Efficient Pollution Regulation: Getting the Prices Right
Appendix A: The Air Pollution Emission Experiments and Policy Analysis Model (APEEP)

1 INTRODUCTION

Conceptually, two approaches to integrated assessment modeling exist. One method attempts to capture the complexities of environmental processes by including exhaustive representations of these mechanisms in the model. The principal advantage of the "process" modeling strategy is the inclusion of methods considered to be the state-of-the-science in each discipline. However, the time and cost necessary to build and implement such a model is often prohibitive. Another approach models the environment with a simpler representation designed to mimic the essential elements of the process. The advantage of the reduced form model is that it is fast and inexpensive to operate across various scenarios. The document describes a new integrated assessment model, The Air Pollution Emissions Experiments and Policy (APEEP) model, that employs this reduced form approach. It is designed for simulating the consequences of policy scenarios and emissions experiments.

APEEP is designed to calculate the marginal damages corresponding to emissions of SO_2, VOC, NO_x, $PM_{2.5}$, PM_{10} and NH_3 on a dollar-per-ton basis. Damages include adverse effects on human health, reduced yields of agricultural crops and timber, reductions in visibility, enhanced depreciation of man-made materials, and damages due to lost recreation services. The model focuses on damages at the margin in order to weigh marginal damages against the marginal costs of abatement.

APEEP is sensitive to the spatial variation in the damages imposed by emissions. Specifically, the model determines the damages stemming from emissions at nearly 10,000 sources in the contiguous U.S. This fine-grained geographic approach is designed to detect possible heterogenous effects of pollution emitted from rural, suburban, and urban sites. APEEP's structure allows the researcher to alter emissions in a particular location by any amount. By holding all other aspects of the model fixed, one is able to determine the effects due to the prescribed change in emissions. This facilitates an assessment of both the spatial distribution of damages (on the county level of detail) resulting from particular emissions and of the magnitude of such damages. This feature has potentially broad application in the analysis of air pollution policy.

Marginal damages are calculated in the following way. The model first estimates baseline damages for each pollutant (corresponding to observed 2002 emissions). Next, APEEP adds one ton to the baseline emissions for a particular source county. The model then computes the difference in damages between the two emissions scenarios. Since all other components of the model are held fixed, the resulting difference is the damage-per-ton of a particular pollutant emanating from the selected source county. APEEP features pre-designed algorithms which make such computations quite rapid. Further, APEEP contains a set of algorithms which repeat this experiment (adding one ton to baseline emissions) for each of the approximately 10,000 sources in the contiguous 48 states and for PM_{10}, $PM_{2.5}$, VOC, NO_x, NH_3 and SO_2 .

2 METHODS

2.1 EMISSIONS

The emissions module consists of annual emission vectors for PM_{10}, $PM_{2.5}$, VOC, NO_x, NH_3 and SO_2[1] provided by the U.S. Environmental Protection Agency (USEPA). APEEP's emission module relies on the USEPA's 2002 National Emissions Inventory (NEI). This is the USEPA's most recent NEI. The USEPA differentiates between emissions from mobile, point and non-point sources. APEEP aggregates emissions from ground-level area sources, including mobile and non-point sources, to the county level. This yields 3110 area sources. Additionally, low point sources (effective height of less than 250 meters) and emissions from mid-level point sources (effective height between 250 and 500 meters) are also aggregated to the county-level. The model encompasses aggregated emissions from low and medium point sources in each of the 3110 counties in the lower 48 states. In contrast, high point sources (effective height greater than 500 meters) are treated at the plant level. This decomposition of sources corresponds to the Climatological Regional Dispersion Model (CRDM) described below (Latimer 1996; USEPA, 2004). Additionally, USEPA distinguishes between anthropogenic sources of $VOC's$ (which fall into the source categories above) and biogenic sources of VOC. The biogenic emission inventory is aggregated to the county level and is provided by the USEPA's Biogenic Emissions Inventory System ($BEIS$).

2.2 AIR QUALITY MODELING

The air quality modeling module makes use of a source-receptor matrix framework. That is, the marginal contribution of emissions in a source county (s) to the ambient concentration in a receptor county (r) is represented as the (s, r) element in a matrix[2]. The model contains source-receptor matrices for the following pollutants in both summer and winter: $NO_x \rightarrow NO_x$ $SO_2 \rightarrow SO_2$. The matrix governing the relationship between NO_x emissions, VOC emissions and O_3 concentrations is calibrated to the summer season. The matrices representing formation and transport of particulates ($PM_{2.5} \rightarrow PM_{2.5}$ $PM_{10} \rightarrow PM_{10}$ $NO_x \rightarrow PM$ $SO_2 \rightarrow PM$ $NH_3 \rightarrow NH_4$ $VOC \rightarrow PM$) produce annual means.

[1] Emissions are represented in short tons = 2000 lbs.

[2] The emission data provided by USEPA represent annual emissions $\left(\frac{tons}{year}\right)$. Since the source-receptor matrices require emissions in $\left(\frac{g}{s}\right)$, the emissions data are converted to such units prior to their introduction to the model. In their raw form, the resulting ambient concentration estimates are in $\left(\frac{g}{m^3}\right)$. These estimates are converted to micro-grams per cubic meter $\left(\frac{\mu g}{m^3}\right)$, parts per billion by volume ($ppbv$), and parts per million by volume ($ppmv$).

2.2.1 Particulate Matter

This portion of the air quality module uses source-receptor matrices produced by the Climatological Regional Dispersion Model (CRDM) (Latimer, 1996; USEPA, 2004). There are four particulate matter (PM) source-receptor matrices installed in APEEP; a primary PM matrix governing directly emitted PM_{10} and $PM_{2.5}$ as well as emissions of primary volatile organic compounds (VOC) which contribute to secondary organic aerosols, a matrix which governs the transformation of NO_x emissions into nitrates, a matrix capturing the relationship between ammonia emissions (NH_3) and ammonium (NH_4) concentrations, as well as a matrix which captures the transformation of SO_2 emissions into sulfates. These matrices accept annual emission vectors as inputs, generating estimates of the annual mean concentrations for each receptor location. Each of these matrices include a distinct set of transfer coefficients for ground level area sources, and the three point source heights explained above.

APEEP employs CRDM to compute the ammonium-sulfate-nitrate equilibrium which determines the amount of ambient ammonium sulfate $(NH_4)_2 SO_4$ and ammonium nitrate (NH_4NO_3) at each receptor county. The equilibrium computations reflect several fundamental aspects of this system. First, ambient ammonium (NH_4) reacts preferentially with sulfate (H_2SO_4). Second, ammonium nitrate is only able to form if there is excess (NH_4) after reacting with sulfate. Finally, particulate nitrate formation is a decreasing function of temperature - so the ambient temperature at each receptor location is incorporated into the equilibrium calculations. In order to translate VOC emissions into secondary organic particulates, APEEP employs the fractional aerosol yield coefficients estimated by Grosjean and Seinfeld (1989). These coefficients represent the yield of particulates corresponding to emissions of gaseous $VOC's$.

Updates to CRDM CRDM was developed in the middle 1990's (Latimer, 1996). The inventory of point sources included in the original model reflects conditions at that time. As a result, using the 2002 NEI with this model requires substantial modifications to encompass new point sources at all three stack heights. The following strategy was employed in order to accommodate new point sources with an effective height of emissions less than 250 meters. Since the low point source matrix embodies source-receptor relationships that are aggregated to the county level, the first step was to determine whether new sources came online in counties not covered by the original CRDM low point source inventory (encompassing 1885 counties). The construction of new sources in many counties outside the extent of CRDM (roughly 700 counties) motivated the development of transfer coefficients for all of the counties in the contiguous states. While accommodating new sources in the 2002 NEI, this universal coverage will also make APEEP able to accommodate new sources in future emission inventories. We used a simple statistical procedure to extrapolate from the low point source transfer coefficients in CRDM to the remaining 1225 counties. For each source county with both a set of

low point transfer coefficients and area source transfer coefficients (s), we compute the ratio of the low-point coefficients (L_{sr}) to the area source coefficients (A_{sr}) at each of the 3110 county receptors (r). This is shown in equation (1).

$$R_{sr} = \left(\frac{L_{sr}}{A_{sr}}\right) \tag{1}$$

Next, the ratio vector (R_{sr}) is ranked according to increasing distance from the source county (s). Then, the ranked ratio vectors for each of the 1885 counties with low-point coefficients (R_{sr} for $s = 1, ..., 1885$) are assembled into a $(1885, 3110)$ matrix (D). The first column of D contains the R_{sr} corresponding to the nearest receptor to each source. We compute the mean of each column.

$$\bar{R}_r = \frac{1}{1885}\sum_{s=1}^{1885}(R_{sr}) \tag{2}$$

Transposing this vector yields a $(3110, 1)$ vector ($\bar{R}$) containing the spatial averaged ratio of low-point coefficients to area source coefficients ranked by distance to the source location. The final step is to multiply ($\bar{R}$) by the area source coefficients for each row that corresponds to counties without low-point source transfer coefficients. However, prior to multiplication by ($\bar{R}$), the area source coefficients are ranked according to increasing distance. This ensures that the A_{s1}, corresponding to the nearest receptor to source (s), is adjusted according to $\bar{R}_1$; the ratio of low-point coefficients to area source coefficients at the minimum distance between source and receptor. The above procedure is repeated for each of the 1225 counties without low-point source transfer coefficients in the original CRDM configuration. We then repeat this process for the 2737 counties without transfer coefficients for medium-height point sources; those with an effective height between 250 and 500 meters. There are 91 new tall point sources in the 2002 emission inventory that were not modeled in the original version of CRDM. These are modeled at the plant level.

2.2.2 NO_x

In addition to modeling the contribution of NO_x emissions to PM levels, APEEP uses a Gaussian dispersion model to characterize the relationship between primary NO_x emissions and concentrations of NO_2, and an empirical model that computes concentrations of tropospheric O_3.

Ambient concentrations of NO_2 at a receptor county (r) are estimated using the following formula[3] (Turner, 1994).

[3] All computations that rely on meteorological data employ observations from the National Oceanic and Atmospheric Administration's (NOAA) Integrated Surface Hourly data sets for (1995-1999).

$$C_r = \sum_{s=1}^{S} \left[\left(\frac{E_s \theta_{sd} f_w f_d f_c}{\pi \mu_{sd} \sigma_{yd} \sigma_{zd}} \right) \; e^{\left(-\frac{H_{sd}^2}{2\sigma_z^2} \right)} \right] \tag{3}$$

C_r is the sum of the contribution from emissions in each of the (S) sources to ambient concentrations in receptor county (r). E_s represents the NO_x emissions from source (s), θ_{sd} denotes the probability that the wind, in the source county, blows from the direction required to send the emissions to receptor (r). H_{sd} is the effective height of emissions in source county (s), conditional on the wind blowing from direction (d). The effective height of emissions is computed using formulae and parameters estimated by Briggs (1969, 1971, 1975) which are summarized by Seinfeld and Pandis (1998) and Turner (1994). The remaining parameters $(\pi, \mu_{sd}, \sigma_{yd}, \sigma_{zd})$ are, respectively: the constant pi, the wind speed in source county (s) conditional on the wind blowing from direction (d), the horizontal dispersion parameter, and the vertical dispersion parameter, both conditional on the wind direction (d), (Pasquill, 1961). The Gaussian model also includes terms for wet and dry deposition (f_w, f_d) and for the loss of NO_x due to its transformation into PM and into tropospheric O_3 (f_c).There are two $NO_x \rightarrow NO_2$ source-receptor matrices, one estimated using summer meteorological conditions and one estimated using winter meteorological conditions. The resulting matrices accept seasonal emission vectors as inputs.

2.2.3 Tropospheric Ozone (O_3)

O_3 is not directly emitted into the troposphere. Instead a series of chemical reactions contribute to its formation. Two directly emitted precursors to tropospheric O_3 are the oxides of Nitrogen (NO_x) and VOC (Seinfeld, Pandis, 1998). Ambient concentrations of tropospheric O_3 are predicted using an empirical model estimated using VOC, NO_x and O_3 observations from the USEPA's AIRS network. The model captures many of the factors contributing to ambient concentrations of O_3; these include forests and agricultural land uses which produce biogenic hydrocarbons, as well as the ambient air temperature and several geographic variables. The model is specified as follows.

$$\log(O_3) = \beta_0 + \beta_1 (Hour) + \beta_2 (Hour)^2 + \beta_3 (NO_x) + \beta_4 (VOC) + \beta_5 (CO) + \beta_6 Veg + \beta_7 T + \beta_8 G \tag{4}$$

where: O_3 = Ambient Ozone (ppbv)
β_i = (for i = 1,...8) statistically estimated (OLS) parameter
$Hour$ = Hour in the day
NO_x = County Ambient NO_x (ppbv)
VOC = County Ambient VOC level (ppbv).
CO = County Ambient CO level (ppbv).

Veg = Index of (%) land area in each county covered by four forest regimes and agricultural land uses
T = County Ambient air temperature (F)
G = Index of geography variables (latitude, longitude, altitude, metropolitan binary variable, California binary variable)

An offline regression model employs ordinary least squares to produce the parameter estimates (β). Using these fixed parameter estimates, this empirical model is used to generate a surface of predicted ambient O_3 concentrations; the summer average value for each county. The inclusion of both the linear and quadratic forms of the NO_x, CO, and VOC variables allow for the nonlinearity known to exist in O_3 production chemistry, (Seinfeld, Pandis, 1998). Specifically, the quadratic forms capture titration in areas where the background concentration of NO_x is sufficiently high. This is critical in certain urban areas, where O_3 readings tend to be lower than the surrounding suburbs and rural areas. APEEP initially produces baseline NO_2 and VOC concentrations and uses those estimates in the above model to derive baseline O_3 concentrations. Following a NO_x emissions experiment, new ambient NO_2 levels are inserted into the O_3 model resulting in new O_3 concentrations. The same experimental structure is used for VOC emission experiments.

2.2.4 SO_2

In addition to modeling the contribution of SO_2 emissions to PM levels in the PM module, APEEP uses a Gaussian dispersion model to characterize the relationship between primary SO_2 emissions and concentrations of SO_2.

Ambient concentrations of SO_2 at a receptor county (r) are estimated using the following formula (Turner, 1994).

$$C_r = \sum_{s=1}^{S} \left[\left(\frac{E_s \theta_{sd} f_w f_d f_c}{\pi \mu_{sd} \sigma_{yd} \sigma_{zd}} \right) \; e^{\left(-\frac{H_{sd}^2}{2\sigma_z^2} \right)} \right] \tag{5}$$

The primary difference between the Gaussian model used for SO_2 dispersion and that employed for NO_x, are the wet and dry deposition terms and the chemical transformation rate for $SO_2 \rightarrow PM$. Much like the approach to modeling NO_x, the above model is used to compute separate source-receptor matrices for summer and winter meteorological conditions. The resulting matrices accept seasonal SO_2 emission vectors as inputs.

2.2.5 Within County Dispersion

For emissions contributing to PM, APEEP relies on the within-county modeling (contributions of emissions from a source county to ambient concentrations in the same county) embodied in the CRDM matrices

(USEPA, 2004). Source-receptor relationships for within-county dispersion of $NO_x \rightarrow NO_2$ and $SO_2 \rightarrow SO_2$ are estimated in the following manner. The model begins by computing the land area of each county. The counties are assigned to one of nine treatment groups based on the land area (see table 1). Within the treatment groups, each county is subdivided into smaller, equally-sized gridcells. Using the Gaussian models shown above, the source-receptor relationships are estimated between each of the gridcells within a county. The emissions in the county are distributed evenly among the gridcells. After estimating the transfer coefficients between each combination of gridcells, the mean coefficient among these "own-county" gridcells is calculated. This mean coefficient is then used to model the relationship between emissions in a county and the resulting ambient concentration in that same county.

When modeling "own-county" dispersion, the model employs Briggs (1973) urban dispersion parameters if the source county lies in a Standard Metropolitan Statistical Area. These parameters are only used for within-county dispersion since Briggs (1973) suggests they are only valid up to a distance of 10,000 meters - roughly 6 miles. If the county is not part of an SMSA, the standard Pasquill-Gifford dispersion parameters are employed.

2.2.6 Removal of Pollutants in the Atmosphere

Wet and dry deposition processes are modelled using constant deposition velocities for NO_x and SO_2. The rates are displayed in Table 2. For dry deposition, the model uses the distance between a source and a receptor, divided by wind speed and the mixing height (M). For wet deposition, the model uses the distance between a source and a receptor, divided by wind speed. These computations are shown below in equations (6), (7), and (8). The output is interpreted as the fraction of material removed by each process. Thus, the model computes one minus the fraction removed, or, the fraction remaining after transport to the receptor. This permits f_d and f_w to enter multiplicatively into the Gaussian models.

Atmospheric transformation (f_c) of SO_2 and NO_x into particulates is modeled using rate constants Φ_{pc} derived from the CRDM (USEPA, 2004). It is important to note that each of these parameter values are those used by the developers of the CRDM source-receptor matrices which, in this model, govern the air quality modeling of PM. By employing these same values, APEEP accounts for the loss of primary emitted NO_x and SO_2 at the same rate as the particulates module. This maintains a critical degree of internal consistency. The loss of NO_x to the formation of O_3 is tabulated in a proportional fashion.

$$f_d = 1 - \left(\left(\frac{\Phi_{pd}(cm)}{s}\right) \times \left(\frac{distance(km)}{1}\right) \times \left(\frac{1(hr)}{\mu(km)}\right) \times \left(\frac{3600s}{hr}\right) \times \left(\frac{1}{M(m)}\right) \times \left(\frac{m}{100(cm)}\right)\right) \quad (6)$$

$$f_w = 1 - \left(\left(\frac{\Phi_{pd}}{in} \right) \times \left(\frac{Rain(in)}{yr} \right) \times \left(\frac{distance(km)}{1} \right) \times \left(\frac{1(hr)}{\mu(km)} \right) \times \left(\frac{yr}{8760(hr)} \right) \right) \tag{7}$$

$$f_c = 1 - \left(\left(\frac{\Phi_{pc}(\%)}{hr} \right) \times \left(\frac{distance(km)}{1} \right) \times \left(\frac{1(hr)}{\mu(km)} \right) \right) \tag{8}$$

2.3 EXPOSURES

Because the consequences of policy are related to the number of sensitive receptors involved, APEEP calculates population-weighted exposures (PE). APEEP captures changes in population-weighted exposures corresponding to changes in emissions by calculating the difference between exposures in the baseline emission scenario, and after each emission experiment.

$$PE_r = [Pop_r] \times [C_{pr}] \tag{9}$$

where: Pop_r = population in receptor county (r)
C_{pr} = ambient concentration of pollutant (p) in receptor county (r)
PE_r = Population-weighted exposures in receptor county (r)

It is important to note that the term population above refers to the inventory of sensitive receptors in a certain receptor location. These inventories are not restricted to counting people. Rather the model includes inventories of each receptor type: crops, forests, people, materials, visibility resources and ecological resources related to recreation uses.

Exposures are modeled in six distinct areas: human health, agriculture, forests, man-made materials, visibility and recreation. The correct measurement of pollution exposures depends on the measure used in the dose-response studies. Most studies rely on the concentration of outdoor air pollution as a proxy measurement for exposures[4]. Hence, APEEP computes exposures using estimates of outdoor air pollution at each receptor county generated by the air quality model. The following discussion addresses how APEEP organizes a variety of data into populations of sensitive receptors and how the model computes exposures of crops, trees, people, recreation services, materials and visibility resources.

2.3.1 HUMAN HEALTH

APEEP calculates population-weighted exposures to each pollution species separately for each of the 19 age groups reported by the U.S. Census Bureau. This permits an analysis of the air pollution exposures for people

[4] Including most epidemiological studies and crop experiments.

of different ages. Such detailed exposure analysis is particularly useful since the epidemiological literature indicates that certain portions of the population show differing levels of susceptibility to pollution. This data is necessary to determine the magnitude of the populations at risk in each county. Local populations at risk are calculated by aggregating among age groups in each county. Thus, if an epidemiological study focuses on persons greater than 65 years of age, the population at risk is calculated by adding the number of persons in each age category greater than 65 years in each receptor county. Exposures are then calculated by multiplying this population at risk by the predicted ambient concentration.

2.3.2 AGRICULTURE

Exposures are calculated by multiplying reported county crop yields times the seasonal mean O_3 concentration. APEEP includes county-level yield inventories of alfalfa, lettuce, tobacco, corn, cotton, peanuts, dry edible beans, grain sorghum, soybeans, spring wheat and winter wheat[5]. This approach stems from the use of empirical dose-response functions which use seasonal mean O_3 concentrations (Lesser et al., 1990).

2.3.3 FORESTS

The forest module measures exposures to O_3 concentrations separately for coniferous and broadleaf species groups, (Hoggsett, et al., 1997; Pye 1988; Reich 1987). The model contains an inventory of the total growth of each species group in each county. The data necessary for this approach is provided by the U.S. Forest Service's Forest Inventory and Analysis Databases[6]. These datasets provide mortality (M), removals (R), and net growth (NG), from which the growth (G) by species group, by county, is derived[7].

$$G_{fr} = NG_{fr} + R_{fr} + M_{fr} \tag{10}$$

where : f = forest species group (Hardwood, Softwood)
r = receptor county

Exposures are computed by multiplying the (G_{fr}) times the seasonal mean O_3 level.

2.3.4 MAN-MADE MATERIALS

Calculating exposures of man-made materials to air pollution requires the development of an inventory that characterizes the quantity of such materials in each county in the lower 48 states (Freeman, 1982). APEEP

[5] County-level crop inventories are available from the USDA Agriculture Census: http://www.nass.usda.gov:81/ipedb/
[6] http://www.ncrs2.fs.fed.us/4801/FIADB/fim_tab/wc_fim_tab.asp
[7] All measurements in cubic board feet

calculates exposures of carbonate stone, galvanized steel, carbon steel, and painted wood surfaces to county seasonal average concentrations of SO_2.

Using empirical results from the U.S. Department of Energy's Residential Energy Consumption Survey and the Annual Housing Survey conducted by the U.S. Census Bureau, the model computes the exposed surface area of each building material in each receptor county. This depends on estimates of the number of buildings (including single-family homes, multi-family homes, and business establishments), the average structure size for each building type, and the probability of each material being used in each region of the country[8].

The calculations take the following form.

$$SA_{rm} = \sum_{t=1}^{3} (N_{rt})(S_{rt})(P_{mr}) \tag{11}$$

where : SA_{rm} = Exposed surface area of building material (m) in receptor county (r)
N_{rt} = Number of Structures type (t) in county (r)
S_{rt} = area of exterior wall space per structure, county (r)
P_{mr} = Probability material (m) used on exterior wall space in county (r)

For infrastructural materials (galvanized and painted carbon steel), the inventory relies on methods developed in the National Acid Precipitation Assessment Program, (SOST III, NAPAP 1990). In particular, researchers in NAPAP calculated surface area estimates for galvanized and carbon steel (focusing on bridges, transmission towers, railroads, and guardrail) for the state of New York. The ratios of exposed surface area to land area are then extrapolated to other geographic areas. Exposures are computed as the product of the estimated seasonal mean SO_2 concentrations and the estimated surface area of each material in each county.

2.3.5 VISIBILITY

APEEP measures visibility using visual range (miles). The empirical studies that examine the economic significance of visibility calculate the willingness-to-pay for small changes in visibility at the household level (Chestnut, Rowe, 1990, Chestnut, Dennis, 1997). Thus, the relevant population for quantifying exposures

[8] The DOE (1983) study provides structure size in terms of floor space (ft^2). Thus, with a simplifying assumption regarding the shape of the structure (we assume that each residential structure is cubic with two stories of living space) the conversion from floor space to wall space is straightforward. That is, the total area of living space is equivalent to twice the area of one story. Thus, given our cubic shape assumption, the area of the four walls is equivalent to four times the area of one story, or two times the total living area.

Characterisitcs of commercial structures are provided by the U.S. DOE Energy Information Administration's Commercial Buildings Energy Consumption Survey. Detailed data is found at the following site: ftp://ftp.eia.doe.gov/pub/consumption/commercial/cb954.pdf

Characterisitcs of residential structures are provided by the U.S. Census Bureau's American Housing Survey. Detailed data is found at the following site:

http://www.census.gov/hhes/www/housing/ahs/ahs.html

is the number of households on the county-level. Exposures are estimated by multiplying the number of households times the baseline visual range times the estimated seasonal mean PM_{10} concentration.

2.3.6 RECREATION

APEEP focuses on the incremental effects of pollution on recreation usage in forest ecosystems (NAPAP, SOST III, 1990). APEEP calculates exposures in the following way; acres of forested land in each county are multiplied by the number of recreation visitor days times the estimated ambient concentrations of O_3, NO_x and SO_2.

2.4 DOSE-RESPONSE

APEEP employs dose-response functions (also frequently called concentration-response functions and exposure-response functions) to translate ambient concentrations and exposures into various physical effects; hospital admissions, premature deaths, decreased agricultural and forestry yields, enhanced depreciation of man-made materials, declining recreation use, and reduced visibility[9]. APEEP relies on peer reviewed studies to provide statistically estimated dose-response functions for the following fields: human health, agriculture, and man-made materials. Since peer-reviewed dose-response functions pertaining to timber, visibility and ecosystem effects are not available, APEEP employs empirical models estimated from experimental data reported in peer-reviewed studies.

2.4.1 HUMAN HEALTH

To model dose-response relationships between human health and exposures to air pollution the model relies on peer-reviewed studies in the epidemiological literature. APEEP is equipped to use results from Pope et al. (2002) to model the impact of long-term exposures to $PM_{2.5}$ on county-level non-accidental mortality rates[10]. The model uses results from Klemm and Mason (2004) to determine the effect of short-term exposures to $PM_{2.5}$ on mortality rates. Findings from Bell et al. (2004) translate acute exposures to O_3 into changes in mortality rates. The impact of each air pollutant on the incidence rates of a variety of illnesses (morbidity states) are modeled using studies cited in table 3.

The statistical models used to estimate dose-response functions are typically log-linear models.

$$\log\left(\frac{Y}{Pop}\right) = \alpha + \gamma X + \beta C + \varepsilon \tag{12}$$

[9] See tables 3 through 6 for the list of dose-response functions used in this analysis.

[10] APEEP is also equipped to use the dose-response functions from Krewski et al. (2000) and the recent update to Dockery et al. (1993) in Laden et al., (2006).

where: α, β, γ = statistically estimated parameters
C = ambient concentration of pollutant
X = factors associated with incidence of health state: age, income, personal habits (smoking, etc.)
ε = stochastic term
$\left(\frac{Y}{Pop}\right)$ = ratio of persons with health state (Y) to total population

In order to convert the logarithmic form of the dependent variable to a linear form we must exponentiate both sides of equation (12). This yields (13).

$$\left(\frac{Y}{Pop}\right) = \exp^{(\alpha+\gamma X+\beta C)} \tag{13}$$

We define the baseline incidence rate (IR) as a function of (X).

$$IR = \exp^{\alpha+\gamma X} \tag{14}$$

Substituting (14) and multiplying through by population, the number of health events is:

$$Y = \left[IR \times \exp^{(\beta C)}\right] \times Pop \tag{15}$$

Finally, the change in the number of health events attributable to a change in concentration is computed using (16).

$$\Delta Y = IR \times \left[\left(\exp^{(\beta C_p)}\right) - \left(\exp^{(\beta C_b)}\right)\right] \times Pop \tag{16}$$

where: C_p = ambient concentration (emission perturbation)
C_b = ambient concentration (baseline emissions)
ΔY = estimated change in health event (cases, deaths, admissions)

2.4.2 AGRICULTURE

Dose-response functions for agricultural crops from the National Crop Loss Assessment Network (Lesser et al.,1990) are employed in APEEP. The dose-response functions are of the following form (table 4):

$$CY^* = \left(1 - \ e^{-\left(\frac{O_3}{\sigma}\right)^{\gamma}}\right) \times CY^b \tag{17}$$

where: CY^* = crop yield after emissions perturbation
CY^b = baseline (observed) crop yield, 1996
O_3 = 7 or 12-hour daily mean O_3 concentrations (ppmv)
γ = statistically estimated dimensionless shape parameter
σ = statistically estimated parameter

The model then calculates the relative yield loss.

$$RYL = 1 - \left(\frac{CY^*}{CY^b}\right) \tag{18}$$

The RYL expresses the change in yield as a proportion of the baseline yield. To derive the yield loss in absolute terms, the model multiplies the estimated RYL times the baseline yield.

$$\Delta CY = RYL \times CY^b \tag{19}$$

2.4.3 MAN-MADE MATERIALS

Dose-response functions for man-made materials damages are obtained from the NAPAP studies (Atteras, Haagenruud, 1982; Baedecker, 1990; Haynie, Spence, Lipfert, 1989) and from more recent experiments conducted by The International Cooperative Programme on Effects on Materials (ICP), (table 6).

The materials corrosion dose-response functions assume three slightly different forms. The functions representing the effect of ambient SO_2 on galvanized steel assume the following form.

$$\Delta M = (\beta_0 SO_2 + \beta_1) \times M \tag{20}$$

where: ΔM = Mass loss of material
β_0, β_1 = statistically estimated parameter
SO_2 = ambient concentration of pollutant
M = existing material mass

The functions representing the effect of ambient SO_2 on painted surfaces include terms for the surface wetness, and annual rainfall.

$$\Delta M = \beta_0 R + \beta_1 SO_2 \times Freq \tag{21}$$

where: ΔM = Mass loss of material
β_0, β_1 = statistically estimated parameters

SO_2 = ambient concentration of pollutant
$Freq$ = fraction of time surface is wet
R = annual rainfall (cm)

The functions representing the effect of ambient SO_2 on carbonate stone surfaces take the following form.

$$\Delta S = (\beta_0 SO_2^{\kappa}) \exp^{\gamma T} + (\beta_1 R)\, H^+ \tag{22}$$

where: ΔS = surface recession of painted surface (μm)
$\beta_0, \beta_1, \kappa, \gamma,$ = statistically estimated parameters
SO_2 = ambient concentration of pollutant
T = ambient temperature (C^o)
R = annual rainfall (mm)
H^+ = Hydrogen$^+$ concentration of precipitation $(\frac{mg}{L})$

2.4.4 FORESTS

APEEP uses linear dose-response functions relating incremental changes in O_3 concentrations to changes in tree growth. The functions are estimated from experimental results in Reich, (1987) and Pye, (1988). The following example illustrates the method used.

Reich (1987) reveals a correspondence between broadleaf tree growth and O_3 dose; a 20 ppm-hour dose produces a 13% reduction in yield. Thus, to extrapolate, the necessary mathematical operation is to normalize the dosage to 1 ppm-hour and calculate the proportional yield reduction associated with this dose.

The relation is characterized as follows:

$$\Delta Y = \beta_H \left(O_3 \ ppm\text{-}hr\right). \tag{23}$$

where: ΔY = change in yield bft^3
β_H = proportional relation between O_3 dose and growth of hardwood species

Using Reich's correspondence:

$$-0.13(bft^3) = \beta_H \left(20^{\ ppm-hour}\right) \tag{24}$$

solving for β:

$$\frac{-0.13}{20} = \beta_H = -0.0065 \left(\frac{bft^3}{ppm - hour}\right) \tag{25}$$

For hardwood species, the dose-response function takes the following form:

$$\Delta Y = (\beta_H O_{3p} - \beta_H O_{3b}) \times G \tag{26}$$

where: ΔY = change in timber growth $\left(bft^3\right)$
β_H = estimated parameter $\left(\frac{bft^3}{ppm-hour}\right)$
G = observed, annual timber growth $\left(bft^3\right)$
O_{3b} = baseline O_3 $(ppm - hour)$
O_{3p} = perturbation O_3 $(ppm - hour)$

For coniferous species, the dose-response function takes the following form:

$$\Delta Y = (\beta_C O_{3p} - \beta_C O_{3b}) \times G \tag{27}$$

where: β_C = proportional relation between O_3 dose and growth of coniferous species

2.4.5 VISIBILITY

APEEP uses an empirical model which describes the visual range in each county as a function of climatic and geographical factors and ambient concentrations of PM_{10}. An off-line regression model estimates the empirical relationship between visual range (observations from NOAA's Integrated Surface Hourly Data) and PM_{10} (USEPA's AIRS network) while controlling for temperature, precipitation, latitude, longitude, and altitude. While this is an innovative approach to translating changes in ambient concentrations of pollution into changes in visibility, the components of the regression model are based on the fundamental principles of atmospheric science pertaining to visibility (Seinfeld, Pandis, 1998) and the parameter estimates characterize empirical relationships existing in the data. In order to calculate local visual range, the following steps are necessary:

1) Due to the log-linear functional form of the regression model, the baseline visual range is equivalent to:

$$VR_1 = exp^{(\beta + \gamma C + \delta G + \theta P + \varepsilon)} \tag{28}$$

where: $\theta, \beta, \gamma, \delta$ = statistically estimated parameters
C = county climate data (temp, precipitation)
G = county geographical data (latitude, longitude, altitude)
P = county baseline PM_{10} concentration
ε = stochastic term
VR_1 = baseline visual range (miles)

2) Design and implement an experimental emissions scheme.
3) Estimate new ambient concentrations of PM_{10}, P'.
Repeat Step 1) to generate VR_2

$$VR_2 = exp^{(\beta+\gamma C+\delta G+\theta P'+\varepsilon)} \tag{29}$$

The regression model serves as a dose-response function for visibility; relating an incremental change in PM_{10} levels to changes in visibility.

2.4.6 RECREATION

The dose-response component of the recreation module employs an empirically estimated regression function to translate changes in ambient concentrations of two air pollutants into changes in forest mortality.

$$M = \beta_0 + \beta_1 SO_2 + \beta_2 O_3 + \beta_3 NO_x + \beta_4 G \tag{30}$$

where: M = Forest Mortality (ft^3)
β = statistically estimated parameters
G = geographic variables: county population, latitude, longitude, altitude, land area
SO_2,O_3, NO_x = ambient concentration (ppbv)

In the second stage regression model, recreation use is described as a function of (among other factors) forest mortality.

$$RVD = \beta_0 + \beta_1 M + \beta_2 C + \beta_3 V \tag{31}$$

where: RVD = recreation visitor days[11]
M = Forest Mortality (ft^3)
β = statistically estimated parameters
C = climate variables: annual average temperature (F), precipitation (in)
V = growing stock (bft)

Using this two-stage approach, emissions perturbations affect ambient pollution levels, impacting forest mortality, which then affects recreation usage. Hence, the regression models characterize the dose-response relationships for recreation effects; relating an incremental change in pollution levels to changes in recreation usage.

[11] RVD's are the total visits to national parks, state parks, national forests, state forests, and Bureau of Land Management land holdings.

2.5 VALUATION

In the dose-response module, APEEP measures the physical consequences of air pollution in terms of different units; visual range reported in miles, timber growth in cubic board feet, crop yields in bushels, recreation in visits, and human health in cases or hospital admissions. Without the application of some common metric to these disparate effects, comparing the effects of emissions would not be possible in a rigorous fashion. To resolve this issue, economists propose using market prices for commodities traded in organized markets and shadow-prices for goods and services not traded in markets (Freeman, 2003; Mendelsohn, 1980). Analytically, valuation establishes a means by which the researcher may directly compare the consequences of emissions. This step also permits a rigorous comparison of the consequences of emissions with the costs of abatement. All dollar values reported in APEEP reflect constant, year-2000 U.S. dollars.

Applying valuation techniques also necessitates a consideration of the time horizon over which commodities affected by pollution are consumed. For market goods that are consumed in the current year (crops), the valuation exercise is reduced to applying market prices to the change in yield due to altered ambient concentrations which stem from emission perturbations. For timber resources, the model computes the present value of changes to the inventory of timber due to emission experiments, since standing timber is harvested in multiple time-periods. For materials, the model values the present value of the cost of maintenance. For example, if, due to pollution, exterior paint must be replaced every four years instead of five, the model calculates the increase in the present value of those costs. Valuation is considerably more complicated for damages corresponding to the goods and services not traded in market settings: visibility, human health, and ecosystem services.

In the non-market valuation literature, economists frequently distinguish between revealed preference and stated preference methods (Cropper and Oates, 1992; Freeman, 2003). Revealed preference methods use market behavior to model the trade-off made between environmental quality and money. Stated preference methods feature the construction of hypothetical markets to ascertain how people would behave if a market for environmental quality did exist. Both methods strive towards the same conceptual quantity; the trade-off, at the margin, between a nonmarket good or service (health or environmental quality) and money (Cropper and Oates, 1992). APEEP employs the results from numerous, peer-reviewed studies that apply these methods to value the physical effects of air pollution.

2.5.1 HUMAN HEALTH

Human health effects associated with ambient pollution levels are commonly divided into two categories: premature mortalities and increased incidence rates of morbidity or illness. Prior efforts to quantify the

damages associated with air pollution indicate that incremental changes in non-accidental mortality rates account for the majority of total damages (USEPA, 1999). This warrants a careful review of how mortality risk is valued in the literature and in this model. This model uses empirical evidence about how society values mortality risks. Specifically, a large literature exists (see Viscusi, 2002 or USEPA, 1999 for summaries) that explores how people value the risk of death; this literature has gathered evidence from observations of people's behavior in market settings and from survey results where people are asked to exchange money for small changes in mortality risks. APEEP employs this evidence in an approach to valuing mortality risk referred to as the value of a statistical life or (VSL). USEPA (1999) and others have employed this general strategy.

Although it may seem ethically objectionable to consider a trade-off between health and money, abundant empirical evidence suggests that people commonly make such trade-offs. This is readily seen in purchases of products which reduce the risk of death and injury: bicycle helmets, bottled water when municipal sources are less clean, smoke detectors, child seats in automobiles. These transactions reveal what consumers are willing to pay for such products and the reductions in health and safety risks stemming from their use. Another common example of individuals valuing safety are the higher wages affixed to dangerous occupations. Several peer-reviewed studies have estimated the wage premium associated with elevated fatality risks in the workplace (Viscusi, 2002). Typically, the magnitude of the extra risk in such jobs is quite small; an additional $\left(\frac{1}{10{,}000}\right)$ chance of death. Using this wage premium is appropriate because the implications of air pollution policy typically involve changes in mortality rates of an approximately equal magnitude. The literature that focuses on estimating this wage premium reports wide variation in the magnitude of this premium. In particular, the premium appears to be quite sensitive to how workplace risk is measured and specification of the hedonic wage model (Mrozek, Taylor, 2002; Black et al., 2003). APEEP's baseline valuation settings employs the central estimate from the recent meta-analysis of over 40 hedonic wage studies conducted by Mrozek and Taylor (2006). This study reports a wage-risk premium (R) of roughly \$200 per $\left(\frac{1}{10{,}000}\right)$ risk of death in the current period. In contrast, USEPA currently uses a wage-risk premium of approximately \$620 per $\left(\frac{1}{10{,}000}\right)$.

APEEP employs the value of a case of chronic bronchitis reported by the USEPA (1999). This estimate is derived from the work of Viscusi (1991) and Krupnick and Cropper (1992). APEEP employs the USEPA's (1999) value for each case of chronic asthma. Aside from chronic bronchitis and chronic asthma, APEEP relies on cost of illness estimates to value the other morbidity states encompassed by the model. Cost of illness[12] (defined as medical expenses plus lost wages) estimates for particular health states are reported in

[12]Source: U.S. Dept. Health and Human Services, Healthcare Cost and Utilization Project, Nationwide Inpatient Sample. http://hcup.ahrq.gov/HCUPnet.asp}

table 7.

2.5.2 AGRICULTURE

Calculating the damages to agricultural crops requires multiplying the 2002 market prices for each cultivar by the estimated yield loss due to exposures to pollution. Crop price data is obtained from the USDA. Crop prices are the marketing year average prices reported by the USDA National Agricultural Statistics Service. The prices are reported in table 10.

2.5.3 FORESTS

Computing the damages to timber resources requires multiplying the 2002 market prices for particular regional hardwoods and softwoods by the estimated yield loss due to exposures to pollution. However, in contrast to agricultural damages which are realized in the current year's harvest, damages to timber resources affect harvests in the current year as well as harvests occurring in the future. APEEP accommodates this multi-year perspective by calculating the present value of timber harvests due to the yield loss attributable to exposures to O_3. Price data is obtained from State Forest Management Agencies. The prices reflect the value of standing timber in 2002 (not delivered logs). These market prices are reported in table 11. The timing of future timber harvests is determined by maximizing the net present value of timber stock using the Faustmann formula as depicted in Sohngen (1995). In the formula shown below, (t) corresponds to the period in which the present value of timber stocks are maximized. This optimal harvest date varies according to major species groups and region (Sohngen, 1995).

APEEP computes the present value of timber harvests, under baseline O_3 conditions, using the following formula.

$$W_{rHb} = \delta \times \left(\frac{PQ_{trb}e^{-\delta t} - C}{1 - e^{-\delta t}} \right) \tag{32}$$

where: W_{rHb} = present value of hardwood timber (H) in receptor county (r), baseline O_3
P_H = 2002 price for hardwood timber $\left(\frac{\$}{MBF}\right)$
Q_{trb} = volume of hardwood timber (MBF) in receptor county (r), baseline O_3
δ = market interest rate (4%)
C = replanting costs $\left(\frac{\$}{MBF}\right)$
t = time of harvest

In order to assess the impact of the NO_x and VOC emission experiments, it is necessary to determine the change in the present value of current and future timber harvests in each affected receptor county (r).

Accordingly, APEEP computes the present value of timber harvests, under perturbation O_3 conditions. O_3 affects tree growth which adjusts the optimal time of future harvests (t^*). Since O_3 reduces growth, if additional NO_x emissions create O_3, then growth is retarded and the (t^*) will be larger, implying harvests on a longer rotation schedule.

$$W_{rHp} = \delta \times \left(\frac{PQ_{trp}e^{-\delta t^*} - C}{1 - e^{-\delta t^*}} \right) \tag{33}$$

where: W_{rHp} = present value of hardwood timber in receptor county (r), perturbation O_3
Q_{trp} = volume of hardwood timber (MBF) in receptor county (r), perturbation O_3
t^* = time of harvest

APEEP then determines the change in the present value of timber harvests in each receptor county (r). The effect of an emission experiment at source (s) is the sum of the change in all affected receptor counties[13].

$$\Delta W_{Hs} = \sum_{r=1}^{R} (W_{rHb} - W_{rHp}) \tag{34}$$

2.5.4 MAN-MADE MATERIALS

The damages to man-made materials encompass a consideration of the effects of pollution on the materials in the current (model) year, and the implications of such damage for the timing of regularly scheduled maintenance and repair activities occurring in the future. For painted surfaces, the dose-response functions generate an estimate of the decay rate (surface recession expressed as a proportion of the decay rate in unpolluted air) under baseline pollution conditions and following each emission perturbation. For limestone surfaces, the dose-response functions generates an estimate of the surface recession$\left(\frac{\mu m}{year}\right)$ under baseline pollution conditions and following each emission perturbation. The model calculates the present value of materials maintenance costs (consisting of maintenance repairs occurring on a 5 year schedule[14]) using the following formula.

$$M_{rb} = \delta \times \left(\frac{RC_r e^{-\delta t}}{1 - e^{-\delta t}} \right) \tag{35}$$

where: M_{rb} = annual maintenance costs in county (r), baseline SO_2
δ = market interest rate (4%)

[13] APEEP also computes the damages to softwood resources, which follows the same methodology as the computation for hardwood damages.

[14] Here we assume that exterior painting occurs on regular five-year intervals as does pointing, pressure-washing and other superficial upkeep to limestone surfacesand galvanized steel. Carbon steel is assumed to be painted on 5-year intervals as well.

RC_{rb} = Replacement costs in receptor county (r), baseline SO_2
t = time of repairs $(5, 10, 15, ..., T)$

In order to assess the impact of emission experiments, it is necessary to determine the change in the frequency of the maintenance activities. This is accomplished by calculating the ratio of the materials inventory under perturbation conditions (I_p) to the materials inventory under baseline conditions (I_b). This ratio is then multiplied by the 5-year maintenance schedule as shown in the following formula.

$$t^* = 5 \times \left(\frac{I_p}{I_b} \right) \tag{36}$$

where: t^* = time of repairs $(5 - \varepsilon, 10 - \varepsilon, 15 - \varepsilon, ..., T - \varepsilon)$
$\varepsilon = t - t^*$

This computation yields the timing of the amended maintenance schedule due to the experimental increase in pollution (t^*). Stated alternatively, if maintenance occurs after a certain, fixed degree of damage to the materials, then as pollution increases, the maintenance will occur sooner.

$$M_{rp} = \delta \times \left(\frac{RC_{rp} e^{-\delta t^*}}{1 - e^{-\delta t^*}} \right) \tag{37}$$

where: M_{rp} = annual maintenance costs in county (r), perturbation SO_2
δ = market interest rate (4%)
RC_{rp} = Replacement costs in receptor county (r), perturbation SO_2
t^* = time of repairs $(5 - \varepsilon, 10 - \varepsilon, 15 - \varepsilon, ..., T - \varepsilon)$

The change in the present value of the maintenance schedules extending into the future constitutes the damages computed by APEEP. Further, the effect of an emission experiment from source (s), is the sum of the change in all affected receptor counties.

$$\Delta M_s = \sum_{r=1}^{R} M_{rp} - M_{rb} \tag{38}$$

2.5.5 VISIBILITY

Several analyses derive estimates of the value affixed to improvements in visibility using contingent valuation methods (Chestnut, Rowe, 1989; Loehman, Boldt 1990; McClelland et al., 1990). We rely on Chestnut and Rowe's (1989) estimates of household willingness to pay (HHWTP) for incremental changes in visibility associated with recreation experiences.

$$HHWTP = \beta \times \left(ln \left(\frac{VR1}{VR2} \right) \right) \tag{39}$$

where: $HHWTP$ = household willingness to pay
β = statistically estimated parameter
$VR2$ = visual range (miles) after emissions perturbation
$VR1$ = visual range (miles) under baseline conditions

The values reported in tables 8 and 9 are the β parameters. The model employs regional estimates of HHWTP for improvements in residential visibility established in Chestnut and Dennis, (1997) and in McClelland et al., (1990).

2.5.6 RECREATION

APEEP relies on peer-reviewed studies which derive values for recreation experiences using the travel cost and contingent valuation methods. In particular, the model employs valuation estimates for recreation usages in forest ecosystems. The United Nations Food and Agriculture Organization report summarizing such values (Kengen, 1997) is used to estimate the average value of a recreation-visitor-day in forest environments. The estimates in the report are associated with a variety of recreation uses: hiking, camping, hunting. The mean value of a recreation day used in APEEP is $62.80.

3 AIR QUALITY MODELING EXPERIMENTS

We evaluate the performance of the air quality model in APEEP using observations from USEPA's AIRS monitor network. These experiments rely on the performance criteria commonly used to evaluate air quality models in the literature (Tong, Mauzerall, 2006; Russell, Dennis, 2000; USEPA, 2005). Since APEEP produces county-average ambient concentrations, we first compute the county averages from the monitor readings for each pollutant for the year 2002. For O_3 the data consist of hourly measurements which are spatially-averaged to the county level.

$$\bar{O}_{ch} = \frac{1}{D_c} \frac{1}{M_c} \sum_{m=1}^{M_c} \sum_{d=1}^{D_c} O_{mdh} \tag{40}$$

where $\bar{O}_{ch}$ = arithmetic mean O_3 in county (c),hour (h).
M_c = number of O_3 monitors in county (c).
O_{mdh} = O_3 level at monitor (m), day (d), hour (h)
D_c = number of days with O_3 observations in county (c).

For $PM_{2.5}$, the data consist of annual county averages.

$$\bar{P}_{pc} = \frac{1}{H_c}\frac{1}{D_c}\frac{1}{M_c}\sum_{m=1}^{M_c}\sum_{d=1}^{D_c}\sum_{h=1}^{H_c} P_{mdh} \tag{41}$$

where $\bar{P}_c$ = arithmetic mean $PM_{2.5}$ in county (c).
M_c = number of $PM_{2.5}$ monitors in county (c).
P_{mh} = $PM_{2.5}$ level at monitor (m), day (d), hour (h)
D_c = number of days with $PM_{2.5}$ observations in county (c).
H_c = number of hourly observations in county (c).

In order to be consistent with prior model evaluation procedures we employ four error statistics used in the literature (Tong, Mauzerall, 2006; USEPA, 2005): the mean error, the mean bias, the normalized mean error and the normalized mean error. Each of the following four statistics are computed separately for each pollutant.

$$ME_p = \frac{1}{C_p}\sum_{c=1}^{C_p}|A_{pc} - \bar{C}_{pc}| \tag{42}$$

where $\bar{C}_{pc}$ = arithmetic mean in county (c) for pollutant (p).
C_p = number of counties with monitors measuring pollutant (p)
A_{pc} = APEEP model predicted pollution level pollutant (p),at county (c).

$$MB_p = \frac{1}{C_p}\sum_{c=1}^{C_p}(A_{pc} - \bar{C}_{pc}) \tag{43}$$

$$NME_p = \frac{1}{C_p}\sum_{c=1}^{C_p}\left(\frac{|A_{pc} - \bar{C}_{pc}|}{\bar{C}_{pc}}\right) \tag{44}$$

$$NMB_p = \frac{1}{C_p}\sum_{c=1}^{C_p}\left(\frac{(A_{pc} - \bar{C}_{pc})}{\bar{C}_{pc}}\right) \tag{45}$$

Finally, for each pollutant we compute Pearson's Correlation Coefficient (ρ). This procedure is helpful in determining if the spatial pattern of the predicted surfaces matches the distribution observed by the monitors.

$$\rho = \frac{E(A_{pc} - \bar{A}_p)(C_{pc} - \bar{C}_p)}{\sigma_A \sigma_C} \tag{46}$$

where $\bar{C}_p$ = observed arithmetic mean for pollutant (p).
$\bar{A}_p$ = model predicted arithmetic mean for pollutant (p)
σ_A = variance of model prediction.
σ_C = variance of monitor observations.
E = expectation operator

Next, we repeat these experiments using nation-wide, county-level ambient pollution predictions generated by the CMAQ model as the standard to which APEEP's predictions are compared. Except for O_3, CMAQ's predictions have been averaged to reflect seasonal county arithmetic means. For O_3, CMAQ's predictions are averaged across the days in the simulation but not across hours. Thus, for each county we have 24 hourly readings. This matches the hourly output from APEEP.

3.1 RESULTS

Tables 12 and 13 report the results of the performance evaluation of the air quality models in APEEP. When compared to hourly measurements drawn from the USEPA's AIRS monitoring network for O_3, APEEP generates a surface with a mean error (ME) of 7.2 ppbv and a mean bias (MB) of 0.57 ppbv. The mean normalized error (MNE) is 29% and the mean normalized bias (MNB) is 12%. The performance of APEEP compares favorably with that of CMAQ. Specifically, previous authors (Tong, Mauzerall, 2006) find that, when applied to monthly averaged O_3 readings for the summer of 1996, CMAQ's predicted O_3 surface generates a ME of 9.6 ppbv, a MB of 6.3 ppbv, a MNE of 30%, and a MNB of 23%. Russell and Dennis (2000) suggest that a NME of between 30 to 35% and that a MNB of ± 5 to 15% indicates acceptable model performance.

Moving to $PM_{2.5}$, table 12 reveals that APEEP generates a ME of 4.4 $\left(\frac{ug}{m^3}\right)$, a MB of -2.6 $\left(\frac{ug}{m^3}\right)$,with a MNE of 35% and a MNB of -20%. In a recent evaluation of CMAQ's $PM_{2.5}$ predictions, USEPA (2005) found that, when compared to 2001 annual means observed drawn from the STN monitor network, CMAQ produced a ME 5.5 $\left(\frac{ug}{m^3}\right)$, a MB -2.1$\left(\frac{ug}{m^3}\right)$, with a MNE of 43%, and a MNB of -16%.

For SO_2, APEEP's performance depends heavily on the season. For summer months, APEEP's predicted surface generates a ME of 1.5 (ppbv), and a MB of -0.25 (ppbv). The USEPA (2005) finds that, when compared to the CASTnet sites, CMAQ's summer predictions produce a ME of 1.36 (ppbv), and a MB of 0.82 (ppbv). The MNE corresponding to APEEP's predictions is 78% while that produced by CMAQ is 53%. Further, the MNB generated by APEEP is 34% and the MNB produced by CMAQ's surface is 32%. In the winter months, table 12 indicates that APEEP predicts the county-average SO_2 readings much less successfully. While the ME (2.3) and the MB (0.02) statistics are comparable to CMAQ ($ME = 2.7$, $MB = 2.2$), the MNE and MNB associated with APEEP (115% and 71%, respectively) are higher than the MNE and the MNB produced by CMAQ; 44% and 37% respectively. For NO_x in the summer season,

APEEP generates a ME of 9.5 and a MB of -6.9 (ppbv). The MNE is 64% and the MNB is -22%. The correlation coefficient is 0.41. For the winter season, APEEP produces a ME of 16.6 and a MB of -3.7 (ppbv). The MNE is 79% and the MNB is 27%. The correlation coefficient in 0.39.

As an additional evaluation of APEEP's air quality model, we compute the four error statistics (ME, MB, MNE, MNB) using the county-average predictions for 2002 produced by CMAQ as the standard for comparison. Since we have CMAQ predictions for each of the 3110 counties in the contiguous United States, this validation exercise provides a more spatially comprehensive set of experiments than comparing the models to USEPA's monitoring networks which are scattered across the country. The results of these experiments are shown in table 13. For $PM_{2.5}$, APEEP's predicted levels are in good agreement with CMAQ's predictions. The ME is 1.8 $\left(\frac{ug}{m^3}\right)$ and the MB is -0.5 $\left(\frac{ug}{m^3}\right)$. Further, the MNE is 26% and the NMB is -2%. The correlation coefficient is 0.77. For PM_{10}, the ME is 4.2 $\left(\frac{ug}{m^3}\right)$ and the MB is 3.8 $\left(\frac{ug}{m^3}\right)$ while the MNE is 50% and the NMB is 47%. The correlation coefficient is 0.74. For NO_x and SO_2, the ME is 1.1 and 0.5 ppbv , respectively, while the MB is 0.21 and 0.06 ppbv for NO_x and SO_2. The MNE is 42% and 47% for NO_x and SO_2 while the MNB is 14% and 19% for NO_x and SO_2. Table 13 reveals that the correlation coefficients for NO_x and SO_2 are 0.86 and 0.78 indicating surfaces that are strongly correlated with CMAQ's surfaces.

For O_3, we match each model's hourly predictions at each hour of the day; 24 hourly pairs across 3110 counties yields nearly 75,000 matched pairs. Using this approach, the ME is 9.2 ppbv and the MB is -1.83 ppbv. The MNE is 20% and the MNB is -4%. The correlation coefficient is 0.69. Next, we match hourly pairs for the 8-hour range from 10:00 am to 6:00 pm; 8-hours times 3110 counties yields approximately 25,000 matched pairs. In this setting, APEEP's performance improves markedly. Table 13 shows that the ME is 6.6 ppbv and the MB is 5.8 ppbv. In addition, the MNE is 12% and the MNB is 11%. Finally, the correlation coefficient is 0.77. So, APEEP is better able to match CMAQ's predictions during the daytime hours. These experiments show that APEEP is competitive with CMAQ in predicting $PM_{2.5}$ and O_3. APEEP is less successful matching observations of SO_2 and NO_x. These results indicate that, although APEEP uses a reduced form approach to modeling a series of complex environmental processes, its performance is quite satisfactory especially in terms of the two pollutants that cause the most harmful effects on society: $PM_{2.5}$ and O_3

Table 1: Within County Dispersion

County Area(mi^2)	# Counties	Dimension	Gridcell Size(mi^2)
< 50	40	4×4	1
50 - 200	107	4×4	9
200 - 500	903	5×5	16
500 - 750	913	5×5	25
750 - 1,000	491	5×5	36
1,000 - 2,500	464	8×8	36
2,500 - 5,000	133	8×8	56
5,000 - 10,000	48	10×10	64
$> 10{,}000$	10	10×10	144

Table 2: Deposition and Chemical Transformation Parameters

$Pollutant$	$Process$	Φ
NO_x	$Dry\ Dep.$	$\left(\frac{1(cm)}{s}\right)$
NO_x	$Wet\ Dep.$	$\left(\frac{0.01}{cm}\right)$
NO_x	$NO_x \rightarrow Nitrate$	$\left(\frac{2(\%)}{hr}\right)$
SO_2	$Dry\ Dep.$	$\left(\frac{0.5(cm)}{s}\right)$
SO_2	$Wet\ Dep.$	$\left(\frac{0.003}{cm}\right)$
SO_2	$SO_2 \rightarrow Sulfate$	$\left(\frac{0.75(\%)}{hr}\right)$

Table 3: Epidemiology Studies Employed in APEEP

Health Event	Pollutant	Study Author
Chronic Exposure Mortality	$PM_{2.5}$	Pope, et al. (2002)
Chronic Exposure Mortality	$PM_{2.5}$	Laden, et al. (2006)
Acute Exposure Mortality	$PM_{2.5}$	Klemm, Mason (2004)
Chronic Bronchitis	PM_{10}	Abbey, et al. (1993)
Chronic Asthma	O_3	McDonnell et al. (1999)
Acute Exposure Mortality	O_3	Bell, et al (2004)
Respiratory Admissions	O_3	Schwartz (1995)
ER-Visits Asthma	O_3	Steib, et al. (1996)
COPD Admissions	NO_2	Moolgavkar (2000)
IHD Admissions	NO_2	Burnett, et al. (1999)
Asthma Admissions	SO_2	Sheppard (1999)
Cardiac Admissions	SO_2	Burnett (1997)

Table 4: Agriculture Dose-Response Functions

Crop	Pollutant	γ	σ	Author
Corn	O_3	2.83	0.124	Lesser, et al. (1990)
Cotton	O_3	2.06	0.111	Lesser, et al. (1990)
Peanut	O_3	2.27	0.109	Lesser, et al. (1990)
Spring Wheat	O_3	2.56	0.136	Lesser, et al. (1990)
Grain Sorghum	O_3	2.07	0.314	Lesser, et al. (1990)
Alfalfa	O_3	1.78	0.179	Lesser, et al. (1990)
Kidney Bean	O_3	2.66	0.114	Lesser, et al. (1990)
Tobacco	O_3	1.66	0.145	Lesser, et al. (1990)

Table 5: Timber Dose-Response Functions

Tree Species	Author, Year	Pollutant	β
Hardwoods	Pye, 1988; Reich, 1987	O_3	0.0065
Softwoods	Pye, 1988; Reich, 1987	O_3	0.0015

Table 6: Man-Made Materials Dose-Response Functions

Material	Author, Year	Pollutant	β_0, β_1
Galvanized Steel	Atteras, Haagenruud, 1982	SO_2	$6.05, 0.22$
Painted Surfaces	ICP	SO_2	$3.22 \times 10^{-5}, 6.0 \times 10^{-3}$
Carbonate Stone	ICP	SO_2	$2.7, 1.9 \times 10^{-2}$

Table 7: Human Health Valuation

Health Event	Unit	$
Chronic Mortality	Case	1,980,000
Acute Mortality	Case	1,980,000
Chronic Bronchitis	Case	320,000
Chronic Asthma	Case	30,800
General Respiratory	Hospital Admission	8,300
General Cardiac	Hospital Admission	17,526
Asthma	Hospital Admission	6,700
COPD	Hospital Admission	11,276
Ischemic Heart Disease	Hospital Admission	18,210
Asthma	ER Visit	240

Table 8: Valuation Estimates for Welfare Endpoints

Welfare	Endpoint	$	Unit	Source
Visibility	Recreation	Table 9	Household	Chestnut and Rowe (1990)
Visibility	Residential	174	Household	McClelland et al., (1993)
Ecosystem	Forest Recreation	62.80	RVD	Kengen, (1997)

Table 9: Recreation Visibility Valuation

Use	Region	$	Unit	Source
In-Region	Southwest	170	Household	Chestnut and Rowe (1990)
Out-of-Region	Southwest	135	Household	Chestnut and Rowe (1990)
In-Region	Southeast	80	Household	Chestnut and Rowe (1990)
Out-of-Region	Southeast	50	Household	Chestnut and Rowe (1990)

Table 10: 2002 Agriculture Prices

Crop	$	Unit
Corn	2.25	Bushel
Cotton	0.61	Lbs.
Peanut	0.17	Lbs.
Grain Sorghum	4.13	Cwt.
Soybeans	5.19	Bushel
Spring Wheat	3.42	Bushel
Alfalfa	108.36	Ton
Tobacco	1.86	Lbs.
Dry Beans	6.82	Cwt.

Table 11: Standing Timber Prices

Region	Timber Type	Unit	$
Northeast	Hardwood	mbf	275
Northeast	Softwood	mbf	90
Southeast	Hardwood	mbf	270
Southeast	Softwood	mbf	312
West	Softwood	mbf	462
Midwest	Hardwood	mbf	275
Midwest	Softwood	mbf	90

Table 12: Air Quality Modeling Diagnostics: APEEP and USEPA AIRS Data

Species	Season	ME	MB	MNE(%)	MNB(%)	ρ	n
O_3 (ppbv)	Summer	7.2	0.57	29	12	0.74	15645
$PM_{2.5}$ $\left(\frac{ug}{m^3}\right)$	Annual	4.4	-2.6	35	-20	0.33	181
SO_2 (ppbv)	Summer	1.5	-0.25	78	34	0.59	333
SO_2 (ppbv)	Winter	2.3	0.02	115	71	0.46	343
NO_x (ppbv)	Summer	9.5	-6.9	64	-22	0.41	166
NO_x (ppbv)	Winter	16.6	-3.7	79	27	0.39	170

Table 13: Air Quality Modeling Diagnostics: APEEP and CMAQ

Species	Season	ME	MB	MNE(%)	MNB(%)	ρ	n
NO_x (ppbv)	Summer	1.1	0.21	42	14	0.86	3110
SO_2 (ppbv)	Summer	0.5	0.06	47	19	0.78	3110
O_3 $(24hr.)$ (ppbv)	Summer	9.2	-1.83	20	-4	0.69	74,640
O_3 $(8hr.)$ (ppbv)	Summer	6.6	5.8	12	11	0.77	24,880
$PM_{2.5}$	Annual	1.8	-0.5	26	-2	0.77	3110
PM_{10}	Annual	4.2	3.8	50	47	0.74	3110

Figure 1: CMAQ Annual Mean $PM_{2.5}$ Concentration

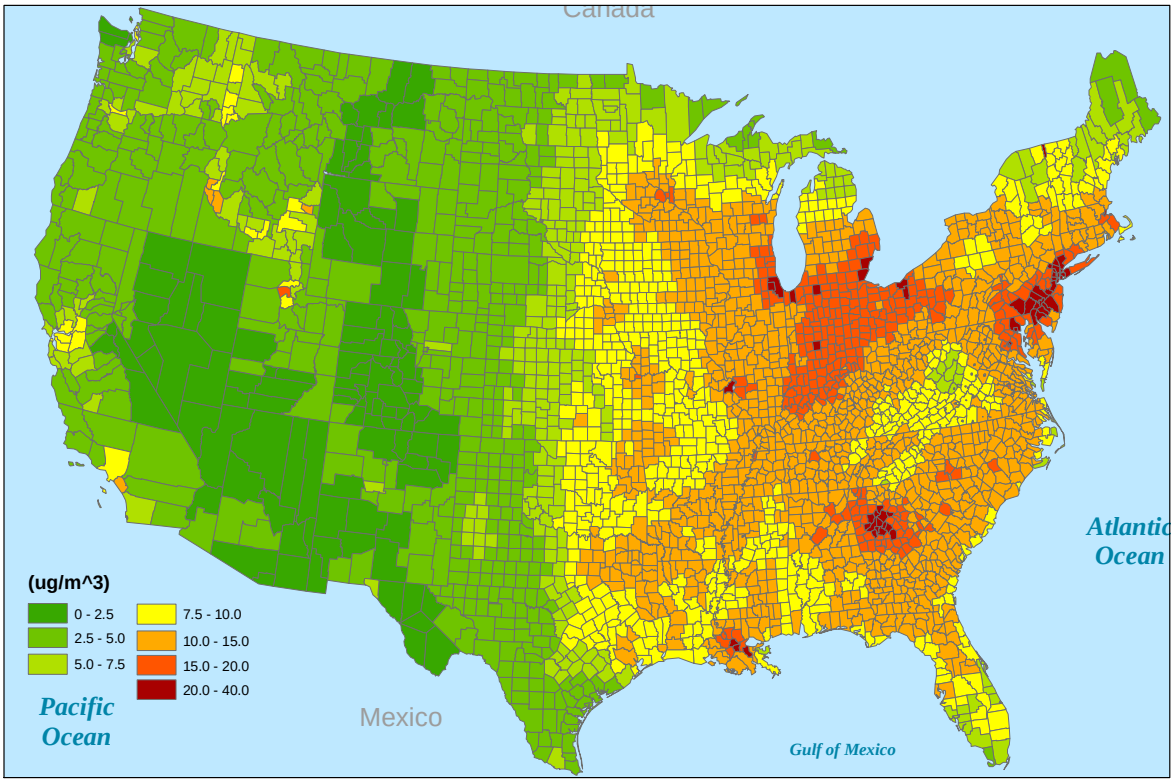


Figure 2: APEEP Annual Mean $PM_{2.5}$ Concentration

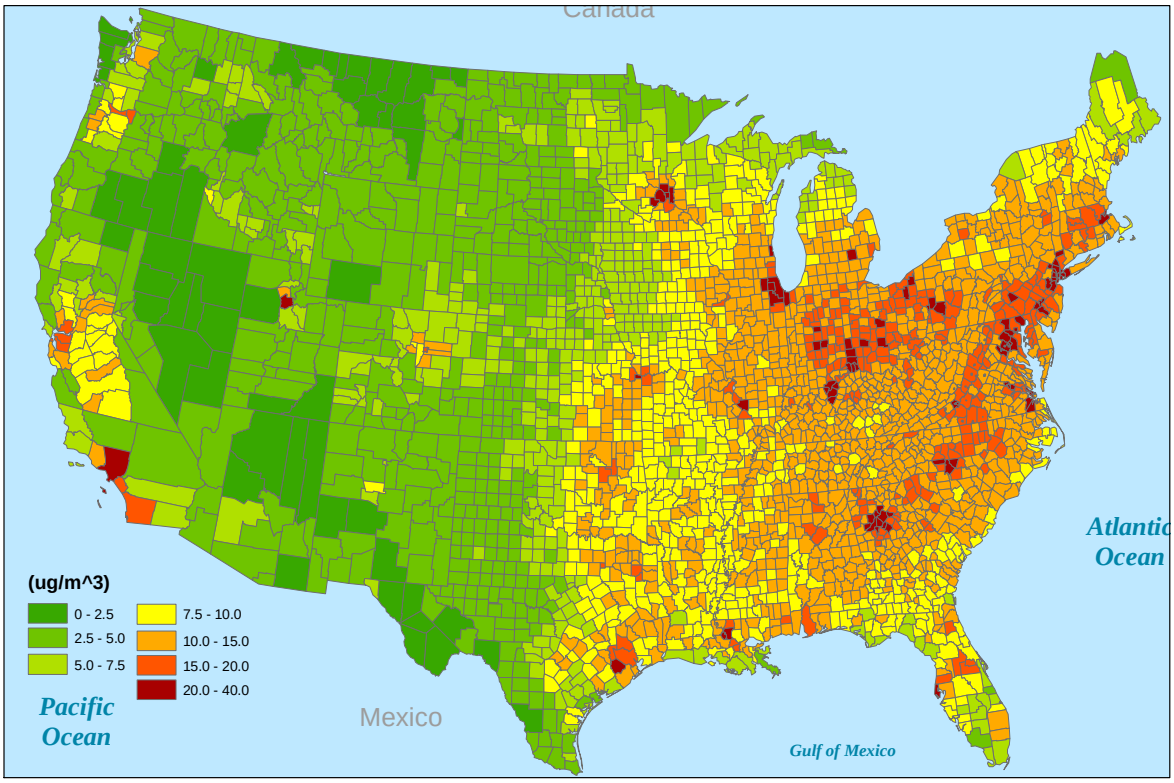


Figure 3: CMAQ Summer 8-Hour Mean O_3 Concentration

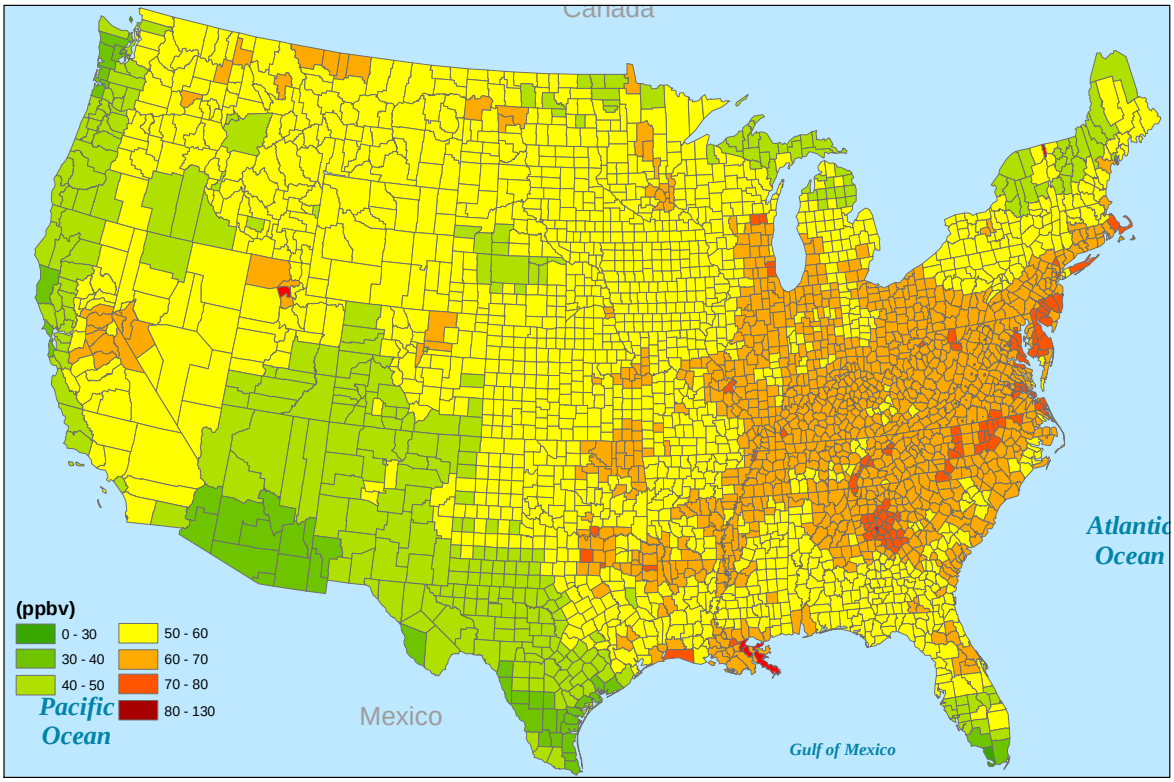


Figure 4: APEEP Summer 8-Hour Mean O_3 Concentration

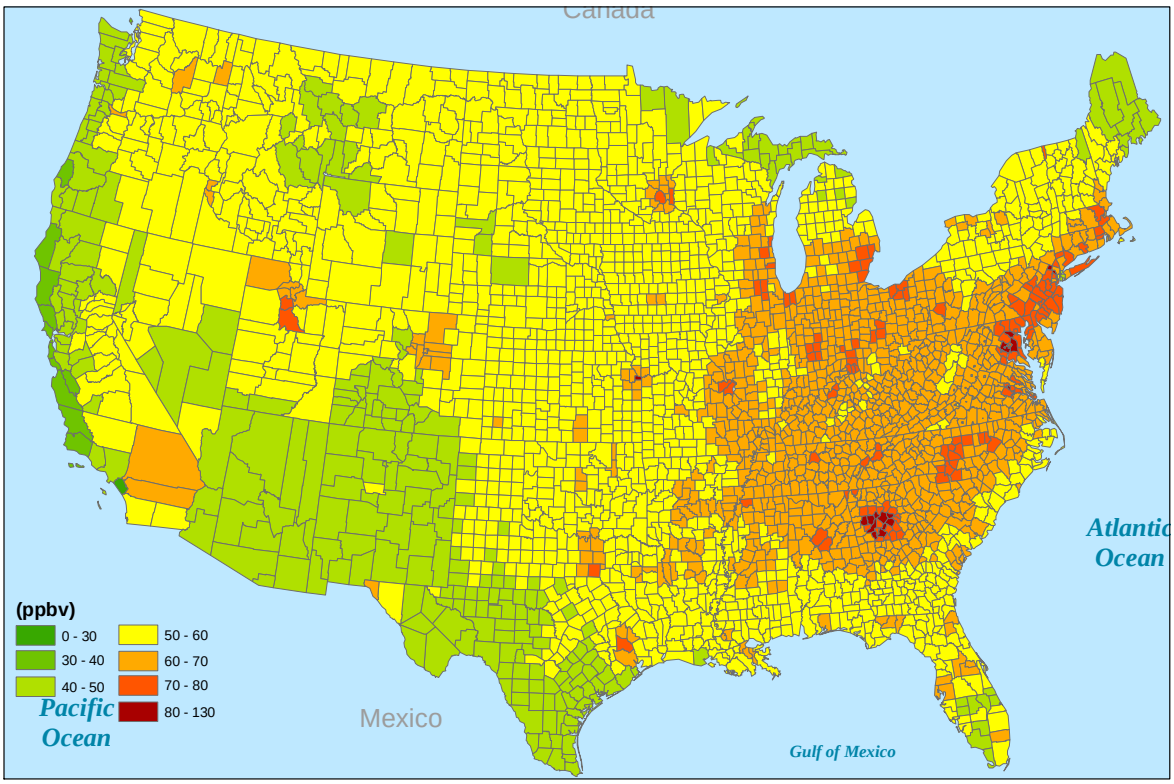


Figure 5: Change in $PM_{2.5}$ Concentration Due to One Ton $PM_{2.5}$ Emission in Cambridge, Mass.

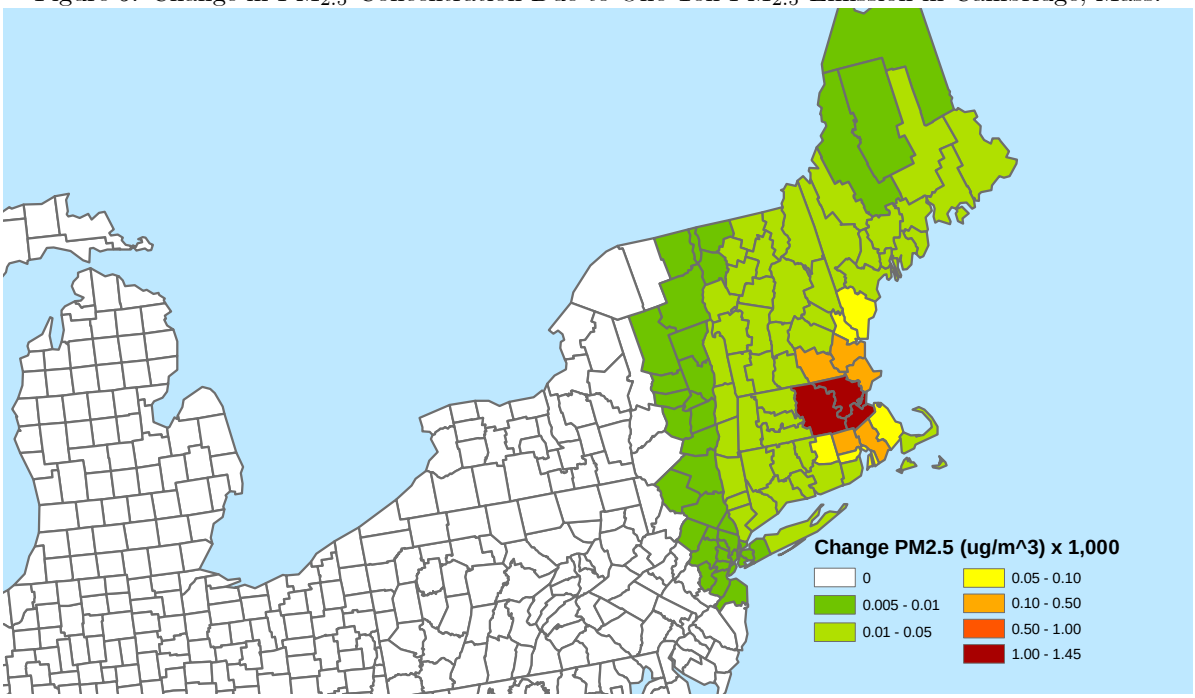
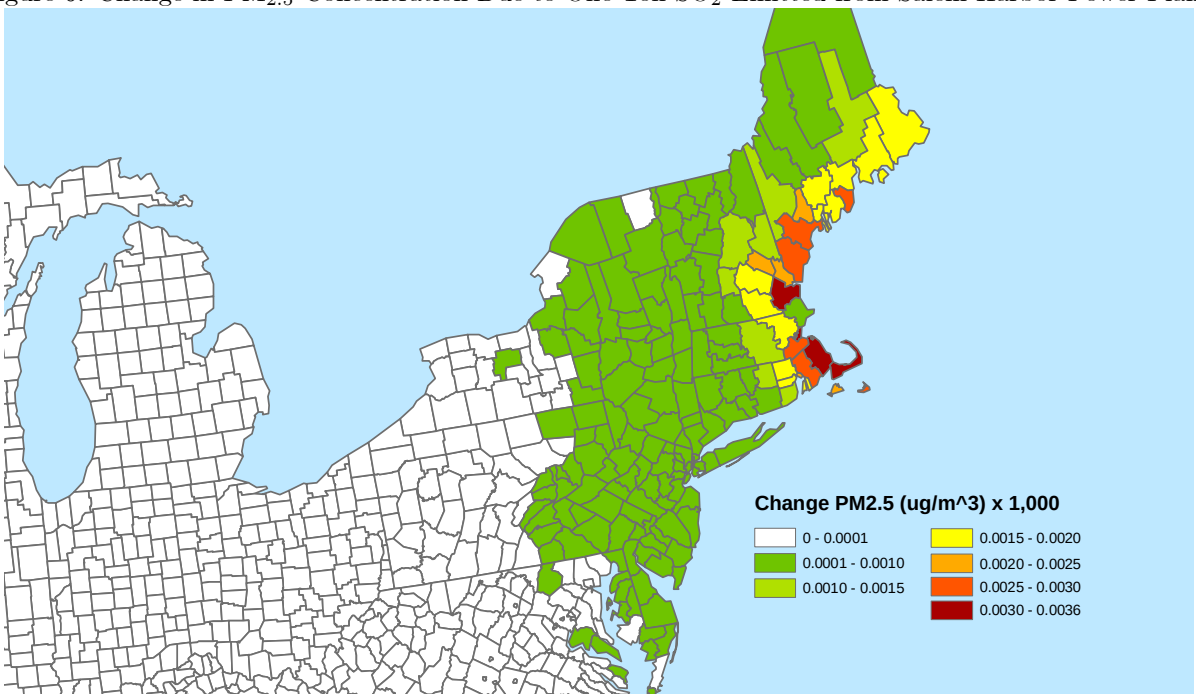


Figure 6: Change in $PM_{2.5}$ Concentration Due to One Ton SO_2 Emitted from Salem Harbor Power Plant.



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