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Impact of 2000–2050 climate change on fine particulate matter ($PM_{2.5}$) air quality inferred from a multi-model analysis of meteorological modes

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Abstract

Studies of the effect of climate change on fine particulate matter ($PM_{2.5}$) air quality using general circulation models (GCMs) have yielded inconsistent results including in the sign of the effect. This reflects uncertainty in the GCM simulations of the regional meteorological variables affecting $PM_{2.5}$. Here we use the CMIP3 archive of data from fifteen different IPCC AR4 GCMs to obtain improved statistics of 21st-century trends in the meteorological modes driving $PM_{2.5}$ variability over the contiguous US. We analyze 1999–2010 observations to identify the dominant meteorological modes driving interannual $PM_{2.5}$ variability and their synoptic periods T. We find robust correlations ($r > 0.5$) of annual mean $PM_{2.5}$ with T, especially in the Eastern US where the dominant modes represent frontal passages. The GCMs all have significant skill in reproducing present-day statistics for T and we show that this reflects their ability to simulate atmospheric baroclinicity. We then use the local $PM_{2.5}$-to-period sensitivity ($dPM_{2.5}/dT$) from the 1999–2010 observations to project $PM_{2.5}$ changes from the 2000–2050 changes in T simulated by the 15 GCMs following the SRES A1B greenhouse warming scenario. By weighted-average statistics of GCM results we project a likely 2000–2050 increase of $\sim 0.1\,\mu g\,m^{-3}$ in annual mean $PM_{2.5}$ in the Eastern US arising from less frequent frontal ventilation, and a likely decrease of $\sim 0.3\,\mu g\,m^{-3}$ in the Northwestern US due to more frequent maritime inflows. These circulation-driven changes are relatively small. Potentially larger regional effects of 2000–2050 climate change on $PM_{2.5}$ may arise from changes in temperature, biogenic emissions, wildfires, and vegetation, but are still unlikely to affect annual $PM_{2.5}$ by more than $0.5\,\mu g\,m^{-3}$.

1 Introduction

Air pollution is strongly sensitive to weather conditions and is therefore affected by climate change. A number of studies reviewed by Jacob and Winner (2009) have used chemical transport models (CTMs) driven by general circulation models (GCMs) to

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diagnose the effects of 21st-century climate change on air quality at northern mid-latitudes. These GCM-CTM studies generally concur that 2000–2050 climate change will degrade ozone air quality in polluted regions by 1–10 ppb, but they do not agree on even the sign of the effect for fine particulate matter ($PM_{2.5}$). Change in ozone is largely driven by change in temperature, but for $PM_{2.5}$ the dependence on meteorological variables is far more complex, including different sensitivities for different $PM_{2.5}$ components (Liao et al., 2006; Dawson et al., 2007; Heald et al., 2008; Kleeman, 2008; Pye et al., 2009; Tai et al., 2010).

Tai et al. (2012) proposed an alternate approach for diagnosing the effect of climate change on $PM_{2.5}$ through identification of the principal meteorological modes driving observed $PM_{2.5}$ variability. For example, it is well known that cold fronts associated with mid-latitude cyclones drive pollutant ventilation in the Eastern US (Cooper et al., 2001; Li et al., 2005). Tai et al. (2012) found that the frequency of cold fronts was a major predictor of the observed interannual variability of $PM_{2.5}$ in the Midwest. GCMs project a general 21st-century decrease in mid-latitude cyclone frequency as a result of greenhouse warming (Bengtsson et al., 2006; Lambert and Fyfe, 2006; Christensen et al., 2007; Pinto et al., 2007; Ulbrich et al., 2008), from which one could deduce a general degradation of air quality. This cause-to-effect relationship has been found in a few GCM-CTM studies (Mickley et al., 2004; Murazaki and Hess, 2006).

However, there is substantial uncertainty in regional projections of future cyclone frequency (Ulbrich et al., 2009; Lang and Waugh, 2011). Indeed, a general difficulty in projecting the effect of climate change on air quality is the underlying GCM uncertainty in simulating regional climate change. This uncertainty arises both from model noise (climate chaos) and from model error (physics, parameters, numerics). Model noise can be important. Tai et al. (2012) conducted five realizations of 2000–2050 climate change in the GISS GCM 3 (Rind et al., 2007) under the same radiative forcing scenario and found that the frequency of cyclones ventilating the US Midwest decreased in three of the realizations, increased in one, and had no trend in one. All GCM-CTM studies to date examining the effect of climate change on $PM_{2.5}$ have used a single

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climate change realization from a single GCM (Jacob and Winner, 2009), so it is no surprise that they would yield inconsistent results. This is less of an issue for GCM-CTM projections of ozone air quality because ozone responds most strongly to changes in temperature (Jacob and Winner, 2009), and all GCMs show consistent warming for the 21st-century climate even on regional scales (Christensen et al., 2007).

The standard approach adopted by the Intergovernmental Panel on Climate Change (IPCC) to reduce uncertainties in GCM projections of regional climate change is to use multiple realizations from an ensemble of GCMs, assuming that model diversity provides some measure of model error (Christensen et al., 2007). Such an ensemble analysis is not practical for GCM-CTM studies of air quality because of the computational expense associated with chemistry and aerosol microphysics. An alternative is to focus on GCM projections of the meteorological modes determining air quality. A resource for this purpose is the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset of 2000–2100 climate change simulations produced by the ensemble of GCMs contributing to the IPCC 4th Assessment Report (AR4).

Here we use this multi-model ensemble to project the responses of $PM_{2.5}$ air quality in different US regions to 2000–2050 climate change. We focus on annual mean $PM_{2.5}$, which is of primary policy interest (EPA, 2012). We first examine the observed sensitivity of annual mean $PM_{2.5}$ to the frequencies of the dominant meteorological modes in different US regions. We then use the CMIP3 archive of 15 GCMs to project the trends of these frequencies in the future climate, and from there we deduce the corresponding regional trends in $PM_{2.5}$. These climate-driven $PM_{2.5}$ projections, independent of trends in anthropogenic emissions, will represent the "climate penalty" or "benefit" for $PM_{2.5}$, which will aid air quality managers to plan emission goals accordingly.

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2 Observed sensitivity of $PM_{2.5}$ to meteorological modes

Previous studies have demonstrated the importance of synoptic weather in controlling $PM_{2.5}$ variability (Thishan Dharshana et al., 2010; Tai et al., 2012). Tai et al. (2012) identified cyclone passage with associated cold front as the meteorological mode whose period T (length of one cycle, i.e., inverse of frequency) is most strongly correlated with interannual variability of $PM_{2.5}$ in the US Midwest. They proposed that the corresponding $PM_{2.5}$-to-period sensitivity ($dPM_{2.5}/dT$) could be used to project the response of $PM_{2.5}$ to future climate change; a change ΔT in cyclone period would cause a change $\Delta PM_{2.5}=(dPM_{2.5}/dT)\Delta T$. The physical meaning of this $dPM_{2.5}/dT$ metric is clear when the meteorological mode acts as a pulse, either ventilating a source region (as in the case of a cold front) or polluting a remote region (as in the case of a warm front). We will attempt here to generalize it to the ensemble of conditions over the continental US.

Daily mean $PM_{2.5}$ data for 1999–2010 were obtained from the EPA Air Quality System (AQS) (http://www.epa.gov/ttn/airs/airsaqs/) Federal Reference Method (FRM) network of about 1000 sites in the contiguous US. The daily site measurements were interpolated following Tai et al. (2010) onto a $4^\circ \times 5^\circ$ latitude-by-longitude grid, and annual means for each of the 12 yr were calculated for each grid cell. Figure 1 shows as an example the 1999–2010 time series of annual mean $PM_{2.5}$ for the $4^\circ \times 5^\circ$ grid cell centered over Chicago (asterisk in Fig. 2). Linear regression indicates a downward trend of $-0.34\,\mu g\,m^{-3}\,yr^{-1}$, reflecting the improvement of air quality due to emission controls (EPA, 2012). Superimposed on this long-term tend is interannual variability that we assume to be meteorologically driven. The standard deviation of the detrended annual mean $PM_{2.5}$ is $0.79\,\mu g\,m^{-3}$, or 5.3 % of the 12-yr mean. For the ensemble of $4^\circ \times 5^\circ$ grid cells in the US we find that the interannual standard deviation of the detrended data ranges from 3 to 19 %. Relative interannual variability is largest in the Western US but there it could be driven in part by forest fires (Park et al., 2007).

We follow the approach of Tai et al. (2012) to determine the dominant meteorological modes for interannual $PM_{2.5}$ variability on the $4^\circ \times 5^\circ$ grid. Daily meteorological

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variables for 1981–2010 (Table 1) were obtained from the National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) Reanalysis 1 (http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.html) (Kalnay et al., 1996; Kistler et al., 2001). We regridded the original 2.5° × 2.5° data onto the 4° × 5° grid and deseasonalized them by subtracting the 30-day moving averages.

Following Tai et al. (2012), we decomposed the daily time series of the meteorological variables (Table 1) for each 4° × 5° grid cell to produce time series of eight principal components ($U_1, \ldots, U_8$):

$$U_j(t) = \sum_{k=1}^{8} \alpha_{kj} \frac{x_k(t) - \overline{x_k}}{s_k} \quad (1)$$

where x_k is the deseasonalized meteorological variable, $\overline{x_k}$ and s_k are the temporal mean and standard deviation of x_k, α_{kj} describes the elements of the orthogonal transformation matrix defining the meteorological modes (Tai et al., 2012), and t is time. Each $U_j(t)$ represents the principal component time series for a distinct meteorological mode. We then applied Fourier transform to $U_j(t)$ with a second-order autoregressive (AR2) filter to obtain a smoothed frequency spectrum for each year (Wilks, 2011), and extracted the median AR2 spectral frequency (f) to calculate the corresponding period of the meteorological mode ($T = 1/f$). See Tai et al. (2012) for further description and example application.

From there we applied reduced major axis regression to the 1999–2010 annual time series of detrended $PM_{2.5}$ and T in each 4° × 5° grid cell to determine $dPM_{2.5}/dT$. The dominant meteorological mode for each grid cell was identified as that whose period is most strongly correlated with annual mean $PM_{2.5}$ and explains more than 25 % of interannual $PM_{2.5}$ variability (p-value < 0.095). Figure 1 shows as an example the time series of the period of the dominant meteorological mode in the Chicago grid cell (frontal passage). The detrended variables correlate with $r = 0.62$ and $dPM_{2.5}/dT = 2.9 \pm 1.4\ \mu g\, m^{-3}\, d^{-1}$ (95 % confidence interval), reflecting the importance of the frequency of frontal ventilation in controlling interannual $PM_{2.5}$ variability in the Midwest.

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Figure 2 shows the interannual correlations between $PM_{2.5}$ and T, and the corresponding slopes $dPM_{2.5}/dT$, for the dominant meteorological modes across the US. If two or more modes show similar correlation in a given grid cell, the leading principal component is shown. The mean values of T range from 5 to 9 days (Fig. 3), a typical synoptic time scale for frontal passages. There are two outlying grid cells in the interior northwest where T exceeds 13 days and the physical meaning is not clear. The slopes $dPM_{2.5}/dT$ are usually positive in the Eastern US, reflecting the ventilation associated with frontal passage. Negative $dPM_{2.5}/dT$ values in two northeast grid cells may reflect transport of pollution in southwesterly flow behind warm fronts. Positive $dPM_{2.5}/dT$ in the northwest can be understood to reflect periodic ventilation by maritime inflow and scavenging by the accompanying precipitation (Tai et al., 2012). In other parts of the Western US the physical interpretation of $dPM_{2.5}/dT$ is less clear, and the $PM_{2.5}$ data may not be representative of the $4^\circ \times 5^\circ$ grid cell because of sparsity of observations, urban bias, and complex topography (Malm et al., 2004; Tai et al., 2010). Nevertheless, we often find significant $PM_{2.5}$-T correlations.

3 GCM simulations of meteorological modes relevant to $PM_{2.5}$

We examined the ability of the IPCC AR4 GCMs to reproduce the present-day synoptic periods of the dominant meteorological modes for $PM_{2.5}$ interannual variability as prelude to applying these GCMs to diagnose future changes in these periods. We used the 15 IPCC AR4 GCMs from the CMIP3 multi-model dataset (https://esg.llnl.gov:8443/index.jsp) that had archived all the daily variables from Table 1 needed to project the GCM data onto the meteorological modes defined by the NCEP/NCAR observations. The GCM data have original horizontal resolution ranging from $1^\circ \times 1^\circ$ to $4^\circ \times 5^\circ$ and were all regridded here to $4^\circ \times 5^\circ$. We analyzed the 20th century simulations (20C3M) for 1981–2000, generated the principal component time series $U_j(t)$ for the meteorological modes defined by the NCEP/NCAR observations, and obtained the median periods of these modes on the $4^\circ \times 5^\circ$ grid to compare to observations.

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Figure 4 compares the GCM median periods T of the dominant meteorological modes with the NCEP/NCAR observations of Fig. 3. The models show strong skill in reproducing the spatial variability of T. We see from Fig. 3 that much of this variability is driven by a meridional gradient in synoptic periods, with shorter periods at higher latitudes. This gradient appears in turn to reflect the baroclinicity of the atmosphere. Mid-latitude synoptic weather is mostly driven by baroclinic instability that arises from strong meridional temperature gradients (Holton, 2004) and can be measured by the maximum Eady growth rate (σ_E) (Lindzen and Farrell, 1980):

$$\sigma_E = 0.31 \frac{g}{NT} \left| \frac{\partial T}{\partial y} \right| \quad (2)$$

where g is the gravitational acceleration, N is the Brunt-Väisälä frequency, T is the zonal mean temperature, and y is the meridional distance. As shown in Fig. 3, σ_E calculated from the NCEP/NCAR data at 850–500 hPa increases sharply between the tropics and 40° N, consistent with the decreasing trend of T. All models can reproduce this observed latitudinal trend in baroclinicity very well, with R^2 values ranging between 0.72–0.95 across the 15 GCMs (see the Supplement). We further found that for a given 4° × 5° grid cell, the inter-model variability across the 15 GCMs in the period T of the dominant meteorological mode is correlated with modeled baroclinicity as measured by σ_E. This is illustrated in Fig. 5 for the Chicago grid cell (see the Supplement for the correlation for other grid cells). Thus the ability of the GCMs to reproduce T and its variability reflects their ability to reproduce atmospheric baroclinicity.

4 Effect of climate change on $PM_{2.5}$

The general skill of the IPCC AR4 GCMs to reproduce present-day synoptic periods relevant to $PM_{2.5}$ variability lends some confidence in their ability to project future changes in these periods. Following the general IPCC strategy, we can expect the ensemble of 15 GCMs to provide a better projection than any single GCM. However, as Fig. 4 shows,

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some models perform better than others, and we should give less weight to poorly performing models. We use here the approach by Tebaldi et al. (2004, 2005), which combines Bayesian analysis with the reliability ensemble average (REA) method (Giorgi and Mearns, 2002) to discount models with large biases (with respect to observations) and outliers (with respect to future projections). This produces weighted averages and confidence intervals for future projections of synoptic periods.

We used the CMIP3 archive of GCM data for 2046–2065 following the SRES A1B greenhouse warming scenario, which assumes CO_2 to reach 522 ppm by 2050 (Nakicenovic and Swart, 2000). Comparison to the GCM data for 1981–2000 (Sect. 3) gives a measure of 2000–2050 climate change. The top panel of Fig. 6 shows the weighted-average changes in periods (ΔT) of the dominant meteorological modes for interannual $PM_{2.5}$ variability, and the bottom panel shows the corresponding changes in annual $PM_{2.5}$ concentrations ($\Delta PM_{2.5}$) obtained by $\Delta PM_{2.5}=(dPM_{2.5}/dT)\Delta T$ where $dPM_{2.5}/dT$ is the observed local relationship (Fig. 2). If two or more modes are similarly dominant in a given grid cell, we calculate an average effect from these modes. Figure 7 shows the aggregated results for nine regions in the US with the distribution across GCMs.

We see from Fig. 6 that the future climate features a general increase in $PM_{2.5}$-relevant synoptic periods in the Eastern US, reflecting a more stagnant mid-latitude troposphere with reduced ventilation by frontal passages. This is a robust result which follows from reduced baroclinic instability and poleward shift of storm tracks associated with greenhouse warming (Geng and Sugi, 2003; Mickley et al., 2004; Yin, 2005; Lambert and Fyfe, 2006; Murazaki and Hess, 2006; Pinto et al., 2007; Ulbrich et al., 2008). This in turn leads to a likely (74–91 % chance) increase in annual mean $PM_{2.5}$ with a weighted mean of about 0.1 $\mu g\,m^{-3}$ in the Eastern US (Northeast, Midwest, and Southeast in Fig. 7). In the Northwest (Pacific and Interior NW in Fig. 7), we find a likely (71–83 % chance) decrease in $PM_{2.5}$ with a weighted mean of about $-0.3\,\mu g\,m^{-3}$ due to reduced synoptic periods, reflecting more frequent ventilation by maritime inflows and scavenging by the associated precipitation. This is consistent with the general IPCC

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finding of increasing westerly flow over the western parts of mid-latitude continents in the future climate (Christensen et al., 2007; Meehl et al., 2007; also see the Supplement). Projections for other parts of the Western US are more uncertain. As pointed out earlier, the physical meaning of synoptic periods in the west is less clear than in the east.

GCM-CTM studies in the literature have reported ±0.1–1 $\mu g\,m^{-3}$ changes in annual mean $PM_{2.5}$ resulting from 2000–2050 climate change, with no consistency across studies (Jacob and Winner, 2009). As pointed out in the introduction, such inconsistency is to be expected since individual studies used a single future-climate realization from a single GCM. Our multi-model ensemble analysis allows us to conclude with greater confidence that changes in synoptic circulation brought about by climate change will degrade $PM_{2.5}$ air quality in the Eastern US but that the effect will be small ($\sim$0.1 $\mu g\,m^{-3}$). Effects in the Western US are potentially larger but of uncertain sign even when the ensemble of IPCC GCMs is considered.

Figure 8 summarizes the projected effects of 2000–2050 climate change on annual $PM_{2.5}$ in the US, drawing from this work for circulation changes and from previous studies for other effects. Tai et al. (2012) pointed out that increasing mean temperature, independently from changes in circulation, could have a large effect on $PM_{2.5}$ in the Southeast and some parts of the Western US through biogenic emissions, wildfires, and nitrate aerosol volatility. Temperature-driven changes in the southeast may reduce ammonium nitrate by $\sim$0.2 $\mu g\,m^{-3}$ due to increased volatility (Pye et al., 2009; Tai et al., 2012), but increase organic PM by $\sim$0.4 $\mu g\,m^{-3}$ due to increased biogenic emissions (Heald et al., 2008; Tai et al., 2012). Wu et al. (2012) projected a 0.1–0.2 $\mu g\,m^{-3}$ increase in organic PM in the Midwest and Western US due to climate-driven changes in vegetation composition. Spracklen et al. (2009) and Yue et al. (2012) projected a $\sim$1 $\mu g\,m^{-3}$ increase in summertime carbonaceous aerosols in the northwest due to increased wildfire activities. All in all, none of these effects (or their ensemble) is likely to affect annual mean $PM_{2.5}$ by more than 0.5 $\mu g\,m^{-3}$. Therefore, for $PM_{2.5}$ regulatory purpose on an annual mean basis, 2000–2050 climate change will unlikely represent

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any significant penalty or benefit for air quality managers toward the achievement of $PM_{2.5}$ air quality goals.

5 Conclusions

$PM_{2.5}$ air quality depends on a number of regional meteorological variables that are difficult to simulate in general circulation models (GCMs). This makes projections of the effect of 21st-century climate change on $PM_{2.5}$ problematic. Consideration of a large ensemble of future-climate simulations using a number of independent GCMs can help to reduce the uncertainty. However, this is not computationally practical in the standard GCM-CTM studies where a chemical transport model (CTM) is coupled to the GCM for explicit simulation of air quality. We presented here an alternative method by first using climatological observations to identify the dominant meteorological modes driving $PM_{2.5}$ variability, and then using CMIP3 archived data from 15 GCMs to diagnose the effect of 2000–2050 climate change on the periods of these modes.

We focused on projections of annual mean $PM_{2.5}$ over a $4^{\circ} \times 5^{\circ}$ grid covering the contiguous US. We showed that the observed 1999–2010 interannual variability of $PM_{2.5}$ across the US is strongly correlated with the periods (T) of the dominant synoptic-scale meteorological modes, particularly in the Eastern US where these modes correspond to frontal passages. The observed local relationship $dPM_{2.5}/dT$ then provides a means to infer changes in $PM_{2.5}$ from GCM-simulated changes in T. We find that all GCMs have significant skill in reproducing T and its spatial distribution over the US, reflecting their ability to capture the baroclinicity of the atmosphere. Inter-model differences in synoptic periods can be largely explained by differences in baroclinicity.

We then examined the 2000–2050 trends in synoptic periods T across the continental US as simulated by the ensemble of GCMs for the SRES A1B greenhouse warming scenario. We find a general slowing down of synoptic circulation in the Eastern US, as measured by an increase in T. We infer that changes in circulation driven by climate change will likely increase annual mean $PM_{2.5}$ in the Eastern US by $\sim 0.1\,\mu g\,m^{-3}$,

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reflecting a more stagnant mid-latitude troposphere and less frequent ventilation by frontal passages. We also project a likely decrease by ~0.3 $\mu g\,m^{-3}$ in the Northwest due to more frequent ventilation by maritime inflows. Potentially larger regional effects of climate change on $PM_{2.5}$ air quality may arise from changes in temperature, biogenic emissions, wildfires, and vegetation. Overall, however, it is unlikely that 2000–2050 climate change will modify annual mean $PM_{2.5}$ by more than 0.5 $\mu g\,m^{-3}$. These climate change effects, independent of changes in anthropogenic emissions, represent a relatively minor penalty or benefit for $PM_{2.5}$ regulatory purpose. Of more concern would be the effect of increased fires on daily $PM_{2.5}$.

Supplementary material related to this article is available online at: http://www.atmos-chem-phys-discuss.net/12/18107/2012/acpd-12-18107-2012-supplement.pdf.

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Table 1. Variables used to define meteorological modes for $PM_{2.5}$ variability [a].

Variable	Description
x_1	Surface air temperature (K) [b]
x_2	Surface air relative humidity (%) [b]
x_3	Precipitation rate ($mm\,d^{-1}$)
x_4	Sea level pressure (hPa)
x_5	Sea level pressure tendency $dSLP/dt$ ($hPa\,d^{-1}$)
x_6	Surface wind speed ($m\,s^{-1}$) [b,c]
x_7	East-west wind direction indicator $\cos\theta$ (dimensionless) [d]
x_8	North-south wind direction indicator $\sin\theta$ (dimensionless) [d]

[a] From the National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) Reanalysis 1 for 1981–2010. All data are 24-h averages and are deseasonalized as described in the text.
[b] "Surface" data are from 0.995 sigma level.
[c] Calculated from the horizontal wind vectors (u, v).
[d] θ is the angle of the horizontal wind vector counterclockwise from the east. Positive values of x_7 and x_8 indicate westerly and southerly winds, respectively.

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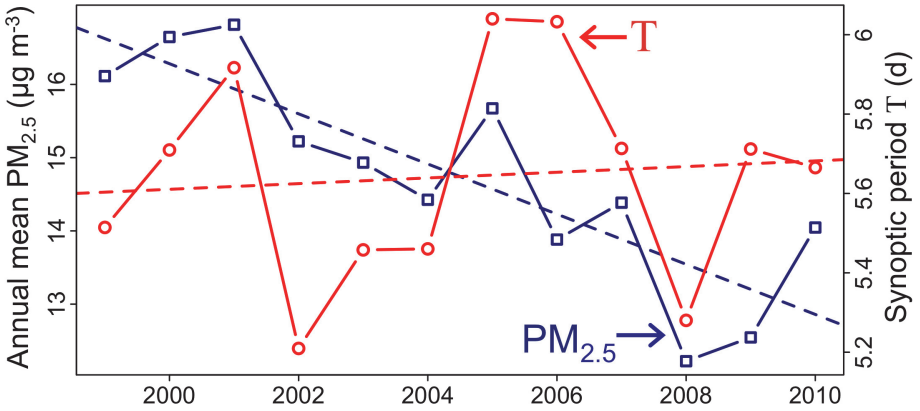

Fig. 1. Observed 1999–2010 time series of annual mean $PM_{2.5}$ and synoptic period T of the dominant meteorological mode (cold frontal passage) for the 4° × 5° grid square centered over Chicago at 42° N 87.5° W (asterisk in Fig. 2). Linear regression lines are shown as dashed. The detrended variables have a correlation of $r = 0.62$.

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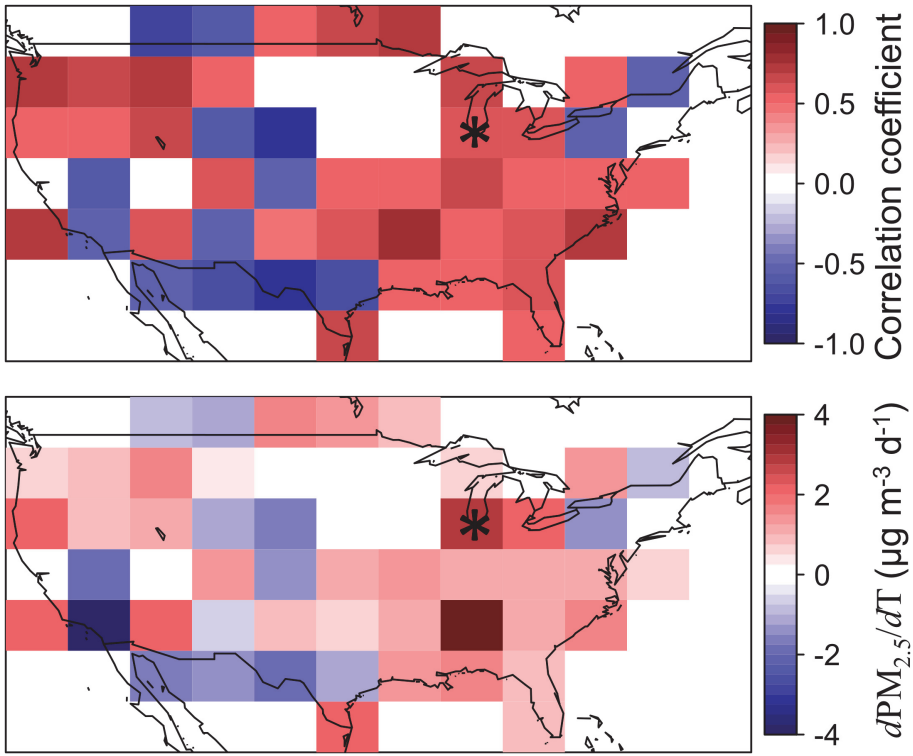

Fig. 2. Interannual correlation of annual mean $PM_{2.5}$ with the period T of the dominant meteorological mode for 1999–2010 observations: correlation coefficients (top) and reduced-major-axis regression slopes $dPM_{2.5}/dT$ (bottom). Only values significant with 90 % confidence (p-value < 0.1) are shown. The asterisk marks the Chicago grid cell for which the time series of $PM_{2.5}$ and T are shown in Fig. 1.

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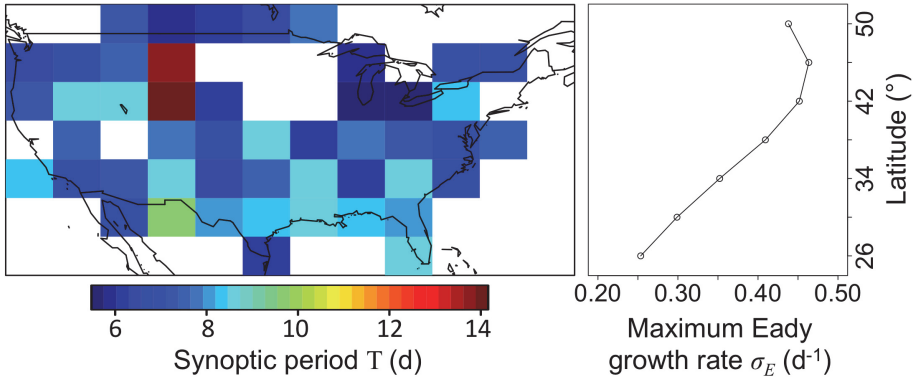

Fig. 3. Mean synoptic periods T of the dominant meteorological modes for interannual $PM_{2.5}$ variability in NCEP/NCAR Reanalysis 1 observations for 1981–2000. Also shown is the latitudinal profile of maximum Eady growth rate σ_E as calculated by Eq. (2) for 0°–180° W and 850–500 hPa.

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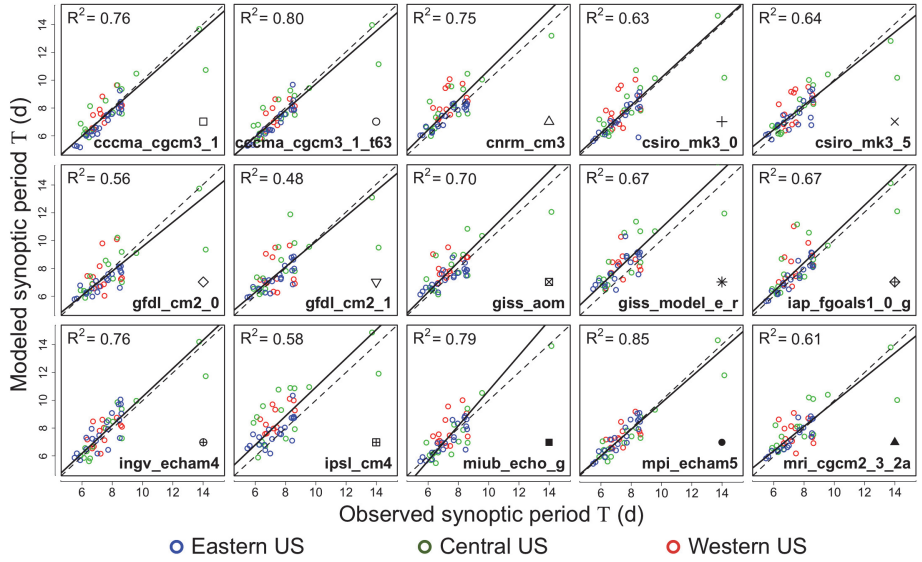

Fig. 4. Scatterplots of modeled vs. observed synoptic periods T of dominant meteorological modes for interannual $PM_{2.5}$ variability in the US for 1981–2000. Observed values are from NCEP/NCAR Reanalysis 1, and modeled values from 15 IPCC AR4 GCMs. GCM names are given in each panel, and the symbol above each name is used to identify the model in Fig. 5 and 7. Each data point represents T for one 4° × 5° grid cell, and the ensemble of points represents the Continental US separated as eastern (east of 95° W), central (110°–95° W), and western (west of 110° W). The solid black line is the reduced major-axis regression slope, with coefficient of variation (R^2) also given. The 1 : 1 line is shown as dashed.

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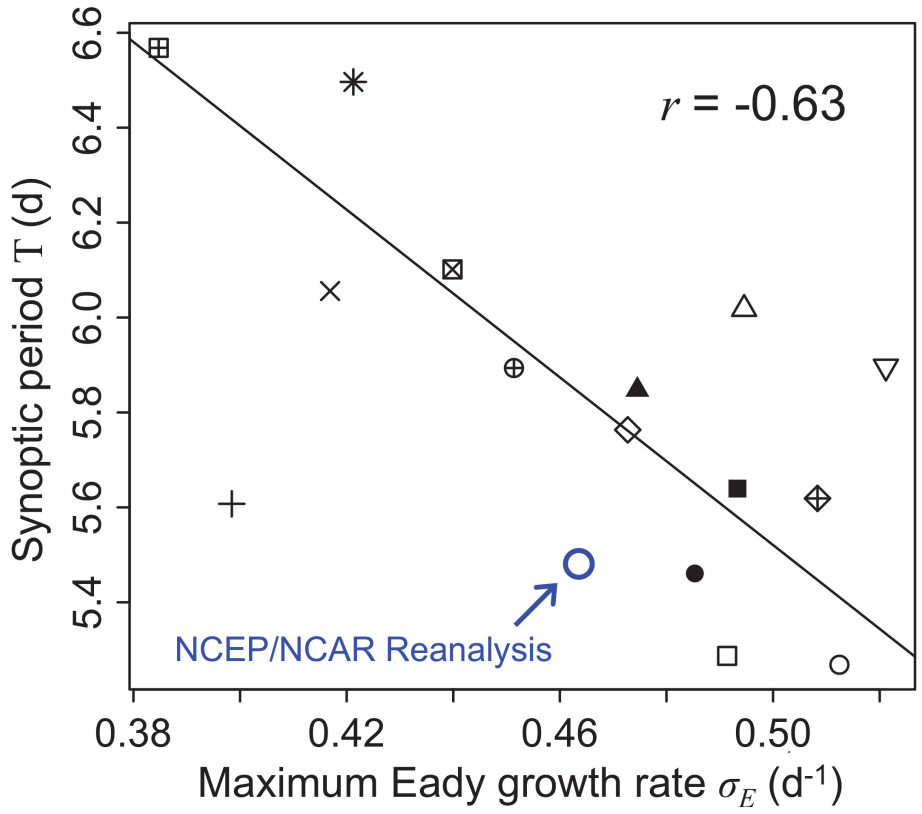

Fig. 5. Relationship between atmospheric baroclinicity and synoptic period T of the dominant meteorological mode for $PM_{2.5}$ variability in the Chicago grid cell as simulated by 15 IPCC AR4 GCMs for 1981–2000. The observed value from the NCEP/NCAR Reanalysis 1 is also indicated. Baroclinicity is measured as the maximum Eady growth rate σ_E for 44°–48° N and 850–500 hPa. Each symbol represents an individual GCM (see Fig. 4). Correlation coefficient and reduced-major-axis regression slope are also shown.

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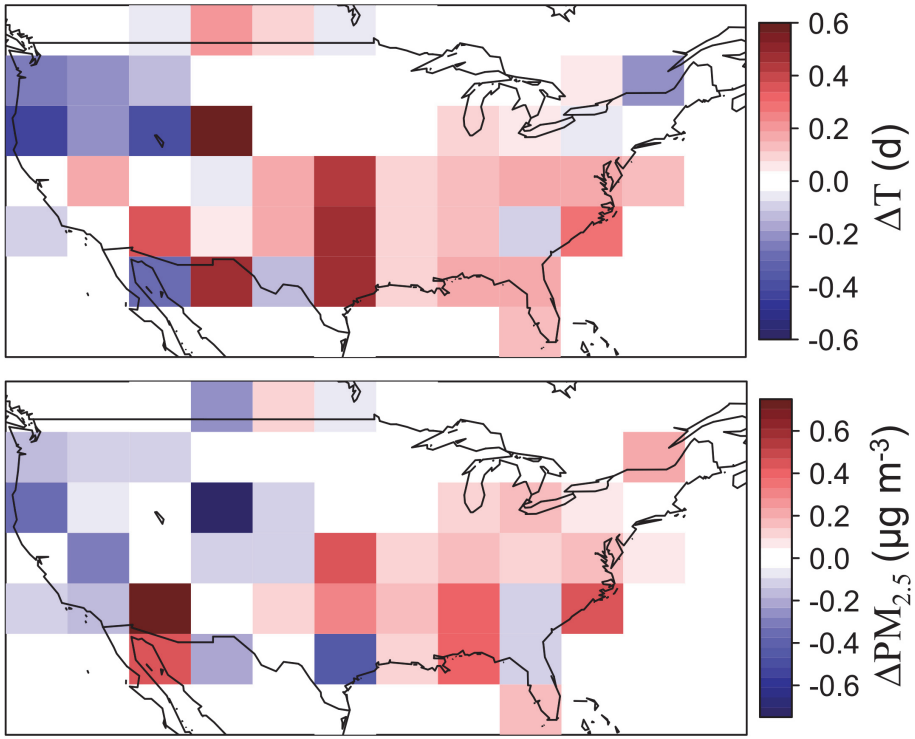

Fig. 6. Projected 2000–2050 changes in the periods of the dominant meteorological modes for $PM_{2.5}$ variability (top), and implied changes in annual mean $PM_{2.5}$ (bottom). The changes in synoptic periods (ΔT) are weighted averages from the ensemble of IPCC AR4 GCMs calculated using the Bayesian-REA approach of Tebaldi et al. (2004, 2005). The implied changes in $PM_{2.5}$ ($\Delta PM_{2.5}$) are calculated as $\Delta PM_{2.5}=(dPM_{2.5}/dT)\Delta T$ where $dPM_{2.5}/dT$ is the local relationship from Fig. 2. When two or more meteorological modes have similar correlation with annual $PM_{2.5}$, an average effect from these modes is calculated.

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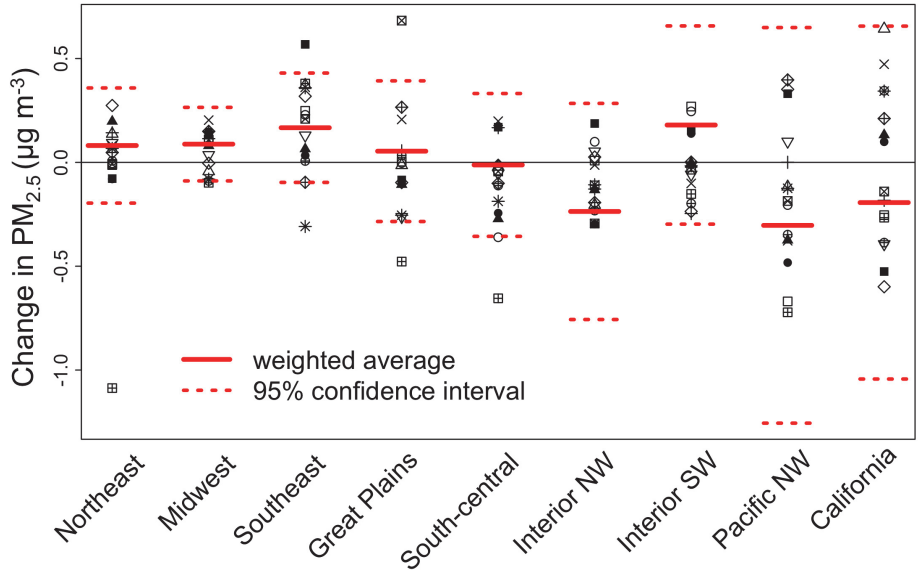

Fig. 7. 2000–2050 regional changes in annual mean $PM_{2.5}$ concentrations due to changes in the periods of dominant meteorological modes for nine US regions. Regional division follows that of Tai et al. (2012). Symbols represent individual IPCC AR4 GCMs (see Fig. 4). Weighted averages and confidence intervals are calculated using the Bayesian-REA approach from Tebaldi et al. (2004, 2005).

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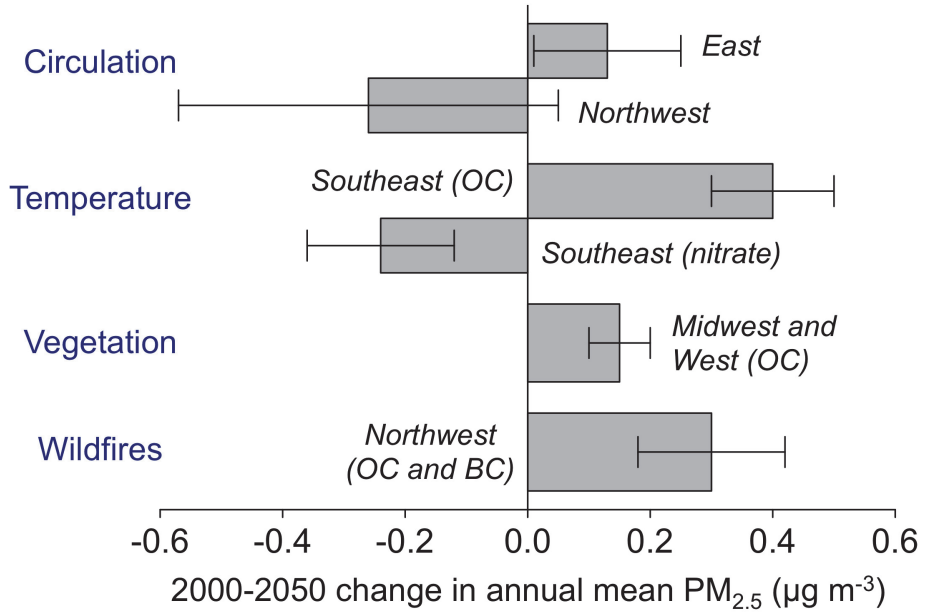

Fig. 8. Summary of projected effects of 2000–2050 climate change on annual $PM_{2.5}$ in the US as driven by changes in circulation (including precipitation), temperature (biogenic emissions and PM volatility), vegetation dynamics, and wildfires. The affected regions and $PM_{2.5}$ components are identified (OC ≡ organic carbon; BC ≡ black carbon). Error bars represent either the approximate range or standard deviation of the estimate. Estimates are from several studies: this work (circulation); Heald et al. (2008), Pye et al. (2009) and Tai et al. (2012) (temperature); Wu et al. (2012) (vegetation); Spracklen et al. (2009) and Yue et al. (2012) (wildfires). All studies used the IPCC SRES A1B scenario for 2000–2050 climate forcing.

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