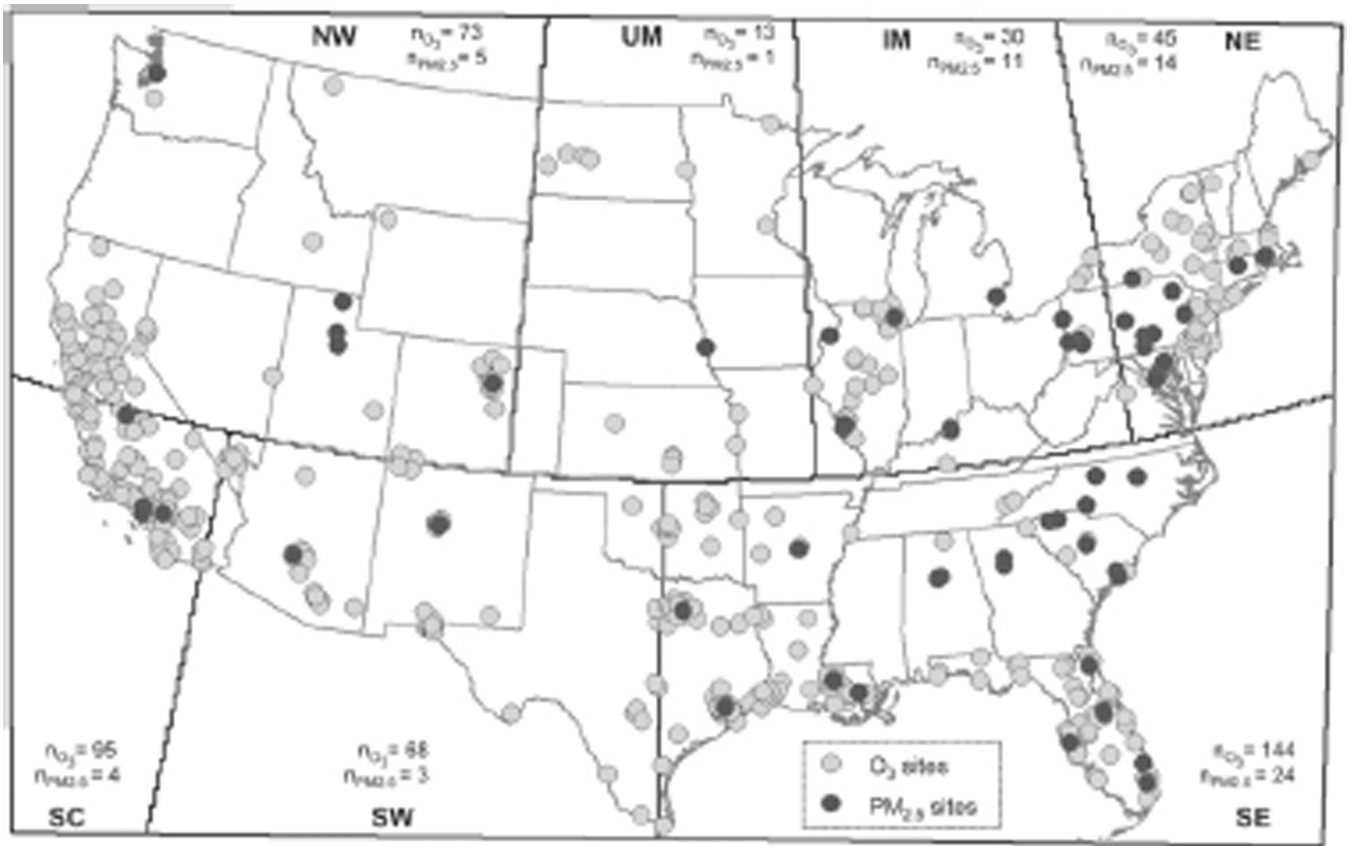


Figure 2. Pollutant monitoring site locations. Number of O_3 and $PM_{2.5}$ monitoring sites are noted by n_{O_3} and $n_{PM_{2.5}}$, respectively (NW: Northwest, UM: Upper Midwest, IM: Industrial Midwest, NE: Northeast, SC: Southern California, SW: Southwest, SE: Southeast).

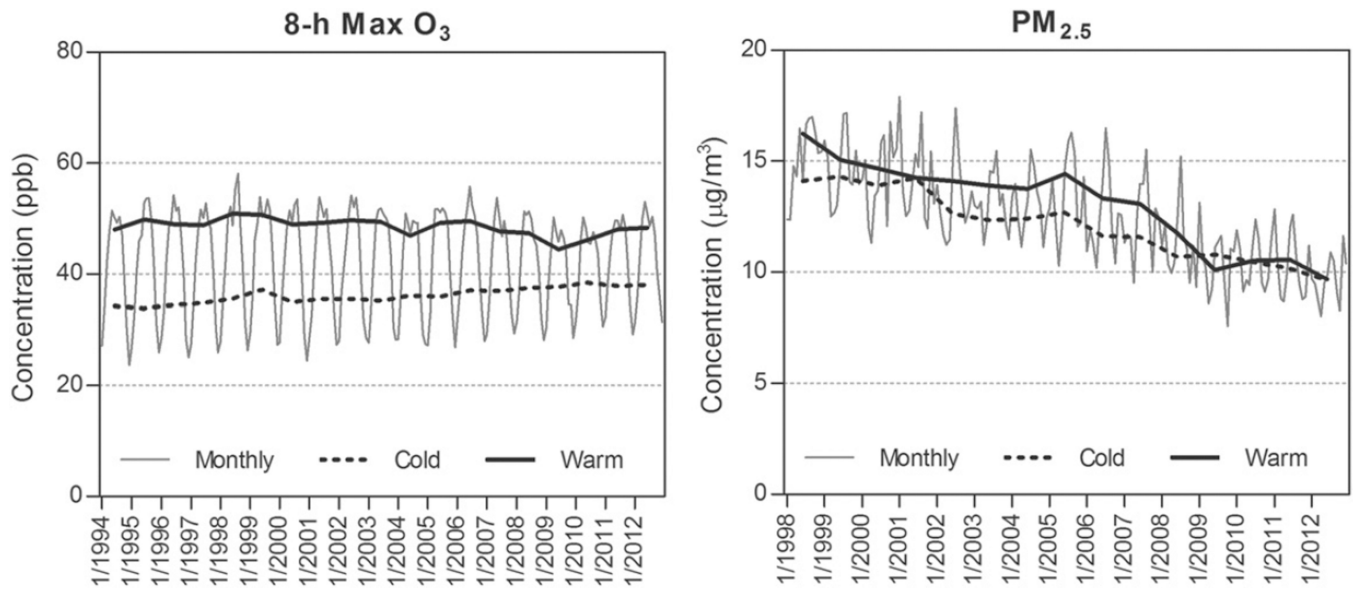


Figure 3. National monthly mean concentration time series of 8 h max O₃ and PM_{2.5}. The cold season (November–April) and warm season (May–October) monthly means were averaged to estimate seasonal time series.

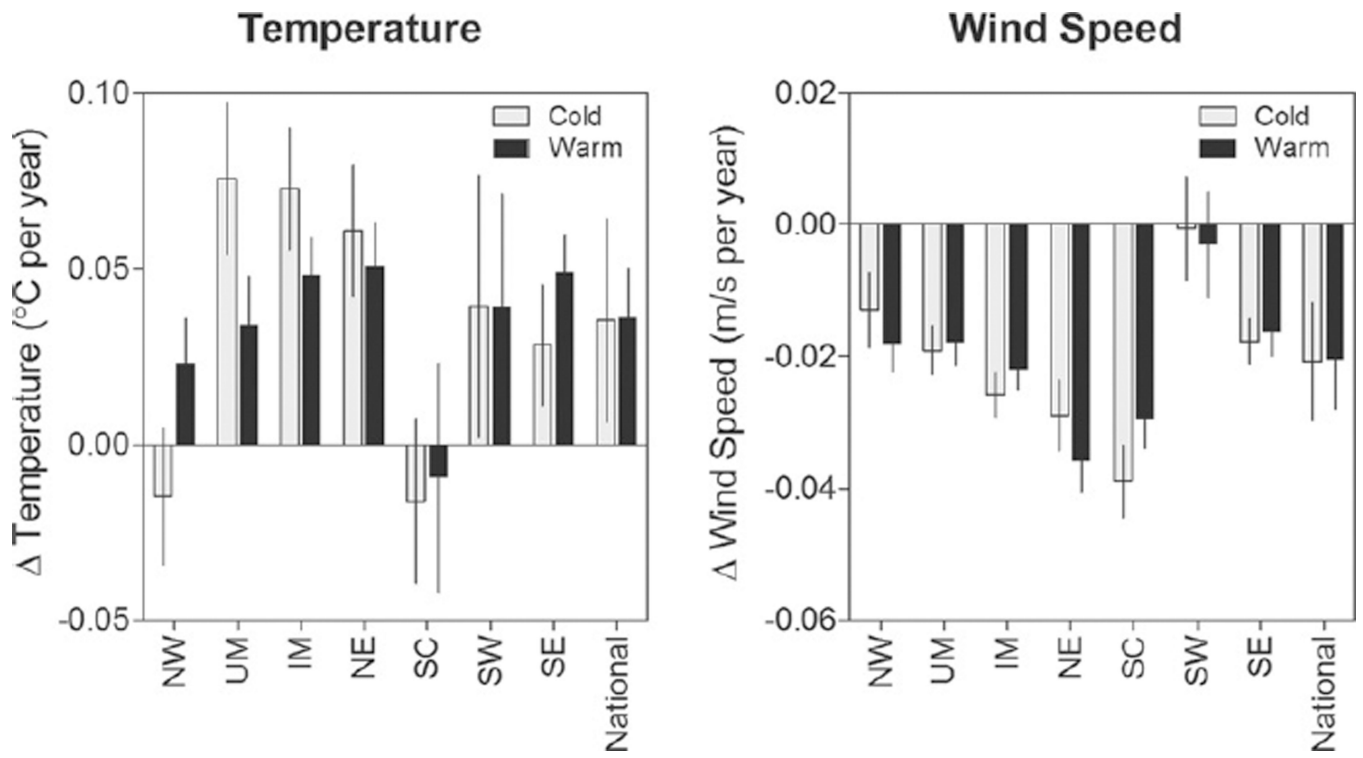


Figure 4. Changes in temperature ($^{\circ}\text{C}$ per year), wind speed (m s^{-1} per year) in 1994–2012 by region and season. The 95% confidence intervals are shown.

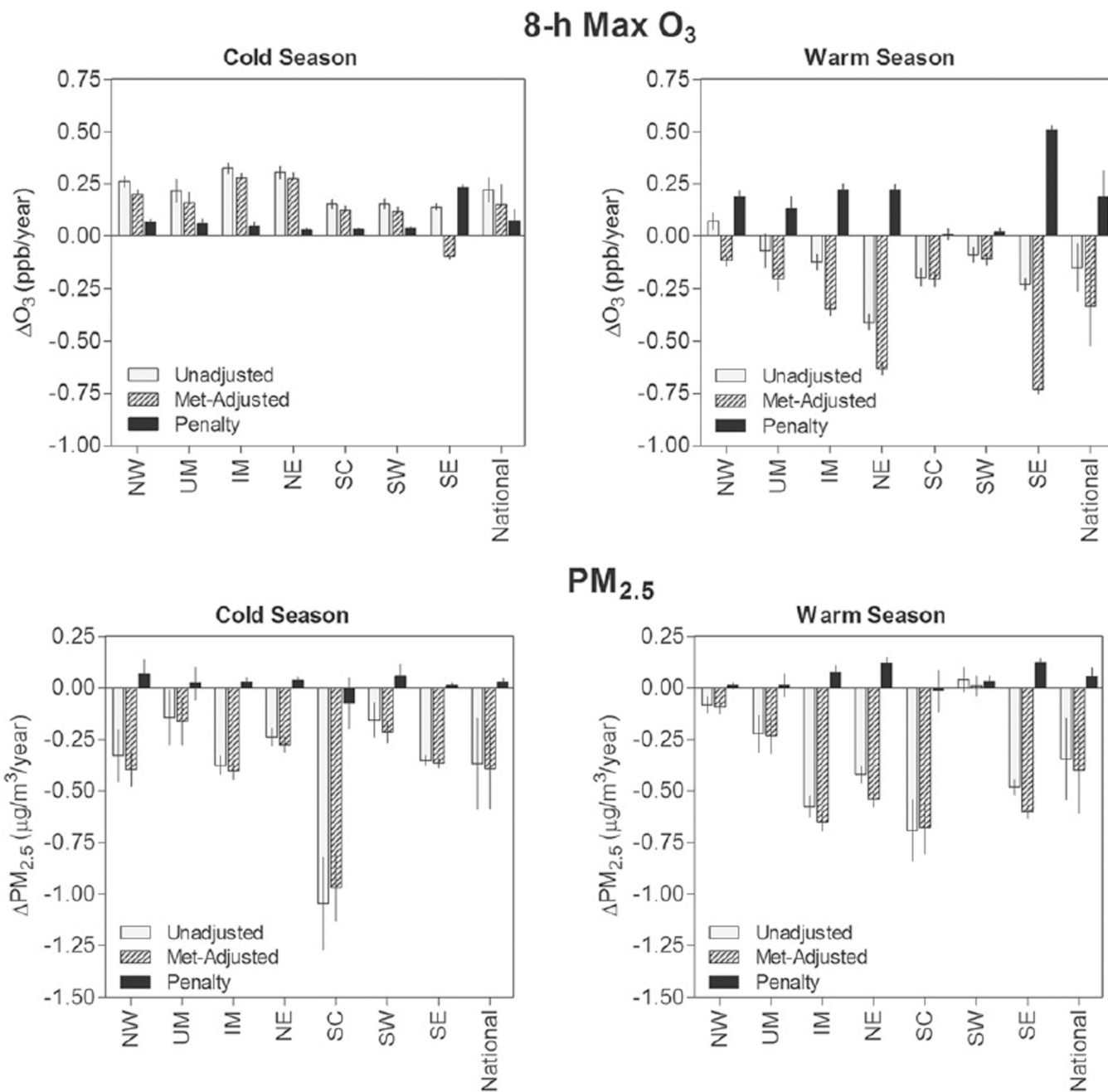


Figure 5. Unadjusted trends, weather-adjusted trends, and weather penalties of 8 h max O₃ and PM_{2.5} in 1994–2012 by region and season. The 95% confidence intervals are shown.

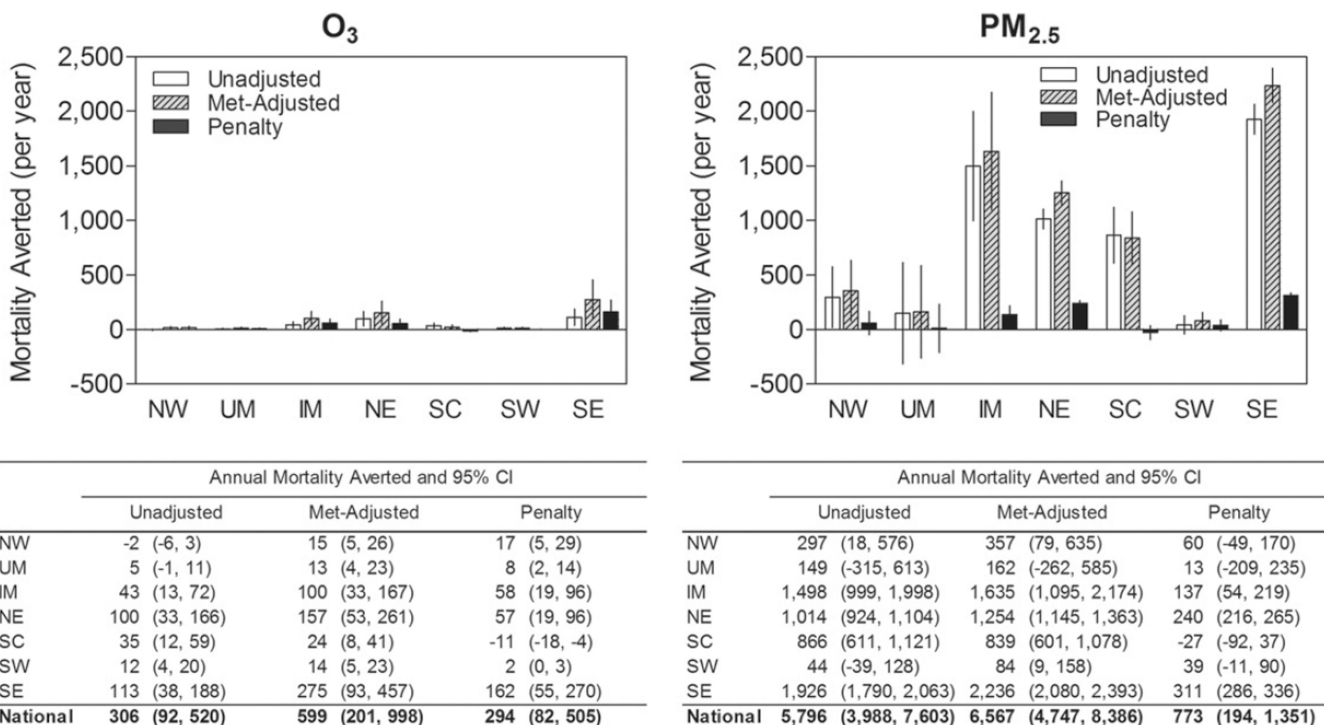


Figure 6. Annual mortalities averted in 1994–2012 as a result of unadjusted and weather-adjusted trends in O₃ and PM_{2.5}, and their difference (penalty) by region. The 95% confidence intervals are shown.

Table 1

Summary of weather trends.

Weather variable	Season	Trends
Temperature	Cold and warm	↑ (IM, NE, UM, SE, SW)
Wind speed	Cold and warm	↓ (all except SW)
Water vapor press.	Cold	↑ (IM, NE, UM, SE)
	Warm	↓ (NW, UM, IM, SE, SW)
Precipitation freq.	Cold	↑ ('94-'03), ↓ ('04-'12)
	Warm	↑ (all except SC)

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript