Atmospheric Environment 89 (2014) 290–297

Contents lists available at ScienceDirect

Atmospheric Environment

journal homepage: www.elsevier.com/locate/atmosenv

A statistical modeling framework for projecting future ambient ozone and its health impact due to climate change

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HIGHLIGHTS

- A statistical framework to estimate future ozone level is developed.
- Ozone projections based on outputs of 8 climate model simulations are examined.
- Calibrated model outputs can reduce projection variation across climate models.
- Higher ozone level and asthma emergency department visit are projected in Atlanta.

ARTICLE INFO

Article history:
Received 4 September 2013
Received in revised form
13 February 2014
Accepted 18 February 2014

Keywords:
Air pollution
Climate change
Emergency department visit
Health impact
Ozone
Statistical model
Uncertainty quantification

ABSTRACT

The adverse health effects of ambient ozone are well established. Given the high sensitivity of ambient ozone concentrations to meteorological conditions, the impacts of future climate change on ozone concentrations and its associated health effects are of concern. We describe a statistical modeling framework for projecting future ozone levels and its health impacts under a changing climate. This is motivated by the continual effort to evaluate projection uncertainties to inform public health risk assessment. The proposed approach was applied to the 20-county Atlanta metropolitan area using regional climate model (RCM) simulations from the North American Regional Climate Change Assessment Program. Future ozone levels and ozone-related excesses in asthma emergency department (ED) visits were examined for the period 2041–2070. The computationally efficient approach allowed us to consider 8 sets of climate model outputs based on different combinations of 4 RCMs and 4 general circulation models. Compared to the historical period of 1999–2004, we found consistent projections across climate models of an average 11.5% higher ozone levels (range: 4.8%, 16.2%), and an average 8.3% (range: −7%–24%) higher number of ozone exceedance days. Assuming no change in the at-risk population, this corresponds to excess ozone-related ED visits ranging from 267 to 466 visits per year. Health impact projection uncertainty was driven predominantly by uncertainty in the health effect association and climate model variability. Calibrating climate simulations with historical observations reduced differences in projections across climate models.

1. Introduction

Tropospheric ozone is an ambient air pollutant regulated worldwide due to its adverse effects on human health (Anenberg et al., 2010) and vegetation (van Dingenen et al., 2009). As a secondary pollutant, ozone is produced through photochemical oxidation of carbon monoxide and volatile organic compounds in the presence of nitrogen oxides and sunlight. Consequently, ozone concentrations are highly sensitive to meteorological conditions and emissions pathways that affect the availability of precursors. Empirical studies have demonstrated associations between observed ozone levels and (1) precursor levels (Nail et al., 2011; Blanchard et al., 2012), and (2) meteorological variables including temperature, air stagnation, wind speed, and cloud cover at various spatial and temporal scales (Jacob and Winner, 2009).

Coherent evidence from climate model simulations suggests that the growing anthropogenic greenhouse gas emissions will likely result in higher surface temperatures and more frequent extreme weather events in the future (Intergovernmental Panel on Climate Change (IPCC) 2012). These environmental changes have

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http://dx.doi.org/10.1016/j.atmosenv.2014.02.037
1352-2310/

the potential to increase future ambient ozone concentrations, which may have important public health implications including increased mortality and morbidity (Murazaki and Hess, 2006). Timely knowledge on the health impacts of climate change can play an important role in supporting regulatory policies that protect public health and maintain environmental sustainability (Menne and Ebi, 2005; Frumkin et al., 2008). While numerous studies have examined projections of future heat-related health outcomes (Huang et al., 2011; Peng et al., 2011), the number of studies on future air pollution-related outcomes is more limited (Sujaritpong et al., 2013).

Previous studies on future ozone projections have predominantly utilized chemical transport models (CTM) driven by climate model outputs (Hogrefe et al., 2004; Knowlton et al., 2004; Bell et al., 2007; Tao et al., 2007; Tagaris et al., 2009; Lei et al., 2012; Orru et al., 2013). These studies have consistently reported global and regional increases in future ozone levels. CTMs are 3-dimensional numerical models that use emissions inventory and meteorological data to simulate the complex atmospheric chemistry and physics involved in ozone formation. While CTMs provide large spatial coverage and incorporate current scientific knowledge on environmental processes, one limitation is that their outputs are deterministic and thus provide only a single projection for a given scenario with no associated measure of uncertainty. Therefore uncertainty quantification on health impact projections based on CTMs has mainly focused on the sensitivity of outputs in response to different emission scenarios and inter-model comparisons (Post et al., 2012).

In this paper we describe a statistical framework for projecting future ozone levels and corresponding emergency department (ED) visit health impacts. In contrast to CTMs, our statistical approach is motivated by its ability to provide measures of uncertainty (in terms of standard errors) for projections under a given scenario. Our approach is also motivated by the increasing interest in evaluating air pollution projection uncertainties that can be used in public health risk assessment (Mastrandrea et al., 2010).

Our framework involves the following steps. First, using historical observations for the period 1999–2004, we develop a statistical *prediction model* of daily ozone concentrations as a function of meteorological variables and important ozone precursors: non-methane volatile organic compounds (VOC), and nitrogen oxides (NO_x). Our prediction model builds upon the extensive literature on statistical models for ambient ozone (Thompson et al., 2001; Cheng et al., 2007; Camalier et al., 2007; Chang et al., 2010). Findings from these models have been used for obtaining air quality forecasts, as well as providing insights on factors that influence ozone concentrations. Second, future ozone concentrations for the period 2041–2070 are then projected using future meteorology from climate model simulations and projected precursor levels as predictors. Finally, using a locally-derived concentration-response function, health impact projections due to climate- and precursor-related changes in future ozone levels are made. Uncertainties in the modeled ozone-meteorology/precursor relationship are propagated through the projection stages and quantified. The approach is applied to the 20-county Atlanta metropolitan area, a region currently with ozone levels exceeding the US National Ambient Air Quality Standards.

An additional important advantage of projecting ozone concentrations using a statistical model is that it requires considerably less computational effort compared to CTMs. Variation in climate simulations by different models is a well-recognized source of uncertainty (Jun et al., 2008; Knutti, 2010). Due to the effort required for running CTMs, previous analyses using these models have typically only examined outputs from one general circulation model (GCM) or one regional climate model (RCM), which makes synthesizing findings across studies difficult. In this analysis using our statistical approach, we made ozone projections based on simulations from multiple climate models. Climate model outputs were obtained from the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al., 2009), which is an international collaboration examining projection variability due to the choice of GCM and RCM. In this study 8 different GCM-RCM combinations were examined.

2. Materials and methods

2.1. Data collection

We acquired individual records of ED visits to acute care hospitals in the 20-county Atlanta metropolitan area for 1999–2004. The ED database is part of the larger Study of Particles and Health in Atlanta (SOPHIA) (Strickland et al., 2010). Using International Classification of Diseases 9th Revision (ICD-9) diagnosis codes, total ED visits due to asthma and wheeze (ICD-9 codes 493 and 786.07) were aggregated on each day. We restricted the study period to the warm months of March to October.

Daily 8-h maximum ozone, 24-h average VOC, and 24-h average NO_x concentrations for 1999–2004 were obtained from the Jefferson St. site, a centrally-located monitor in the SouthEastern Aerosol Research and Characterization (SEARCH) network. Daily meteorological conditions for 1999–2004, including minimum, maximum and average temperature, dew-point temperature, total precipitation, and total solar radiation (global horizontal irradiance), were obtained from the National Climatic Data Center and the National Solar Radiation Data Base for monitors located at the Hartsfield-Jackson Atlanta International Airport.

Climate model outputs of daily maximum surface temperature, 3-h precipitation and 3-h solar radiation were obtained from NARCCAP for the historical period of 1999–2000 and for the future period of 2041–2070. NARCCAP is a public database of RCM simulations available as 50 km by 50 km gridded output. All NARCCAP simulations were conducted under the IPCC Special Report on Emissions Scenarios (SRES) A2 emissions scenario (Nakicenovic, 2000). The A2 scenario represents the higher end of IPCC emission scenarios and entails large population increases, high carbon dioxide emissions, and weak environmental concerns.

To assess uncertainties in RCM projections, we examined NARCCAP simulations from 8 combinations of different RCMs driven by boundary conditions of different GCMs, as available at the time of this analysis. The RCMs include: the Canadian Regional Climate Model (CRCM, http://www.cccma.ec.gc.ca/data/crcm.shtml), the Handley Regional Model 3 (HRM3, http://www.metoffice.gov.uk/precis/), the Regional Climate Model version 3 (RCM3, users.ictp.it/~pubregcm/RegCM3), and the Weather Research & Forecasting model (WRFG, http://www.wrf-model.org/index.php). The GCMs include: the Community Climate model version 3 (CCSM3), the Canadian Global Climate Model version 3 (CGCM3), the Geophysical Fluid Dynamics Laboratory (GFDL) Climate Model version 2.1, and the United Kingdom Hadley Centre Climate Model version 3 (HadCM3). Detailed descriptions on the RCM and GCM characteristics are summarized by NARCCAP online (http://www.narccap.ucar.edu/). The following 8 RCM-GCM combinations were conducted by NARCCAP and examined in this study: CRCM-CCSM, CRCM-CGCM3, HRM3-GFDL, HRM3-HadCM3, RCM3-CGCM3, RCM3-GFDL, WRFG-CCSM, and WRFG-CGCM3. For each combination, we extracted data for the one grid cell that contained the airport monitoring station, as calibrations were not improved when considering data from all grid cells. The 3-h data were processed to obtain daily total precipitation and total solar radiation for the historical and future periods.

2.2. Ozone prediction models

We considered the following process-based statistical model for predicting daily 8-h maximum ozone concentrations: on each day t,

$$Y_t = \beta_0 + \beta_1 \mathrm{NO}_{x_t} + \beta_2 (\mathrm{NO}_{x_t})^2 + \beta_3 \mathrm{NO}_{x_t} \log(\mathrm{VOC}_t) + \nu_t, \qquad (1)$$

where Y_t is the square-root of daily 8-h maximum ozone and ε_t represents daily variation (residual error) not explained by the predictors. The above model is based on work by Nail et al. (2011) and it is intended to account for the complex non-linear relationship between ozone and its precursors. We further assume the regression coefficients are linearly dependent on meteorology. Based on best prediction performance (as described below), in the final model we parameterized β_0 as a function of maximum temperature, solar radiation, and precipitation; β_1 as a function of maximum temperature and precipitation; β_2 as a function of maximum temperature; and β_3 as a function of precipitation. These meteorological variables were selected because of their availability in climate model outputs. We included all main effects of the meteorology, even though some are weakly correlated with ozone, because these variables are related to the ozone production and removal process (Jacob and Winner, 2009). See Supplementary Material Section 1 for detailed model specification. Finally, we allowed for autoregressive residual errors ν_t in order to model additional temporal-dependence due to other unmeasured variables. The residual error accounts for additional physical and chemical processes that are not captured by the predictors. We assumed $\nu_t = \alpha\nu_{t-1} + \varepsilon_t$, where coefficient α is a parameter that controls the strength of temporal correlation, and component ε_t represents independent Normal error. Additional model formulations such as inclusion of relative humidity and wind speed as predictors, transformation of the meteorological variables, and non-linear effects of the meteorological variables, did not improve model fit or prediction performance.

We assessed the prediction performance of the ozone models using an out-of-sample cross-validation approach. Specifically, we divided the complete dataset into ten parts of equal sample size. Repeating the process for each part, one part was then treated as a test dataset while the other nine parts were used for model fitting. Root-mean-squared errors (RMSE) between the back-transformed predicted levels and observed levels for each left-out dataset were evaluated, as well as the empirical coverage probabilities of the prediction intervals.

2.3. Climate model calibration

Prior to application in ozone projections, we performed a statistical calibration of the NARCCAP climate model outputs. This was accomplished by modeling the differences between climate model outputs and observed meteorology during the historical period of 1999–2000 for each parameter of interest (i.e., daily maximum temperature, total precipitation, and total solar radiation). For CRCM-CCSM and WRFG-CCSM, only data during 1999 were available for calibration. Because our objective was not to project daily meteorology, but to assess climate change over a long future period, we considered a rank-based approach that resolves the *distributional* difference between two variables. Specifically, let $x_{[i]}$ and $z_{[i]}$ denote the ith largest value of the observed value and the climate model output, respectively. The rank-based bias correction assumes $x_{[i]} = G(z_{[i]})$, where G denotes a calibration function. We modeled G as a non-linear function using penalized cubic splines. We also constrained G to be non-decreasing in order to maintain a one-to-one mapping between observed and modeled values. In our application, the numbers of observed and modeled values were the same; hence the rank-based approach is equivalent to methods based on sample quantiles (Maurer, 2007; Zhou et al., 2012). This calibration procedure was carried out for each of the three meteorological variables from each RCM-GCM combination separately. The resulting calibration functions were applied to corresponding climate model outputs for the future 2041–2070 period to obtain calibrated future daily meteorological data. We note that one central assumption in this calibration approach is that the bias function estimated using historical data remains unchanged in the future period.

2.4. Ozone projections

Future VOC and NO_x levels were obtained by multiplying the 1999–2004 VOC levels by 8% and NO_x levels by 29%, based on the A2 scenario comparing 2050 to 2000 emission levels for industrialized countries (OECD90) (IPCC, 2000; Hogrefe et al., 2004). To cover the 30-year future period, we repeated the 6-year historical VOC/NO_x time series (increased by 8 and 29%, respectively) 5 times. These data where then combined with future daily meteorological variables (raw and calibrated variables from each of the 8 RCM-GCM combinations) and used as predictors in the ozone prediction models to obtain time-series of daily ozone forecasts for March to October during the period 2041–2070. Because the statistical model was developed based on historical observations, our estimates represent a counterfactual experiment of what ozone levels would have been if future meteorology, VOC and NO_x levels had occurred in the historical period.

Uncertainties in the ozone predictions were quantified by Monte Carlo simulations. Specifically, we first generated 5000 realizations of the regression coefficients from a multivariate Normal distribution based on the parameters' estimated values and covariance matrix. For each parameter realization, we generated a corresponding time-series of the autoregressive ν_t errors. The future VOC, NO_x, and meteorological variables were then applied to the 5000 regression equations for each ozone prediction model, resulting in a total of 5000 simulated time-series of future daily ozone levels for each climate model combination from which the projection intervals were obtained. In the end, for each RCM-GCM combination, our approach incorporated ozone projection uncertainties from two sources: (1) estimation of the ozone model parameters (uncertainty in β's); (2) variations in daily ozone not explained by the predictors (uncertainty due to ν_t).

2.5. Health impact projections

Finally, annual excess ED visits (EED) for asthma/wheeze attributable to future climate-related changes in ambient ozone levels was estimated by

$$\mathrm{EED} = M \times \left(e^{\lambda \Delta X} - 1\right)$$

where M is the expected number of annual ED visits; λ is the estimated association between 3-day moving average 8-h maximum ozone concentrations obtained from a Poisson time-series analysis (See Supplementary Material Section 1); and ΔX is the estimated change in 3-day moving average of 8-h maximum ozone levels between the future period (2041–2070; projected levels) and the historical period (1999–2004; observed levels). Again a Monte Carlo approach was used to obtain estimates of EED and their associated uncertainties. Specifically, 5000 simulations of λ were generated from a Normal distribution based on its estimated value and standard error from the Poisson model. Then, for each RCM-GCM combination, 5000 realizations of EED were obtained by randomly combining realizations of the 5000 β's and 5000 ΔX's based on the ozone projections. Here we report the mean, the 2.5% quantile, and the 97.5% quantile of the EED sampling distribution as the estimated value and its 95% projection/prediction interval (PI) for EED, respectively.

Additional details on all the statistical model formulation and estimation algorithms are provided in the Supplementary materials Section 1.

3. Results

The study included 178,645 asthma/wheeze ED visits (mean of 146 per day) for the 1999–2004 period. Table 1 gives the summary statistics for the observed ozone, NO_x, and VOC levels, and meteorological variables. During this period, the average daily 8-h maximum ozone level at the Jefferson St. monitor was 51.8 ppb (range: 2.2–139 ppb). NO_x and VOC levels were only weakly correlated with the three meteorological variables (correlation <0.20).

We estimated that an interquartile range (IQR, 22 ppb) increase in three-day moving average 8-h maximum ozone concentration was associated with a 1.033 (95% confidence interval, CI_{95}: 1.017, 1.049) increase in daily asthma/wheeze ED visits during March to October. The relative risk estimates were robust against increasing temporal control (Supplementary Fig. S1).

Table 1
Summary statistics of daily 8-h maximum ozone, 24-h NO_x, and 24-h VOC levels and meteorological variables for 1999–2004 (March–October).

	Mean	Median	SD
Ozone (ppb)	51.8	49.5	21.1
Maximum temperature (°F)	79.1	81.0	10.1
Solar radiation (W/m^2)	5128	5484	1787
Precipitation (mm)	0.12	0.00	0.38
NO_x (ppm)	0.037	0.028	0.030
VOC (ppmc)	0.255	0.209	0.161

SD: standard deviation.

Parameter estimates in Equation (1) are given in Supplementary Table S1. Fig. 1 shows daily 8-h maximum ozone levels as a function of NO_x and VOC, given fixed values of maximum daily temperature, solar radiation, and precipitation. The contour lines denote the ozone levels predicted by the model and show clear non-linear relationship. Also higher maximum temperature was associated with higher ozone levels (panel A versus B); and precipitation was associated with lower ozone levels (panel B versus C). We found evidence of moderate temporal correlation between daily ozone levels with the autoregressive parameter α estimated to be 0.54 (CI_{95}: 0.49, 0.58). Our prediction algorithm resulted in an RMSE of 12.6 ppb (range: 12.4–20.0) in daily ozone concentrations. Prediction intervals obtained from the ozone models were also well calibrated where the 95% PI's included the true daily ozone levels 94.3% of the time. Across the entire study period, the out-of-sample predictions gave an average daily 8-h maximum ozone level of 52.4 ppb (95% PI: 51.2–53.7 ppb), which is similar to the true observed average value (Table 1).

Across RCM-GCM combinations, the range of correlation between daily observed and simulated meteorological variables during 1999–2000 were 0.62–0.71 for maximum temperature, 0.15 to 0.34 for solar radiation, and −0.06 to 0.06 for precipitation. To compare the distribution differences between the observations and climate model output, Supplementary Figs. S2–S4 show the empirical cumulative distribution function for each meteorological variable for each RCM-GCM combination. In our study region, climate simulations consistently produced higher than observed daily total solar radiation. The distributions of simulated daily total precipitation differed considerably from the observed data, largely due to discrepancies in simulating no or low precipitation days.

Table 2 presents the changes in maximum temperature, solar radiation, and precipitation (March–October) between the future period (2041–2070) and the historical period (1999–2004) based on climate model outputs from the 8 NARCCAP RCM-GCM combinations. Calibration of climate model outputs reduced variability among the projections as measured by the lower between-model standard deviation. Direction of the projected changes also changed for several models and meteorological variables. Overall,

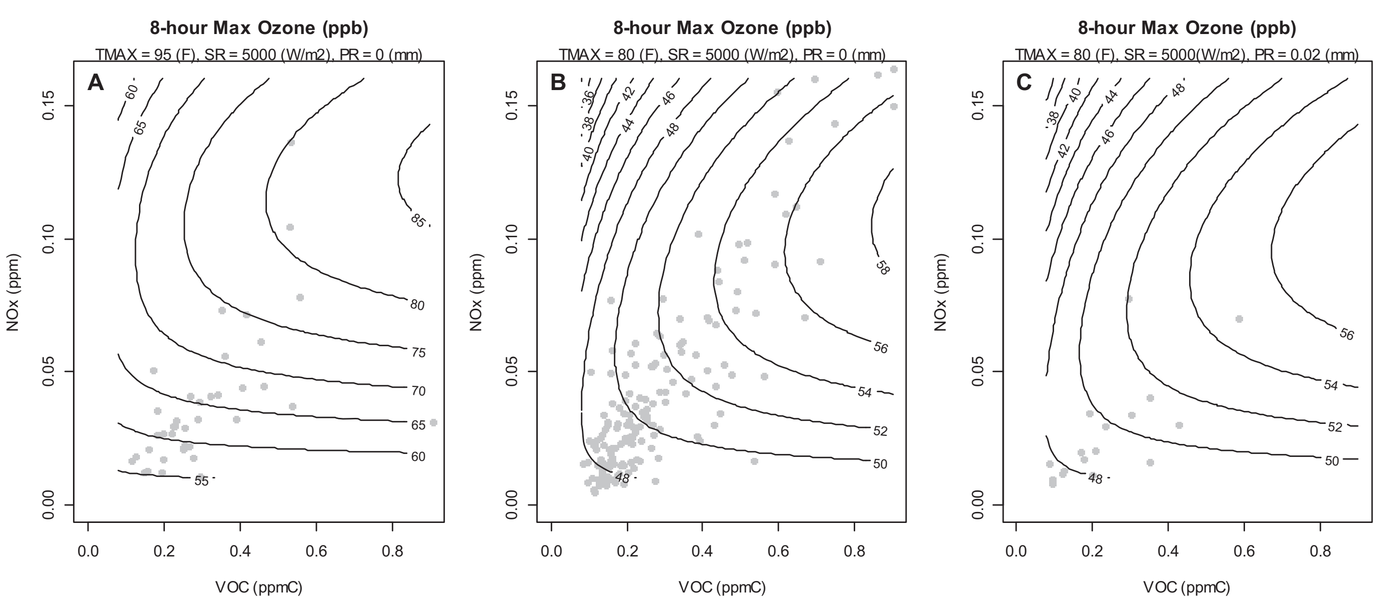

Fig. 1. Contour plots of estimated 8-h maximum ozone as a function of NO_x and VOC at fixed values of maximum daily temperature (TMAX), solar radiation (SR), and daily precipitation (PR). The overlayed scatter plot shows the observed NO_x and VOC values that occurred on days for which TMAX, SR, and PR values were within 7 °F, 1000 W/m^2, and 0.015 mm of the TMAX, SR, and PR values used to calculate the contour plots, respectively. These ranges were selected as half the IQR for each meteorology distribution. Therefore the points represent observed combinations of precursor levels and depict the range of ozone levels associated with these meteorology conditions.

Table 2
Projected changes in average meteorological conditions (March–October) between 2041–2070 and 1999–2004. Quantile calibration was based on climate model outputs from years 1999 and 2000.

Climate models	Max temperature (°F)		Solar radiation (W/m^2)		Precipitation (mm)	
	Raw	Calibrated	Raw	Calibrated	Raw	Calibrated
CRCM-CCSM[a]	10.6	1.8	1068	65	−0.033	0.028
CRCM-CGCM3	4.1	3.9	860	340	0.004	−0.011
HRM3-GFDL	4.9	4.1	693	206	−0.011	−0.014
HRM3-HADCM3	−0.6	−0.1	−89	−320	0.016	−0.002
RCM3-CGCM3	−1.2	4.3	574	257	0.020	−0.036
RCM3-GFDL	−3.6	3.4	417	296	0.015	−0.009
WRFG-CCSM[a]	4.5	2.5	824	−26	−0.046	−0.021
WRFG-CGCM3	−0.5	2.9	427	165	0.001	−0.029
Between-model average	2.25	2.86	597	123	−0.005	−0.013
Between-model SD[b]	4.58	1.48	355	216	0.024	0.019

[a] Only year 1999 was available for calibration.
[b] SD: standard deviation.

using calibrated climate model outputs, we found consistent projections of increased future maximum temperature (3.6%) and solar radiation (2.4%) and decreased future precipitation (9.8%) in the Atlanta region compared to observed levels in 1999–2004.

Table 3 presents projected average daily 8-h maximum ozone levels for 2041–2070 using the raw and calibrated climate model outputs. The 95% projection intervals account for uncertainties in the associations between daily ozone levels, and meteorology and precursor levels. The ensemble estimates were obtained by pooling Monte Carlo simulations from all RCM-GCM pairs. Overall, average ozone levels were projected to be 6.0 ppb (11.5%) higher in the period 2041–2070 compared to the historical period when using calibrated climate model outputs. Again, we found that using calibrated climate model outputs reduced the variability of average projected ozone levels across the different climate model combinations (range: 54.3–60.2 ppb, SD: 1.90 ppb) relative to using the raw outputs (range: 54.0–74.6 ppb, SD: 6.71 ppb). Since most of the PIs of the ozone projections overlapped, it was not possible to identify systematic differences in results by RCM or GCM. We also note that the projection intervals are relatively low (about 3 ppb) and are similar across RCM/GCM.

As an indication of the regulatory and health relevance of these projected ozone levels, we examined the number of days per year during March–October with daily 8-h maximum ozone concentrations exceeding 75 ppb. This threshold corresponds to the US National Ambient Air Quality Standard for ozone, above which levels are considered to be unhealthy for sensitive groups by the US EPA Air Quality Index. The number of exceedance days during the historical period was 34 per year. Calibrated climate simulations projected an increase in the number of exceedance days ranging from −2.6 to 8.3 (−7%–24%) with mean 2.8 (8.3%) per year between 2041–2070 and 1999–2004. Climate model specific estimates and 95% projection intervals are given in Supplementary Table S2.

Table 3
Projected average daily 8-h maximum ozone concentrations (ppb) (March–October) for the 2041–2070 period. 95% projection intervals are given in parenthesis. Estimates are based on 5000 Monte Carlo simulations from ozone prediction model estimated during 1999–2004.

Climate models	Raw	Calibrated
CRCM-CCSM	74.6 (72.6, 76.7)	54.3 (52.8, 55.8)
CRCM-CGCM3	65.0 (63.2, 66.7)	57.5 (56.0, 59.2)
HRM3-GFDL	65.7 (63.9, 67.4)	56.9 (55.3, 58.4)
HRM3-HADCM3	61.1 (59.5, 62.8)	58.8 (57.3, 60.4)
RCM3-CGCM3	56.8 (55.2, 58.4)	60.2 (58.6, 61.9)
RCM3-GFDL	54.0 (52.5, 55.5)	59.9 (58.3, 61.6)
WRFG-CCSM	65.4 (63.6, 67.2)	56.8 (55.3, 58.4)
WRFG-CGCM3	56.4 (54.8, 58.0)	57.7 (56.1, 59.2)
Between-model SD[a]	6.71	1.90
Pooled ensemble	62.4 (53.3, 75.5)	57.8 (53.7, 61.1)

[a] Calculated using the point estimates.

We estimated an expected annual ED visit count for asthma/wheeze of $M = 33{,}551$ based on observed data. Fig. 2 shows the estimated annual EED visits attributable to climate and precursor-related changes in future ozone levels relative to the historical ozone level of 52 ppb (i.e., the 3-day moving average 8-h maximum ozone concentration during 1999–2004). Across RCM-GCM pairs, we found consistent increases in estimated EED visits in the future compared to historical period, especially when calibrated model outputs were used (range of EED visits point estimates: 267 to 466; average of 377 across GCM/RCM combinations). We also considered health impact projections that did not incorporate uncertainties in future ozone levels (indicated by gray color). Specifically, for each RCM-GCM combination, we averaged the projected changes across the 5000 Monte Carlo simulations and used them directly in the EED visit calculations. This only led to a minor reduction in the interval lengths.

4. Discussion

This paper presents an analytic framework that combines observed air pollution, meteorological, and health data, and climate model simulations for estimating future health impacts of air quality. For predicting future ozone concentrations, the advantages and disadvantages associated with using an empirical statistical model versus a CTM are analogous to that between statistical and dynamical downscaling of numerical model outputs (Murphy, 1999; Cooney, 2012). One limitation of a statistical model is that prediction performance can depend on the choice of predictors. Therefore it is crucial that the projection estimates incorporate prediction standard errors that can reflect lack of fit, as done here. A statistical model may also not fully account for the complex non-stationary spatial relationship between ozone and its predictors. To minimize this effect, the study area should be restricted to a geographical region where all variables exhibit limited spatial heterogeneity, as is the case for ozone and meteorology in Atlanta (Wade et al., 2006). Consequently, the local projection provided here does not account for changes in transport of ozone and its precursors, which can contribute to large projection uncertainties (Lei et al., 2012). Moreover, the statistical model developed for projection is specific to both the study location and the chosen reference period. The complex relationship between precursors, other chemicals, and meteorology for ozone production is likely to vary across region and time (Lei and Wang, 2014).

CTM simulations are known to exhibit bias due to errors in inputs and inadequate mathematical representation of the underlying atmospheric processes. For example, Davis et al. (2011) showed that the Community Multiscale Air Quality Model (CMAQ) tends of underestimate how ozone increases with temperature. In the health impact analysis by Hogrefe et al. (2004), the R^2 value between observed and CMAQ modeled daily 8-h maximum ozone values was 0.63, while our ozone prediction model had a slightly higher average R^2 value of 0.66. For CTM projections, changes in ozone levels are obtained by comparing CTM simulations conducted between a historical and a future period. Here the algorithms describing atmospheric processes are assumed to be identical in both periods. In contrast, a statistical modeling approach is based on the empirical association between ozone and meteorology/precursors, which is assumed to hold in the future period.

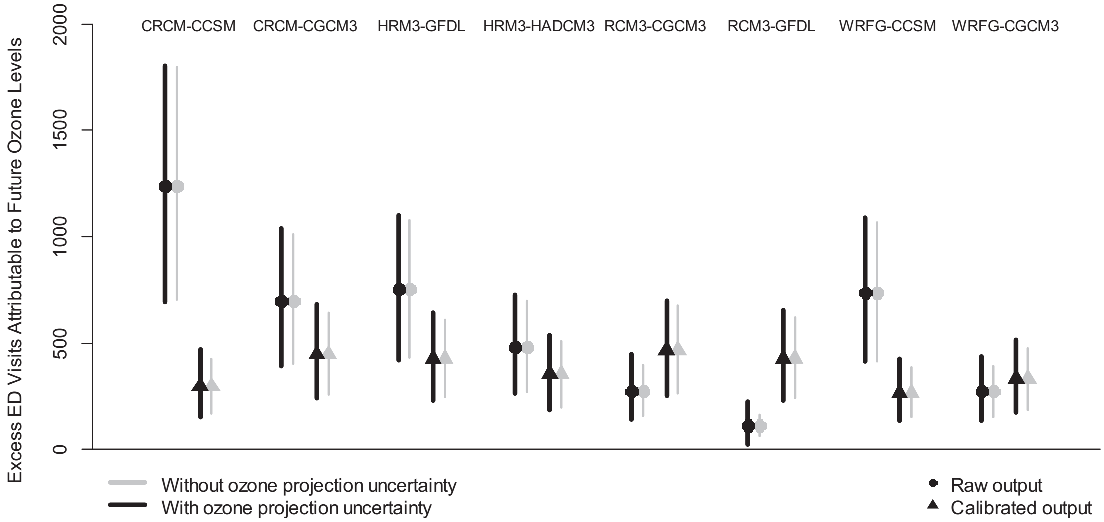

Fig. 2. Projected annual excess number of asthma/wheeze emergency department visits within March to October attributed to changes in average ambient ozone levels between 2041–2070 and 1999–2004. 95% projection intervals are given in parenthesis.

The gain in computational efficiency for projection of future ozone levels allowed us to examine EED visits from 8 GCM-RCM combinations under the common IPCC A2 emissions scenario. There is evidence that the numerical biases in GCM can be amplified by RCM (Noguer et al., 1998). Our results demonstrate that by calibrating and downscaling gridded raw climate model output against historical observations, we reduced disagreement in the projection estimates from different climate models. Similar findings have been shown recently for modeling extremes (Ahmed et al., 2013). An important future research direction is developing ensemble approaches to synthesize results from different climate models (Kang et al., 2012; Chanlder, 2013).

This work has potentially significant public health implications. EDs are likely to be particularly stressed under climate change based on the specific populations that they serve, including the very young, elderly, and underserved (Hess et al., 2009). Characterizing acute morbidity via ED visits is thus central for public health planning and emergency preparedness related to climate change. We note that our applied findings of 377 EED visits per year attributable to climate-related changes in ozone levels in the future compared to historical period in Atlanta suggest only a small percentage ($\approx$1%) increase over the current expected annual ED visit numbers of 33,551. However, our estimates should be viewed as conservative from a public health impacts perspective for several reasons. ED visits more likely represent severe asthma exacerbation, and do not account for less severe morbidity experienced by the broader population, for which patients may self-medicate or visit outpatient clinics.

Previous analyses on the health impacts of future ozone levels have mainly focused on mortality and hospital admissions due to cardiovascular and respiratory disease and over a larger geographical domain. Nonetheless, our results are consistent with several studies using CTMs in the United States. Under the A1B business-as-usual emission scenario, Tagaris et al. (2009) found a moderate increase in annual daily maximum 8-h ozone between 2050 and 2001 in the state of Georgia. Under the A2 emissions scenario, both Hogrefe et al. (2004) and Bell et al. (2007) found an increase in summertime daily maximum ozone in the 2040's and 2050's over the Atlanta region compared to historical levels. For example, focusing solely on the impact of altered future climate, Bell et al. (2007) observed a 4–8% increase in summertime 1-h daily maximum ozone levels between the 2050's and 1990's in Atlanta using current-day precursor levels. The average number of 8-h maximum ozone NAAQS exceedance days per summer were estimated to increase to approximately 34 in the 2050's compared to approximately 28 in the 1990's (a 21% increase) (Bell et al., 2007), similar to the estimated increase in ozone exceedance days of −7% to 24% per year in the current analysis. Across 50 eastern US cities in the Bell et al. study, climate-related changes in ozone were projected to result in an average 2.1% increase in hospital admissions for asthma. This estimated percentage increase in hospital admissions was larger than observed in the current analysis for ED visits. Comparison of results, however, is difficult considering the different geographic scales, health outcome types, and ages considered (e.g., focus on the nonelderly by Bell et al.) and differences in specificity of the concentration-response function (e.g., Bell et al. applied a previously published function observed for the Seattle population).

The proposed framework to project future ozone levels can also be utilized to examine additional uncertainties. First, this study only examined the SRES A2 scenario in order to compare variation due simulations from different GCM/RMC combinations; however different emission scenarios can contribute large variability in projections (Tao et al., 2007; Lei et al., 2012). Second, we only considered one scenario for future VOC and NO_x levels. Other future projections of changes in VOC/NO_x levels can be used to account for technological development and policy implementations in response to climate change (Liao et al., 2007; Wardekker et al., 2012). Particularly, we did not distinguish biogenic versus anthropogenic VOC. Because biogenic emission is more sensitive to climate change, a more in-depth account of VOC associated with future vegetation growth is desirable (Guenther et al., 2012).

For the IPCC 5th Assessment Report, future climate simulations have been conducted under 4 representative concentration pathways (RCPs), reflecting a range of possible trajectories of future greenhouse gas concentrations (Moss et al., 2010). The A2 scenario in this study falls within the higher end of the RPC projections based on future temperature increases (Rojelj et al., 2012). Concurrently, a set of Shared Socio-economic Pathways (SSPs) have been developed to examine how various socio-economic scenarios can result in future climates associated with the 4 RCPs (van Vuuren et al., 2011). Under different storylines, the SSPs include quantitative projections in population demographics (accounting for fertility and migration), urbanization, and economic development from different projection models. The SSP data will play an important role in evaluating additional uncertainties related to health impact assessment not examined in this study. For example, health impact projections can be sensitive to age-structure because children and the elderly may be more susceptible to the acute health effects of air pollution (Silverman and Ito, 2012; Park et al., 2013). Sensitivity to changes in wealth distribution is also possible as ED utilization varies across socioeconomic strata (Largent et al., 2012), possibly due to disparity in effective asthma management and access to health care (Ungar et al., 2011). Finally, population growth and the influence of increasing asthma prevalence, especially in vulnerable populations, should also be considered (Moorman et al., 2012.) In this study, uncertainty in the health effect of ozone contributes considerably in the health impact interval estimates. This underscores the need of continual epidemiological research on identifying vulnerability to environmental stressors among sub-populations and obtaining the corresponding concentration-response functions for health impact assessment.

In summary, we describe a computationally efficient statistical modeling approach to project future ozone level and its health impacts. We found an increase in ED visits due to asthma and wheeze that is attributable to future increases in ambient ozone concentrations during 2041–2070 in the Atlanta metropolitan area. Sensitivity of EED projections to choice of climate model combination, climate model calibration, and ozone projection uncertainty was assessed. Ultimately, uncertainties in the EED projections were mainly due to uncertainties in the health association and climate model variation.

Acknowledgments

This study was partially supported by USEPA grant R834799 and NIH grant 1R21ES023763. Its contents are solely the responsibility of the grantee and do not necessarily represent the official views of the USEPA. Further, USEPA does not endorse the purchase of any commercial products or services mentioned in the publication. We wish to thank the NARCCAP for providing the data used in this paper. NARCCAP is funded by the National Science Foundation (NSF), the U.S. Department of Energy (DoE), the National Oceanic and Atmospheric Administration (NOAA), and the USEPA Office of Research and Development.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.atmosenv.2014.02.037.

References

Ahmed, K.F., Wang, G., Silander, J., Wilson, A.M., Allen, J.M., Horton, R., Anyah, R., 2013. Statistical downscaling and bias correction of climate model outputs for climate change impact assessment in the U.S. northeast. Global and Planetary Change 100, 320–332.

Anenberg, S.C., Horowitz, L.W., Tong, D.Q., West, J.J., 2010. An estimate of the global burden of anthropogenic ozone and fine particulate matter on premature human mortality using atmospheric modeling. Environmental Health Perspectives 118, 1189–1195.

Bell, M.L., Goldberg, R., Hogrefe, C., Kinney, P., Knowlton, K., Lynn, B., Rosenthal, J., Rosenzweig, C., Patz, J.A., 2007. Climate change, ambient ozone, and health in 50 US cities. Climate Change 1, 61–76.

Blanchard, C.L., Hidy, G.M., Tanenbaum, S., 2012. NMOC, ozone, and organic aerosol in the southeastern United States, 1999–2007: 2. Ozone trends and sensitivity to NMOC emissions in Atlanta, Georgia. Atmospheric Environment 44, 4840–4849.

Camalier, L., Cox, W., Dolwick, P., 2007. The effects of meteorology on ozone in urban areas and their use in assessing ozone trends. Atmospheric Environment 33, 7127–7137.

Chanlder, R.E., 2013. Exploiting strength, discounting weakness: combining information from multiple climate simulators. Philosophical Transactions of the Royal Society A. http://dx.doi.org/10.1098/rsta.2012.0388.

Chang, H.H., Zhou, J., Fuentes, M., 2010. Impact of climate change on ambient ozone level and mortality in Southeastern United States. International Journal of Environmental Research and Public Health 7, 2866–2880.

Cheng, C.S., Campbell, M., Li, Q., Li, G., Auld, H., Day, N., Pengelly, D., Gingrich, S., Yap, D., 2007. A synoptic climatological approach to assess climatic impact on air quality in South-central Canada. Part I: historical analysis. Water, Air, & Soil Pollution 182, 131–148.

Cooney, C.M., 2012. Downcaling climate models: sharpening the focus on local-level changes. Environmental Health Perspectives 120, a22–a28.

Davis, J., Cox, W., Reff, A., Dolwick, P., 2011. A comparison of CMAQ-based and observation-based statistical models relating ozone to meteorological parameters. Atmospheric Environment 45, 3481–3487.

Frumkin, H., Hess, J., Luber, G., Malilay, Josephine, McGeehin, 2008. Climate change: the public health response. American Journal of Public Health 98, 435–445.

Guenther, A.B., Jiang, X., Heald, C.L., Sakulyanontvittaya, T., Duhl, T., Emmons, L.K., Wang, X., 2012. The model of emissions of gases and aerosols from Nature version 2.1 (MEGAN2.1): an extended and updated framework for modeling biogenic emissions. Geoscientific Model Development Discussion 5, 1503–1560.

Hess, J.J., Heilpern, K.L., Davis, T.E., Frumkin, H., 2009. Climate change and emergency medicine: impacts and opportunities. Academic Emergency Medicine 16, 782–794.

Hogrefe, C., Lynn, B., Civerolo, K., Ku, J.Y., Rosenthal, J., Rosenzweig, C., Golberg, R., Gaffin, S., Knowlton, K., Kinney, P.L., 2004. Simulating changes in regional air pollution over the eastern United States due to changes in global and regional climate and emissions. Journal of Geophysical Research 109. http://dx.doi.org/10.1029/2004JD004690.

Huang, C., Barnett, A.G., Wang, X., Vaneckova, P., FitzGerald, G., Tong, S., 2011. Projecting future heat-related mortality under climate change scenarios: a systematic review. Environmental Health Perspectives 119, 1681–1690.

Intergovernmental Panel on Climate Change (IPCC), 2000. In: Nacenovic, N., Swart, R. (Eds.), Special Report on Emissions Scenarios. Cambridge Univ. Press, New York.

Intergovernmental Panel on Climate Change (IPCC), 2012. In: Barros, C.B.,V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA.

Jacob, D.J., Winner, D.A., 2009. Effect of climate change on air quality. Atmospheric Environment 43, 51–63.

Jun, M., Knutti, R., Nychka, D.W., 2008. Spatial analysis to quantify numerical model bias and dependence: how many climate models are there? Journal of the American Statistical Association 103, 934–947.

Kang, E.L., Cressie, N., Sain, S.R., 2012. Combining outputs from the North American regional climate change assessment program by using a Bayesian hierarchical model. Journal of the Royal Statistical Society: Series C (Applied Statistics) 61, 291–313.

Knowlton, K., Rosenthal, J.E., Hogrefe, C., Lynn, B., Gaffin, S., Goldberg, R., Rosenzweig, C., Ku, J.-Y., Kinney, P.L., 2004. Assessing ozone-related health impacts under a changing climate. Environmental Health Perspectives 112, 1557–1563.

Knutti, R., 2010. The end of model democracy? Climatic Change 102, 395–404.

Largent, J., Nickerson, B., Cooper, D., Delfino, R.J., 2012. Paediatric asthma hospital utilization varies by demographic factors and area socio-economic status. Public Health 126, 928–936.

Lei, H., Wuebbles, D., Liang, X.-H., 2012. Projected risk of high ozone episodes in 2050. Atmospheric Environment 59, 567–577.

Lei, H., Wang, J.X.L., 2014. Sensitivities of NOx transformation and the effects on surface ozone and nitrate. Atmospheric Chemistry and Physics 14, 1385–1396.

Liao, K.J., Tagaris, E., Manomaiphiboon, K., Napelenok, S.L., Woo, J.H., He, S., Amar, P., Russell, A.G., 2007. Sensitivities of ozone and fine particulate matter formation to emissions under the impact of potential future climate change. Environmental Science & Technology 41, 8355–8361.

Mastrandrea, M.D., Field, C.B., Stocker, T.F., Edenhofer, O., Ebi, K.L., Frame, D.J., Held, H., Kriegler, E., Mach, K.J., Matschoss, P.R., Plattner, G.C., Yohe, G.W., Zwiers, F.W., 2010. Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties. Intergovernmental Panel on Climate Change (IPCC), Geneva, Switzerland.

Maurer, E.P., 2007. Uncertainty in hydrologic impacts of climate change in the Sierra Nevada, California under two emission scenarios. Climate Change 82, 309–325.

Mearns, L.O., Gutowski, W.J., Jones, R., Leung, L.-Y., McGinnis, S., Nunes, A.M.B., Qian, Y., 2009. A regional climate change assessment program for North America. EOS 90, 311–312.

Menne, B., Ebi, K.L. (Eds.), 2005. Climate Change and Adaptation Strategies for Human Health. Dr Dietrich Steinkopff Verlag GmbH & Co. KG, Germany.

Moorman, J.E., Akinbami, L.J., Bailey, C.M., Zahran, H.S., King, M.E., Johnson, C.A., Liu, X., 2012. National surveillance of asthma: United States, 2001–2010. Vital Health Statistics 3, 1–67.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P., Wilbanks, T.J., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747–756.

Murazaki, K., Hess, P., 2006. How does climate change contribute to surface ozone change over the United States? Journal of Geophysical Research 111. http://dx.doi.org/10.1029/2005JD005873.

Murphy, J., 1999. An evaluation of statistical and dynamic techniques for downscaling local climate. Journal of Climate 12, 2256–2284.
Nail, A.J., Hughes-Oliver, J.M., Monohan, J.F., 2011. Quantifying local creation and regional transport using a hierarchical space–time model of ozone as a function of observed NO_x, a latent space–time VOC process, emissions, and meteorology. Journal of Agricultural, Biological, and Environmental Statistics 16, 17–44.
Nakicenovic, N. (Ed.), 2000. Special Report on Emissions Scenarios: a Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, New York, NY, USA.
Noguer, M., Jones, R., Murphy, J., 1998. Sources of systematic errors in the climatology of a regional climate model over Europe. Climate Dynamics 14, 691–712.
Orru, H., Andersson, C., Ebi, K.L., Langner, J., Astrom, C., Forsberg, B., 2013. Impact of climate change on ozone-related mortality and morbidity in Europe. European Respiratory Journal 41, 285–294.
Park, M., Luo, S., Kwon, J., Stock, T.H., Delclos, G., Kim, H., Yun-Chul, H., 2013. Effects of air pollution on asthma hospitalization rates in different age groups in metropolitan cities of Korea. Air Quality, Atmosphere and Health 6, 543–551.
Peng, R.D., Bobb, J.F., Tebaldi, C., McDaniel, L., Bell, M.L., Dominici, F., 2011. Toward a quantitative estimate of future heat wave mortality under global climate change. Environmental Health Perspectives 119, 701–706.
Post, E.S., Grambsch, A., Weaver, C., Morefield, P., Huang, J., Leung, L.Y., Nolte, C.G., Adams, P., Liang, X.Z., Zhu, J.H., Mahoney, H., 2012. Variation in estimated ozone-related health impacts of climate change due to modeling choices and assumptions. Environmental Health Perspectives 120, 1559–1564.
Rojelj, J., Meinshausen, M., Knutti, R., 2012. Global warming under old and new scenarios using IPCC climate sensitivity range estimates. Nature Climate Change 2, 248–253.
Silverman, R.A., Ito, K., 2012. Age-related association of fine particles and ozone with severe acute asthma in New York City. Journal of Allergy and Clinical Immunology 2010, 367–373.
Strickland, M.J., Darrow, L.A., Klein, M., Flanders, W.D., Sarnat, J.A., Waller, L.A., Sarnat, S.E., Mulholland, J.A., Tolbert, P.E., 2010. Short-term associations between ambient air pollutants and pediatric asthma emergency department visits. American Journal of Respiratory and Critical Care Medicine 182, 307–316.
Sujaritpong, S., Dear, K., Cope, M., Walsh, S., Kjellstrom, T., 2013. Quantifying the health impacts of air pollution under a changing climate – a review of approaches and methodology. International Journal of Biometeorology. http://dx.doi.org/10.1007/s00484-012-0625-8.
Tagaris, E., Liao, K., Delucia, A.J., Deck, L., Amar, P., Russel, A.G., 2009. Potential impact of climate change on air pollution-related human health effects. Environmental Science & Technology 43, 4979–4988.
Tao, Z., Williams, A., Huang, H.-C., Caughey, M., Liang, X.-Z., 2007. Sensitivity of US surface ozone to future emissions and climate changes. Geophysical Research Letters 34, L08811.
Thompson, M.L., Reynolds, J., Cox, L.H., Guttorp, P., Paul, Sampson, 2001. A review of statistical methods for the meteorological adjustment of tropospheric ozone. Atmospheric Environment 35, 617–630.
Ungar, W.J., Paterson, J.M., Gomes, T., Bikangaga, P., Gold, M., To, T., Kozyrskyj, A.L., 2011. Relationship of asthma management, socioeconomic status, and medication insurance characteristics to exacerbation frequency in children with asthma. Annals of Allergy, Asthma & Immunology 106, 17–23.
van Dingenen, R., Dentener, F.J., Raes, F., Krol, M.C., Emberson, L., Cofala, J., 2009. The global impact of ozone on agricultural crop yields under current and future air quality legislation. Atmospheric Environment 43, 604–618.
van Vuuren, D., Riahi, K., Moss, R., Edmonds, J., Thomson, A.M., Nakicenovic, N., Kram, T., Berkhout, F., Swart, R., Janetos, A., Rose, S., Arnell, N., 2011. A proposal for a new scenario framework to support research and assessment in different climate research communities. Global Environmental Change 22, 21–35.
Wade, K.S., Mulholland, J.A., Marmur, A., Russell, A.G., Hartsell, E.E., Edgerton, E., Klein, M., Waller, L., Peel, J.L., Tolbert, P.E., 2006. Effect of instrument precision and spatial variability on the assessment of the temporal variation of ambient air pollution in Atlanta, Georgia. Journal of Air Waste Management 56, 876–888.
Wardekker, J.A., de Jong, A., van Bree, L., Turkenburg, W.C., van der Sluijs, J.P., 2012. Health risks of climate change: an assessment of uncertainties and its implications for adaptation policies. Environmental Health 11, 67.
Zhou, J., Chang, H.H., Fuentes, M., 2012. Estimating the health impacts of climate change with calibrated model output. Journal of Agricultural, Biological, and Environmental Statistics 17, 377–394.