Estimating Health Benefits Associated with Reductions in PM and NOx Emissions: Detailed Description

1. Introduction

CARB estimates premature death and other health effects related to PM2.5 exposure using one of two methods, a health model or the *incidence-per-ton* (IPT) method. In most cases, CARB uses the IPT method to estimate health effects from emissions data. The IPT methodology is a simplified procedure that uses pre-calculated results, obtained by running the health model on a baseline scenario, to compute estimates of the number of cases of adverse health outcomes. In cases where measured or modeled PM2.5 concentrations are available, CARB staff input them directly into a health model to obtain estimates of health effects.

2. Health model

The health model is based on the methodology used by US EPA's BenMAP benefits mapping and analysis software [US EPA BenMAP]. The health model enables automation of repetitive tasks and facilitates the incorporation of California-specific data. The health model uses a multi-step process to estimate health impacts from measured or modeled PM2.5 concentrations. These steps are described below.

The health model estimates the incidence of premature death and other health outcomes at each census tract or modeling grid cell using the equation:

$$\text{Incidence} = [\text{population}]_i \times [\text{baseline incidence}]_i \times [\ 1 - \exp(\ -\beta \times \text{PM2.5}\ )\ ]$$

where the subscript *i* indexes the age groups. The specific form of this equation is determined by the type of statistical model used by the health studies to model the relationship between PM2.5 exposure and health risk. All the studies selected by CARB use a log-linear relationship, which takes the form shown above. The incidence is summed over age groups to obtain the total incidence for the census tract. The coefficient β is taken from one of the health studies discussed below. The source of PM2.5 comes from monitored or modeled air quality data.

CARB draws upon health studies used by the U.S. EPA for its risk assessments (US EPA 2010). CARB uses a subset of the endpoints used by U.S. EPA, chosen on the basis of their strength and robustness. For premature mortality, CARB uses the cardiopulmonary mortality risk coefficient for the 1999-2000 time period from Krewski et al., 2009, among the largest studies of its kind, with 360,000 participants. For cardiovascular and respiratory hospitalizations, CARB used Bell et al., 2008, and for emergency room visits for asthma CARB used Ito et al., 2007. The process for selecting these studies was described in detail in CARB's 2010 PM2.5 mortality report (CARB 2010a).

Estimating exposure from measured PM2.5

The health model estimates population-weighed exposure to primary and secondary PM2.5 from annual average concentrations measured at monitors located throughout California. The model estimates exposure between monitor locations. This is accomplished using a spatial interpolation method known as inverse distance-squared weighting. Separate exposure estimates are made for PM2.5 emitted directly from diesel sources (primary PM2.5) and from PM2.5 formed from precursor gases (secondary PM2.5).

<u>Estimating Diesel particulate matter concentrations</u>

Annual diesel particulate matter (DPM) concentrations are not measured directly. Rather, they are estimated from annual average NOx concentrations by multiplying them by air basin and year-specific DPM/NOx emission ratios computed from CARB emission inventories.

The methodology and its rationale is described in greater detail in CARB 2010b and Propper et al., 2015. DPM concentrations were estimated at 106 monitors located throughout the state. In order for a measurement to be considered valid, the data were required to be at least 75% complete.

<u>Estimating secondary ammonium nitrate concentrations</u>

In addition to DPM, CARB computes health impacts for secondary ammonium nitrate PM2.5 formed in the atmosphere from NOx. To estimate ammonium nitrate PM2.5 exposure, CARB staff use speciated PM2.5 nitrate ion (NO_3^-) concentration data from two sources: the air quality monitoring network maintained by CARB and local air quality districts and the IMPROVE visibility network (IMPROVE Visibility Network).

CARB and air pollution control districts operate a network of PM2.5 monitors around the state, mostly in urban areas (CARB AQMN). PM2.5 samples are collected as 24-hour filter samples, once every 3-6 days. Samples from some monitors are further analyzed to determine the concentration of nitrate ion and other constituents. During 2014-2016, nitrate data were available from 18 urban monitors. Data for these monitors are retrieved from CARB's ADAM air quality database (CARB ADAM).

In addition to the urban monitors, the national IMPROVE visibility network operated 20 PM2.5 nitrate ion monitors in California during 2014-2016, mainly in national parks and other remote locations (IMPROVE Visibility Network). These instruments collected one sample every three days. IMPROVE data were retrieved from the project web site (IMPROVE Visibility Network).

Daily samples were aggregated by monitor to obtain annual averages. In order for an annual average to be considered valid, the data were required to be at least 75% complete. To convert from nitrate ion concentration to ammonium nitrate (NH_4NO_3), the annual averages were multiplied by the ratio of the molecular weight of ammonium nitrate to that of the nitrate ion.

Prior to May, 2019 CARB used PM10 nitrate data instead of more accurate PM2.5 nitrate data to estimate ammonium nitrate aerosol concentrations to compute health impacts. This is because speciated PM10 data was available for more locations than speciated PM2.5. However, the number of monitors in the speciated PM10 network has shrunk and is now comparable in size and coverage to the speciated PM2.5 network. Therefore, in May, 2019 CARB began using PM2.5 nitrate data to compute health effects. The PM2.5 nitrate monitors are more accurate because they store the filters in a refrigerated compartment, and less of the sample is lost to volatilization. Consequently, the estimated PM2.5 nitrate concentrations and associated IPT factors for NOx emissions are approximately 50% higher than those used prior to May, 2019.

Estimating exposure using modeled PM2.5 concentrations

The health model can also be run with concentrations derived from an air quality model instead of monitored data. Air quality models include dispersion models, which model how pollutants are dispersed by the wind, and photochemical models, which are more elaborate and capture the effects of sunlight, temperature, and chemical reactions on pollutants. Dispersion models are only used for primary pollutants, as they are not capable of modeling formation of secondary pollutants. Air quality models generate gridded results, with grid cells typically in the range of 500-2,000m square.

Population projections at the census tract level

The health model uses age-resolved population data at the census tract level. CARB uses data from the 2010 Census (U.S. Census Bureau). These were projected to 2011-2060 using age-resolved county population projections from the California Department of Finance (CDOF).

Age-specific growth factors for each county, for each year, were computed from the CDOF projections by dividing each county population for the target year by the average county population for the base years 2014-2016. These growth factors were applied to each census tract in every county, for each age group separately. Population was projected for five-year age groups 0-4 through 80-84, and for age 85 and older.

This method of projection reflects growth in overall county population, but does not model changes in population distribution within counties, such as expansion of urban areas into surrounding rural land.

Estimating baseline incidence

The health model uses incidence data for cardiopulmonary mortality extracted from the Center of Disease Control (CDC) Wonder database. Incidence data for hospitalizations for cardiovascular and respiratory causes, and emergency room visits for asthma are taken from US EPA BenMAP benefits mapping software (US EPA BenMAP). Baseline incidence rates vary by age bracket. Incidence was estimated separately for five-year age groups 0-4 through 80-84, and for age 85 and older. Mortality incidence data are county-specific. Incidence data for other health outcomes is uniform throughout California.

Aggregating health outcomes by air basin

To aggregate results from census tracts to larger geographical subdivisions such as counties or air basins, the health model uses a geospatial technique called areal interpolation. Areal interpolation is a procedure for translating spatial data from one set of geographical subdivisions to another when the boundaries do not overlap. Numerous variants of the technique exist, but for the purpose of this analysis the simplest form, which uses area of polygon intersection, was employed (Goodchild and Lam, 1980, Flowerdew and Green, 1994). The precision of this method depends on the size of the geographical subdivisions and the spatial homogeneity of the quantity being apportioned. In urban areas, where census tracts are small and population is distributed more evenly, areal interpolation to larger subdivisions such as air basins yields relatively precise estimates. In rural areas where the population is distributed unevenly over large census tracts, estimates are less precise.

3. Incidence-per-ton methodology

CARB uses the IPT methodology to quantify the health benefits of regulations and programs that reduce PM2.5 and precursor emissions. It is based on an approach developed by the US EPA, as described by Fann et al. (2009, 2012, 2018). The mathematical relationship between changes in emissions and changes in health outcomes is approximately linear. The IPT methodology is based upon this relationship, and makes the following assumptions:

(1) Changes in health outcomes are proportional to changes in PM concentration;
(2) Changes in primary pollutant concentrations are proportional to changes in emissions; and
(3) Changes in secondary pollutant concentrations are approximately proportional to changes in emissions. It should be noted that there may be cases where the relationship between emission of oxides of nitrogen (NOx) and ammonium nitrate aerosol is not linear.

Due to the approximately linear relationship between premature deaths (or other health outcomes) and emission concentrations, the number of premature deaths can be estimated by multiplying emissions by a scaling factor: the *IPT factor*. IPT factors are developed by applying a health model to air pollution concentrations for a baseline period to estimate the number of health outcomes associated with PM2.5 exposure, then dividing by emissions of PM2.5 or a precursor.

Current IPT factors were developed from a baseline scenario using air quality data, incidence data and emission inventories for 2014-2016, and age-stratified population projections for 2010 through 2060. IPT factors were calculated separately for each air basin.

IPT factors are currently available for two types of PM: diesel particulate matter (DPM) primarily from on-road sources, and secondary ammonium nitrate particles formed from NOx. Health effects of primary PM2.5 from sources other than on-road diesel engines are estimated by using IPT factors developed for DPM and multiplied by a relative potency factor, as described below.

In addition to premature mortality from cardiopulmonary causes, CARB currently uses IPT factors to estimate hospitalizations due to cardiovascular and respiratory causes and respiratory emergency room visits including asthma.

Since the total incidence of heath effects is proportional to population, results for future years are adjusted by the ratio of the projected population in the target year to the average population in the base years 2014-2016.

4. Relative potency factors for non on-road diesel sources

To quantify the health benefits of reductions in primary PM2.5 from sources other than on-road diesel vehicles, CARB uses IPT factors developed for DPM and multiplies the results by a relative potency factor specific to the source and location of the emissions.

Relative potency may be determined in several ways, including but not limited to

- The ratio of the intake fraction of the source to the intake fraction for DPM. The intake fraction is a measure of the fraction of the emissions from a given source that is inhaled by the receptor population. It is specific to a source and a location; e.g., a particular type of facility in a given air basin.
- Comparison of IPT results with direct estimation results for the same scenario. The ratio of the results obtained by the two methods may then be used to adjust the results obtained by IPT factors in a larger setting. For example, the ratio of results obtained by IPT and the health model for one air basin may be used to adjust results for other air basins.
- General consideration of conditions under which emissions take place are also important. For example, if an on-road vehicle delivers goods from a facility in a remote location to a facility located in an urban area, half of idling emissions may be considered to occur far from receptor populations. Hence an adjustment factor of 0.5 may be appropriate for computing the health benefits of reducing idling emissions.

5. Uncertainty in health impact estimates

This methodology is well-established and includes up-to-date information. However, there are uncertainties in the underlying data and assumptions:

- Air quality data is subject to natural variability from meteorological conditions, local activity, etc.
- The assumption that changes in concentrations of pollutants are proportional to changes in emissions of those pollutants or their precursors is an approximation. There may be cases where actual changes in concentrations are higher or lower than predicted.
- The estimation of DPM concentrations and DPM/NOx emission ratios is subject to uncertainty. Emissions are reported at an air basin resolution, and do not capture local variations.
- Inverse distance-squared weighting, a spatial interpolation method, is used to estimate concentrations each census tract. Compared with other geospatial estimation methods such as Kriging, inverse distance-squared interpolation has the virtue of simplicity, and does not require selection of parameters. When data are abundant, most simple interpolation techniques give similar results (Jarvis et al.,

2001). All geospatial estimation techniques exhibit greater uncertainty when data points are sparser, and uncertainty increases with distance from the nearest data points.

- Future population estimates are subject to increasing uncertainty as they are projected further into the future. For reasons of computational efficiency, the spatial resolution of population estimates is limited to census tract resolution.
- Observed baseline incidence rates change over time, and are subject to random year-to-year variation and systematic shifts as population characteristics and medical treatments evolve. Sample size requirements necessitate estimating baseline incidence rates at large geographic scales, state or county.
- Relative risks in the concentration response function are estimated with uncertainty and reported as confidence ranges.

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