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**TECHNICAL REPORT DOCUMENTATION PAGE**

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Executive Summary

The executive summary should serve as a high-level, standalone project brief (up to two pages) that succinctly describes the problem, the work conducted, and outputs, outcomes, and impacts resulting from the study. Please include the following sections:

1. Problem statement—describe the motivation and need for the project, including a statement of the problem to be solved or the research needed.
2. Technical objectives—describe the technical objectives of the study, including the approach and methodology used to achieve the research goals.
3. Key findings—highlight the key study findings, including relevant outputs and outcomes.
4. Project impacts—describe the impacts of the study on:

* The effectiveness of the transportation system.
* The adoption of new practices.
* The body of scientific knowledge.
* Transportation workforce development.

Acknowledgments

(Optional) Acknowledge any other contributors and sources of project funding other than CARTEEH.

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# Report Guidelines (FOR REFERENCE—Delete This Section)

## Formatting and Content

Follow these guidelines in preparing your report:

* Use only the styles provided in this template if possible:
* Heading 1, Heading 2, Heading 3, and Heading 4.
* Body Text, List Bullet, List Bullet 2, and List Number.
* Figure and Figure Caption.
* Table Caption, Table Header, and Table Text.
* Organize the report into sections or chapters to give a complete description of the project, including data gathered, analyses performed, and results achieved. Use appendices as needed for supplementary materials.
* Heading names (Methods, Results, etc.) in this document are solely for demonstration purposes. Rename or rerrange section headings as necessary, but make sure to include a description of the following required elements:
* The research problem.
* Current literature and the state of the practice.
* The approach and methodology.
* Data collection, analysis, and results.
* Findings, conclusions, and recommendations.
* Research outputs, outcomes, and impacts.
* Technology transfer outputs, outcomes, and impacts.
* Education outputs, outcomes, and impacts.
* Cite your sources using a consistent format.

If you would like information on how to use templates, please visit <http://tti.tamu.edu/group/communications/word-template-instructions/>.

## Review and Publication Process

The principal investigator (PI) should submit the Project Closeout Checklist and draft Final Research Report within **60 days** after the project completion date. CARTEEH leadership will then review the report and determine whether additional edits are necessary prior to its approval. If edits are required, the report will be returned to the PI with comments on requested revisions.

Once revisions are completed, the final documents should be returned to CARTEEH for final approval. After notifying the PI of the final approval, CARTEEH administration will upload the research report to the CARTEEH website and various repositories, per the grant’s requirements.

## Figures

High-resolution images are preferred if possible. Use automatic cross references to mention each figure in the text (Figure 1).



Figure 1. Sample image with caption. (Use sentence case; end with a period.)

## Tables

Use automatic cross references to mention each table in the text (Table 1). Tables should be created using Word’s formatting if possible.

Table 1. Sample Table Caption (Capitalize Each Word, and Do Not End with a Period)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Title 1 | Title 2 | Title 3 | Title 4 | Title 5 |
| The table should be centered on the page. | Headers for the columns should be in Table Header style and shaded 20 percent gray. | Units should be given in the header and not repeated in cells. | All table text should use the Table Text style and be centered. | Tables should not split across the page unless absolutely necessary. |
| Info 1 | Info 2 | Info 3 | Info 4 | Info 5 |

# Sample Level 1 Heading

## Sample Level 2 Heading

In order to use a subheading, you need to divide chunks of information. Therefore, you should have at least two subheadings.

Use **Body Text** style for paragraphs. Use a sentence to introduce bullets:

* Bullet. Use **List Bullet** style.
* Bullet.
* Bullet.
* Sub-bullet. **Use List Bullet 2** style.
* Sub-bullet.
* Sub-bullet.

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1. List element. Use **List Number** style.
2. List element.
3. List element.

#### Sample Level 4 Heading

Use **Body Text** style. Try not to go beyond level 4 headings.

# Background and Introduction

### Asthma

Asthma is a chronic air way disease characterized by episodes of shortness of breath, coughing, wheezing and sputum production, caused by a reversible or partially reversible airway obstruction and hyperresponsiveness with varying degrees of severity ranging from mild self-resolving to sever episodes resulting in mortality (National Heart Lung and Blood Institute, 2007). In 2015, a global burden of disease study estimated that more than 358 million individuals had asthma around the world making it the most prevalent chronic respiratory disease worldwide (Soriano et al., 2017). In the United States (U.S.) the National health Interview Survey in 2017 showed that 19 million adults and 6.2 million children currently had asthma.

Each year so and so are hospitalized from asthma

Each year $$$ are spent on asthma

Each year so and so miss school days due to asthma

Children are more vulnerable to asthma

### Causation of asthma

Asthma is a disease with complex causal pathways in which genetic and environmental factors interact leading to multiple sub-phenotypes with different biological, pathological and clinical characteristics (Gowers et al., 2012; Wenzel, 2012). It is well established that asthma can be exacerbated by exposure to ambient air pollution of varying concentrations and sources (WHO, 2005). However, there was debate over whether air pollution can initiate asthma. Studies showed that exposure to general ambient air pollution is not associated with the initiation of new cases of asthma(Anderson et al., 2011). However, new evidence indicates that exposure to a more specific mixtures of air pollutants, most notably, traffic-related air pollution (TRAP), are associated with an increase risk in developing asthma among children (H. Anderson et al., 2013; Khreis, Kelly, et al., 2017).

In light of this new evidence, we aim to estimate the childhood asthma burden of disease attributable to the exposure to urban pollutants that are commonly associated with traffic-related air pollution. A full project work plan has been already submitted and approved by CARTEEH. Henceforward, the reports submitted, including this report, will focus on describing the work completed to date, and give clear account of the methodologies adopted to ensure the work is replicable and rigorous. Further, project results will be described as they emerge.

In this report, we will give a summary of what TRAP and TRAP exposure is. Review the evidence suggesting an association between TRAP and risk of developing asthma among children by presenting the biological plausibility of this association and the exposure-response functions. We will review the burden of disease estimation model and discuss some papers that applied it. We will then discuss the methods we used to estimate the exposure of interest and compare it to different modeling techniques. We will present the exposure data collated and analyzed to date. We will overview the US census data and underlying definitions. Finally, we will describe how childhood asthma incidence rates were estimated.

### Traffic related air pollution

Text here ….

### New evidence of traffic related air pollution induced asthma

#### Biological plausibility

#### Asthma is a complex disease with a complex causal pathway (Martinez, 2007). The complexity of asthma can be seen through its various phenotypes and endotypes which can be characterized by the different triggering factors, clinical presentations, pathological features, disease severity and responsiveness to treatment, to name a few (Corren, 2013). Advancement in biological techniques has given us a better understanding how different genetic and environmental factors interact resulting in the different endotypes (Holgate, 2007; Holgate et al., 2000; Mauad et al., 2007; Tgavalekos et al., 2007; Wenzel et al., 2009). In particular, advances in genetic techniques showed a wide range of biological mechanisms in which groups of genes control different pathways that result in the susceptibility to the development of asthma. For example, certain groups of genes control airway development, repair and remodeling while another group of genes control the level of response of the immune system to different triggering factors (Holgate, 2007; Martin et al., 2008; Nadeem et al., 2008; Ober et al., 2011). Interactions between genes and environmental factors have been proposed as potential mechanisms that may explain the development of asthma in association with the environment. Some mechanisms include damage to the airways from pollutants through oxidative stress depleting anti-oxidants in the airways, pollutants interacting with airway walls resulting in airway remodeling, influencing the expression of inflammatory mediators and enhancing respiratory sensitization to allergens (Gowers et al., 2012).

#### Significance of association

Studies examining the exposure to ambient air pollution at the community level and risk of developing asthma concluded that there is no association. A meta-analysis of cross-sectional studies by Anderson et al. (2011) which included 21 studies examining the community level concentrations of multiple air pollutants (NO2, PM10, Ozone and Sulphur Dioxide) found no association with asthma prevalence at the community’s level. However, studies that examined air pollution concentrations associated with traffic sources showed positive and statistically significant associations with asthma incidence and prevalence. A more recent meta-analysis by H. Anderson et al. (2013) of cohort studies included 17 studies examining within-community exposure contrasts dominated by traffic pollution found that NO2, but not PM2.5, concentrations had a significant association with asthma incidence. A more recent meta-analysis by Khreis, Kelly, et al. (2017) examined the associations between exposure to TRAP and risk of developing asthma among children as addressed in case control, cohort, and cross-sectional studies. The meta- analysis included 41 studies and found positive and statistically significant associations between Black Carbon, NO2, PM2.5 and PM10 and childhood asthma incidence and/or prevalence.

### Burden of disease estimation model

The public health and policy relevance of the positive and statistically significant associations between TRAP and childhood asthma incidence is largely unknown as the impact of TRAP exposures on the burden of childhood asthma incidence or prevalence is poorly documented. Due to the ubiquity of TRAP and the high number of exposed children, the relatively small individual risks of TRAP-associated asthma could translate into significant public health impacts with significant health care costs. Yet, this deduction is unconfirmed and is contested as supporting evidence and calculations are scarce.

To estimate the burden of childhood asthma in association with TRAP within the Contiguous United States, we will use standard risk assessment methods that have been previously applied in the context of childhood asthma (Künzli et al., 2008; Perez et al., 2013; Perez et al., 2009; Perez et al., 2012). The aim is to estimate how many new (i.e. incident) childhood asthma cases can be attributable to the exposure of interest, on an annual basis. We will compare these estimates across two years for which we have air pollution exposure data for: 2000 and 2010. The attribution of incident asthma cases to TRAP has substantial implications for the burden of asthma-related exacerbations as well. As air pollution increases the risk of developing new asthma cases, then all future acute exacerbations of these cases, regardless of subsequent (immediate) cause of the exacerbation, should be again attributed to air pollution. This is a conceptual model which has been suggested by Künzli et al. (2008) and is illustrated in Figure 1.

The model illustrated in Figure 1 expands on traditional risk assessment methods. Traditional methods attribute the exacerbations of chronic diseases to exposures of interest that directly induce the episode of exacerbation [direct], while not accounting for episodes of exacerbations induced by different exposures that occur among cases with underlying chronic disease caused by exposure of interest [indirect]. On the other hand, the conceptual model shown in Figure 1 accounts for both [direct] and [indirect] induction of exacerbations. When this model is followed, the burden of disease estimates associated with air pollution are revised to account not only for asthma symptoms that are directly triggered by air pollution (Boxes C and E in Figure 1); but also for asthma symptoms triggered by other causes in children who developed asthma *because* of their air pollution exposure (BoxD in Figure 1). As such, traditional risk assessment methods underestimate the health impacts of exposures that do have a role in the causal pathway of chronic disease.

Certain assumptions are accepted when using the expanded model (Figure 1), first, that the exposure has a causal role in the disease development, second, that the exposure has a causal role in the disease exacerbations, and third, that those who developed the disease due to the exposure wouldn’t have developed the disease without the exposure.

Whilst we focus on the estimation of Boxes A and B in this project, we pave the way forward for future analysis aiming at estimating boxes C, D, E and F.

### Traffic related air pollution exposure modeling

Land-use regression modelling (LUR) is a commonly used empirical-statistical method in air pollution epidemiology. The method has become widely used for estimating within-urban variability in air pollution, typically associated with traffic emissions (H. R. Anderson et al., 2013; Bechle et al., 2015). The method uses least squares regression to combine measured pollutant concentrations with geographical information system (GIS) -based predictor data (reflecting pollutant sources and surrounding land use characteristics) to build a prediction model applicable to non-measured locations (Khreis & Nieuwenhuijsen, 2017). The general pros and cons of LUR models, in comparison to other exposure models, have been previously described in Khreis and Nieuwenhuijsen (2017) and are summarized in [Table].

Using land use regression model to assign exposure values has several limitations. The exposure model assumes that pollutant exposure is from ambient outdoor air pollution but does not take into account indoor air pollution. The model also assigns exposure source at one single location and does not take into account time-activity patterns, for example how much of the exposure happens at school or at the playground. Another limitation is exposure misclassification error, the precision of the LUR model varies within urban areas leading to misclassification of exposure in either direction depending the direction of error of the pollutant prediction, for example if the model is over predicting this will lead to overexposure classification but if the model is under predicting the opposite might be true.

# Problem

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# Approach

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# Methodology

### Study area and time period

We analyzed census, air pollution and asthma incidence rates data for the contiguous U.S. (48 states and the District of Columbia) for the years 2000 and 2010. The analysis was done using the finest geographical level in the hierarchy of census geographic entities within U.S. when available [Figure]. The census block is the bases and building block for each of the hierarchies and is the finest geographical unit for census data. Data available at the census block level included population counts, urban or rural living location and air pollution data. The median household income data was only available at the census group level (one level higher than the census block). Childhood asthma incidence rates were only available at the state level. States not within the contiguous U.S., namely Alaska, Hawaii and Puerto Rico, were excluded from the analysis due to the unavailability of air pollution data.

### Census data

#### Geographical hierarchy of the US census

The U.S. Census Bureau recognizes multiple geographical hierarchies to address the needs of different users [Figure of census hierarchy]. The “Census Block” is the basic building unit for each of the geographical hierarchies. Census blocks do not cross the boundaries of higher level hierarchies unlike other geographic entities, for example zip codes may cross county lines but census blocks do not cross neither the boundaries of zip codes nor the boundaries of counties. The hierarchy used by the census bureau to conduct population counts includes regions, divisions, states, counties, census tracts, block groups and census blocks. For our analysis we used the latter hierarchy for our main analysis and “Places” when summarizing our data at the city level.

#### Identify a census block unique code

Each census block is identified with a Federal Information Processing System (FIPS) code. A FIPS code is a sequence of numbers that uniquely identify each level of geographical entity depending on the geographical hierarchy used. For example, the Texas A&M Transportation Institute building at the Rellis campus lies within the following FIPS code [48-041-000202-3-001] where:

* State code [48] is for Texas
* County code [041] is for Brazos County
* Tract code [000202]
* Block group code [3]
* Block code [001]

#### Census data sources and description

We obtained decennial census data for the years 2000 and 2010 for each census block from the National Historical Geographic Information System database (Manson et al., 2018). Each census block complete population counts of children <18 years of age and was classified into urban or rural. Urban classified census blocks were either urban clusters or urbanized areas based on multiple criteria by the census bureau. Urban clusters generally have a population threshold of ≥2,500 and <50,000, while urbanized areas have a threshold of ≥50,000 people. Annual median household income at the census block group level was categorized into five categories: <$20,000, $20,000 to <$35,000, $35,000 to <$50,000, $50,000 to <$75,000 and ≥$75,000. These five categories were consistent with a previously published study by Clark et al. (2017). Each census block was assigned the median household income category of the census block group which it resides in. Census blocks with a missing median household income category were assigned as “Not defined”.

### Air pollution exposure

Air pollution exposure was based on the annual average pollutant concentration at the centroid of each census block for the years 2000 and 2010. We estimated the burden of disease due to exposure of three pollutants; NO2, PM2.5 and PM10. Pollutant concentrations were obtained from satellite-based regression models (LUR) developed by other research teams [(Bechle et al., 2015; Kim et al., In prep)]. Air pollution concentrations were available at populated census blocks. The following sections present adscription of the modeling method used and each pollutant.

#### NO2 model and concentrations

In this project, exposure to NO2 was used as the main analysis in our study since it is a good predictor for traffic related air pollution sources, and studies have associated NO2 pollution with multiple adverse health outcomes including asthma and asthma exacerbations (Anderson et al., 2011; H. R. Anderson et al., 2013; Khreis, Kelly, et al., 2017). To measure NO2 exposure we adopt the US-wide LUR model developed by Bechle et al. (2015) to estimate the annual 2000 and 2010, NO2 concentrations at the centroid location of each populated census block. The development of the model incorporated two components, a “spatial” and “temporal” component. For the spatial component data were sourced using satellite readings, Environmental Protection Agency (EPA) air quality monitor readings and multiple geographical information systems (GIS) covariates including impervious surfaces, tree canopies, population count, major road length, minor road length, total road length, elevation, and distance to coast. The model had a spatial resolution typical for urban-scale LURs (∼100 m scale) and covered 100% of US Census blocks. For the temporal component, a scaling factors derived using monthly NO2 mean concentrations for 11 consecutive years from EPA air quality monitors were added to increase the predictive ability of the model. Data from air quality monitors were only included when at least 75% of the hourly values were available. The validation of the spatial model was satisfactory with an R2 = (0.63-0.82) using hold-out cross-validation. The R2 of the model was consistent with other continental-scale NO2 models. For example, Novotny et al. (2011) reported on a US National NO2 LUR model with an R2 = 0.78, Hystad et al. (2011) reported on a Canadian National NO2 LUR model with an R2 = 72%, Beelen et al. (2009) reported on an EU NO2 LUR model with an R2 = 61%, and Vienneau et al. (2013) reported on a Western European NO2 LUR model with an adjusted R2 = 58%.

#### PM2.5 concentrations and exposure

Annual average air pollution concentrations for PM2.5 were estimated using 17 years of data (1999-2015) from regulatory monitors. The model was constructed using a universal kriging framework (Kim et al., In prep). The model incorporated hundreds of geographic variables including land use, population counts, and satellite data. The validation of the model was performed using a hold-out cross validation with a satisfactory performance of 10-fold CV-R2 reaching 0.86 and 0.85 in 2000 and 2010, respectively.

#### PM10 concentrations and exposure

Annual average air pollution concentrations for PM10 were estimated using 27 years of data (1988-2015) using a similar method for PM2.5. The validation had a 10-fold CV-R2 reaching 0.60 and 0.57 in 2000 and 2010, respectively.

### Asthma incidence rate

For our initial analysis, we used a single national level childhood asthma incidence rate of 12.5 per 1000 at-risk children (95% CI = 10.5-14.4) obtained from a published paper by Winer et al. (2012). The study extracted data from the Behavioral Risk Factor Surveillance System (BRFSS) and the Asthma Call Back Survey (ACBS) for the years 2006-2008 which included 31 states and the District of Columbia with a sample size of 200,993 children from the BRFSS and 8,437 children from the ACBS. The incidence rate was assigned to the years 2000 and 2010. We then repeated our analysis for the year 2010 using state-specific childhood asthma incidence rates and compared the results with the results for the year 2010 from our initial analysis. The state-specific asthma incidence rate were estimated following the methods described by Winer et al. (2012) but expanded to include surveys conducted from 2006 through 2010. The following section and diagram describe how childhood asthma incidence rates were estimated for our repeated analysis.

A childhood asthma incidence rate is defined as the number of newly diagnosed asthma cases among at-risk children over a period of time. From this definition we notice the following, “newly” means have been diagnosed with asthma during the past 12 months, “diagnosed asthma case” means a doctor or healthcare professional diagnosis of asthma, “at-risk children” are children that are newly diagnosed ***or*** never have been diagnosed before. To obtain the asthma incidence rate of children within the US we used the following surveys; the Behavioral Risk Factor Surveillance System (BRFSS) and the Asthma Call Back Survey (ACBS). The BRFSS is a health-related telephone survey established in 1984 that collects data from US residents regarding health related behavior, chronic health conditions and preventive services (CDC, 2009). The ACBS is a follow up survey of BRFSS respondents established in 2005 that collects detailed data on asthma. While the BRFSS is conducted I all 50 states and the District of Columbia (DC), the ACBS is limited to a number of participating states that differ each year.

The BRFSS and ACBS samples are designed to represent the overall population of the state. To achieve this, each sample is assigned a weight within the survey. The weights adjust for disproportionate population sample selection relative to the state’s population, the variability in the probability of selection, and the actual response or non-response rates (Garbe et al., 2011; Korn et al., 2011). For example, if a respondent is assigned a weight of 200, then his or her answers to the questionnaires would represent the answers of 200 of the state’s population with similar characteristics based on the variables used for weighting by the survey design like age, gender, race and/or other variables. The sum of the BRFSS weights represent the total population within a state and the sum of the ACBS weights represent the total population with “Ever asthma” within a state.

The “Asthma status” of children was determined through the BRFSS question: “Has a doctor, nurse, or other health professional EVER said that the [child’s name] has asthma?” if the respondent said “Yes” the respondent’s child is designated as an “Ever asthma”, if the answer was “No” the status of “Never asthma” is designated. Respondents with children who answered “Yes” to the previous BRFSS question are asked to participate in the ACBS. The ACBS then follows up with the following question; “How old was the [name of child] when a doctor or other health professional first said [he/she] had asthma? How long ago was that?”, if the answer was “within 12 months” the child is considered an “Incident case”. To estimate the “At-risk children” are the sum of weighted “Incident cases” and weighted “Never asthma” (Equation 1). The “Asthma incidence rate” is the product of weighted “Incident cases” divided by “At-risk children” (Equation 2), while the “Aggregated incidence rate” is the product of the sum of weighted “Incident cases” divided by the sum of “At-risk children” across available years (Equation 3). The “Asthma prevalence rate” is the product of weighted “Ever asthma” divided by the sum of weighted “Ever asthma” and weighted “Never asthma” (Equation 4), while the “Aggregated prevalence rate” is the product of the sum of weighted “Ever asthma” divided by the sum of weighted “Ever asthma” and weighted “Never asthma” across available years from 2006 through 2010 (Equation 5). State-specific asthma incidence rates were estimated following the aforementioned steps using available data sets for each state. States with no available data from the ACBS and BRFSS during 2006 through 2010 (19 states) were assigned the aggregate incidence and prevalence rate of all available states combined [Table].

### Concentration response function

The concentration-response functions (CRF) for the association between exposure to NO2, PM10 and PM2.5 and childhood asthma development was extracted from a systematic review and meta-analysis study by Khreis, Kelly, et al. (2017). The review included 41 studies examining the association between exposure to traffic related air pollution and risk of developing asthma incidence or life time prevalence among children 18 years or younger. The risk estimates for each pollutant was summarized across available studies using a random-effect meta-analysis. The CRF for NO2 was 1.05 (95% CI=1.02–1.07) per 4 μg/m3 based on 20 studies. For PM10 it was 1.05 (95% CI=1.02–1.08) per 2 μg/m3 based on 12 studies and for PM2.5 it was 1.03 (95% CI=1.01–1.05) per 1 μg/m3 based on 10 studies. The meta-analysis did not adjust for co-pollutants meaning the number of attributable asthma cases due to either pollutants should not be added up.

### Burden of disease methodology

To estimate the burden of disease due to each pollutants we combined the census population count of children with the exposure data, asthma incidence rate and pollutant specific CRF’s [Diagram]. We first calculated the relative risk difference (RRdiff) and the population attributable fractions (PAF) using the CRF, CRF unit and exposure levels (in this case the air pollution concentrations at the census block). We then estimated for each year separately the number of childhood asthma incident cases, the incident cases attributable to each pollutant (attributable cases) and the fraction of attributable cases from the total number of incident cases (attributable fraction), following the steps below:

The RRdiff is the risk difference between exposure (air pollution concentration) and counterfactual exposure (zero air pollution concentration) and is calculated as shown in equation 6.

Equation 6

Were RR is the CRF and RRunit is the exposure unit. The PAF was then calculated using equation 7.

Equation 7

For each year we estimate the total at-risk children at the census block by subtracting the total children within the block by the total children within the block multiplied by the aggregate prevalence rate, as shown in equation 10.

Equation 8

The asthma incident cases within each block were estimated by multiplying the at-risk children with the aggregate incidence rate, as shown in equation 11.

Equation 9

The attributable cases were estimated by multiplying the asthma incident cases with the population attributable fraction within each census block, as shown in equation 12.

Equation 10

The total attributable cases is the sum of the attributable cases across all census blocks for each year and pollutant separately.

### Counterfactual scenarios

We examined two counterfactual scenarios for our initial analysis. In the first scenario we assumed the air pollution concentrations did not exceed the annual average air quality guidelines by the WHO (WHO, 2005) with the following limits:

* NO2 was 40 μg/m3 (annual average);
* PM10 was 20 μg/m3 (annual average);
* PM2.5 was 10 μg/m3 (annual average).

In the second scenario, we assumed air pollution concentrations did not exceed the lowest modeled concentration by the LUR model in either year for all the census blocks with the following concentrations:

* NO2 was 1.48 μg/m3 (annual average);
* PM10 was 0.72 μg/m3 (annual average);
* PM2.5 was 0.55 μg/m3 (annual average).

We reran the analysis for each year using the above two scenarios and estimated the number of cases due to TRAP that could have been prevented among census block exceeding the air pollution concentrations from the above scenarios.

### Sensitivity analysis

To examine the range of uncertainty in our burden estimates we re-ran the initial analysis using a combination of the upper and lower 95% CI of the CRF and asthma incidence rate. We examined the most conservative estimate, using the lowest CI interval of the CRF and asthma incidence rate, and the most extreme estimate using the upper CI intervals. We also produced a sensitivity analysis matrix combining the lower mean and upper limits of the CRF and the asthma incidence rate.

### Running the analysis

The analysis was conducted using R statistical software (R Core Team, 2018). Data sets were joined using a unique identifier for each census block. We produced open-access interactive maps summarizing the burden results at the county level, and look up tables summarizing the results at the city level for 498 major US cities selected using the CDC’s 500 cities project (CDC, 2017). The cities of Anchorage, Alaska and Honolulu, Hawaii were excluded from the look-up table since we did not include them in our analysis. The Interactive maps and tables were published at the CARTEEH website at the following link [<https://carteehdata.org/l/s/TRAP-burden-of-childhood-asthma>].

# Results

### Census description

[Table of demographic summary] summarizes the demographic and geographic characteristics of the census data. The total population of children were at 71,807,328 (26% of total population) and 73,690,271 (24%) in 2000 and 2010 respectively. 79% and 81% of children lived in an urban designated area (encompassing both urban clusters and urbanized areas) in 2000 and 2010. The table provides the population distribution by median household income group for each year.

### Asthma incidence

For our first analysis we used a single childhood asthma incidence rate of 12.5 per 1,000 at-risk children as published by Winer et al. (2012) for 2000 and 2010. The asthma incidence rate was an average rate across the years 2006-2008 which included samples of 8,437 children from 31 states and the District of Columbia (D.C) throughout the time period. We then repeated our analysis for the year 2010 using state-specific asthma incidence rates for the years 2006-2010 following Winer et al. (2012) proposed method. We then compared the change in burden estimates when using state-specific childhood asthma incidence rate with using a single childhood asthma incidence rate.

For the period 2006-2010, childhood asthma incidence rates were available for 32 states from a total sample of 16,153. States with missing childhood asthma incidence rates (16 states) were assigned an average asthma incidence rate of 12.1 per 1,000 at-risk children. The incidence rate was the average across all available states for the period 2006-2010. The District of Columbia had the highest childhood asthma incidence rate of 17.1 per 1,000 while Montana had the lowest incidence rate of 4.3 per 1,000 for the period 2006-2010. [Table of asthma incidence rate] provides a detailed summary of the asthma incidence rates across all available states. The following section provides a detailed description of the ACBS and BRFSS surveys used to estimate the state-specific asthma incidence rates.

### ACBS and BRSS survey

Text here ….

### Exposure data

#### NO2 concentrations

NO2 concentrations dropped between the years 2000 and 2010 in the whole of the US and across all the 48 states and D.C. with a national mean and median difference of - 37% (Figures 2-5). District of Columbia had the highest NO2 levels compared to other states: in 2000 the mean NO2 concentration was 20.58 ppb which dropped to 14.12 ppb in 2010 with an absolute difference of 6.47 ppb and a 31.4% reduction. North Dakota was the state with the lowest mean NO2 concentration in 2000 of 3.13 ppb which dropped to 2.42 ppb in 2010. The state with the highest absolute mean NO2 concentration difference between 2000 and 2010 was New Jersey with a difference equal to 7.09 ppb (17.86 to 10.76 ppb) while the state with the highest percent mean change of NO2 concentrations between 2000 and 2010 was Florida with a 47.2% reduction in mean NO2 concentrations (9.86 to 5.21 ppb)

* National
* Mean concentration
* Absolute and relative difference
* Concentration by living location
* Concentration by median income
* Concentration by living location stratified into median income
* State specific comparison
* Highest vs lowest for two years
* Largest absolute diff
* Largest relative diff
* State specific 2010
* Concentration by living location
* Concentration by median income

#### PM10 concentrations

#### PM2.5 concentrations

### Burden of disease

#### Attributable cases and fraction

#### Attributable cases and fraction by living location

#### Attributable cases and fraction by median household income

### Counterfactual scenarios

#### WHO guidelines

#### Lowest modeled air pollution concentrations

### Sensitivity analysis

#### Most conservative estimates

#### Most extreme estimates

# Conclusions and Recommendations

Use **Body Text** style.

# Outputs, Outcomes, and Impacts

**[Delete these section instructions]**

**Outputs**: new or improved processes, practices, technologies, software, training aids, or other tangible products resulting from this activity.

**Outcomes**: changes made to the transportation system, or its regulatory, legislative, or policy framework, resulting from research outputs.

**Impacts:** the effects of an outcome on the transportation system, or society in general, such as reduced fatalities, decreased operating costs, etc.

## Research Outputs, Outcomes, and Impacts

**[Delete these section instructions]**

Please provide a detailed description of all **research** outputs, outcomes, and impacts resulting from this study.

Examples include:

* Peer-reviewed publications.
* Presentations at conferences and technical meetings.
* Changes to policy or regulations, or decisions that were informed by research findings.

## Technology Transfer Outputs, Outcomes, and Impacts

**[Delete these section instructions]**

Please provide a detailed description of all technology transfer outputs, outcomes, and impacts resulting from this study.

Examples include:

* Data sets produced, including digital object identifier (doi).
* Code developed, including links to a repository.
* Software developed, including doi.
* Intellectual property generated, including subject inventions, patent applications, and issued patents.
* Strategic partnerships formed to inform decision-making or drive technology adoption, including public and private sectors.

## Education and Workforce Development Outputs, Outcomes, and Impacts

**[Delete these section instructions]**

Please provide a detailed description of all education and workforce development outputs, outcomes, and impacts resulting from this study.

Examples include:

* Students involved in the project.
* Outreach to students conducted at the K-12 and university level as part of the project.
* Training and educational materials developed, including curricula, lectures, and classroom exercises.
* Innovative educational and outreach methods deployed as a result of the project.

[Table 1. Sample Table Caption (Capitalize Each Word, and Do Not End with a Period) 2](#_Toc13490563)

[Table 2. Geographical and demographic characteristics 15](#_Toc13490564)

[Table 3. Incident cases 18](#_Toc13490565)

[Table 4. Air pollution concentrations 18](#_Toc13490566)

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[Table S2. Air pollution concentrations by state 19](#_Toc13490569)

[Table S3. Incident cases by state 21](#_Toc13490570)

[Table S4. Burden estimates due to NO2 by state 22](#_Toc13490571)

[Table S5. Burden estimates due to PM10 by state 23](#_Toc13490572)

[Table S6. Burden estimates due to PM2.5 by state 24](#_Toc13490573)

Table 2. Geographical and demographic characteristics

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | **Populated Census Blocks** | | | **Total Population** | | | **Total Children** | | |
|  | | **2000** | **2010** | **Change (%)** | **2000** | **2010** | **Change (%)** | **2000** | **2010** | **Change (%)** |
| **Total** |  | 5,280,214 | 6,182,882 | 17% | 279,583,437 | 306,675,006 | 10% | 71,807,328 | 73,690,271 | 3% |
| **Living Location** | Urbanized Area | 2,245,602 | 2,793,824 | 24% | 191,210,242 | 218,634,292 | 14% | 49,057,184 | 52,932,624 | 8% |
| Urban Cluster | 724,745 | 796,454 | 10% | 29,630,815 | 28,899,597 | -2% | 7,447,648 | 6,994,464 | -6% |
| Rural | 2,309,867 | 2,592,604 | 12% | 58,742,380 | 59,141,117 | 1% | 15,302,496 | 13,763,183 | -10% |
| **Median Household Income** | Not Defined | 0 | 2,686 |  | 0 | 1,022,300 |  | 0 | 13,555 |  |
| <$20,000 | 251,146 | 201,663 | -20% | 15,003,590 | 11,021,823 | -27% | 4,055,407 | 2,614,804 | -36% |
| $20,000 to <$35,000 | 1,876,701 | 1,185,560 | -37% | 79,329,475 | 51,269,356 | -35% | 20,694,588 | 12,770,843 | -38% |
| $35,000 to <$50,000 | 1,829,414 | 1,978,146 | 8% | 88,439,385 | 78,430,814 | -11% | 21,974,042 | 18,573,954 | -15% |
| $50,000 to <$75,000 | 984,837 | 1,860,065 | 89% | 68,510,768 | 93,716,911 | 37% | 17,350,990 | 21,953,876 | 27% |
| >=$75,000 | 338,116 | 954,762 | 182% | 28,300,219 | 71,213,802 | 152% | 7,732,301 | 17,763,239 | 130% |

Table S1. Geographical and demographical characteristics by state

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Populated Census Blocks** | | | **Total Population** | | | **Total Children** | | |
| **State** | **2000** | **2010** | **Change** | **2000** | **2010** | **Change** | **2000** | **2010** | **Change** |
| Alabama | 114,211 | 135,439 | 18.6% | 4,447,100 | 4,779,736 | 7.5% | 1,123,422 | 1,132,459 | 0.8% |
| Arizona | 80,553 | 114,742 | 42.4% | 5,130,632 | 6,392,017 | 24.6% | 1,366,947 | 1,629,014 | 19.2% |
| Arkansas | 84,150 | 96,096 | 14.2% | 2,673,400 | 2,915,918 | 9.1% | 680,369 | 711,475 | 4.6% |
| California | 344,356 | 403,398 | 17.1% | 33,871,648 | 37,253,956 | 10.0% | 9,249,829 | 9,295,040 | 0.5% |
| Colorado | 83,672 | 105,025 | 25.5% | 4,301,261 | 5,029,196 | 16.9% | 1,100,795 | 1,225,609 | 11.3% |
| Connecticut | 42,575 | 47,412 | 11.4% | 3,405,565 | 3,574,097 | 5.0% | 841,688 | 817,015 | -2.9% |
| Delaware | 13,184 | 15,933 | 20.9% | 783,600 | 897,934 | 14.6% | 194,587 | 205,765 | 5.7% |
| D.C. | 4,324 | 4,440 | 2.7% | 572,059 | 601,723 | 5.2% | 114,992 | 100,815 | -12.3% |
| Florida | 254,409 | 300,524 | 18.1% | 15,982,378 | 18,801,310 | 17.6% | 3,646,340 | 4,002,091 | 9.8% |
| Georgia | 144,008 | 167,353 | 16.2% | 8,186,453 | 9,687,653 | 18.3% | 2,169,234 | 2,491,552 | 14.9% |
| Idaho | 37,740 | 54,223 | 43.7% | 1,293,953 | 1,567,582 | 21.1% | 369,030 | 429,072 | 16.3% |
| Illinois | 254,521 | 300,384 | 18.0% | 12,419,293 | 12,830,632 | 3.3% | 3,245,451 | 3,129,179 | -3.6% |
| Indiana | 153,168 | 181,534 | 18.5% | 6,080,485 | 6,483,802 | 6.6% | 1,574,396 | 1,608,298 | 2.2% |
| Iowa | 122,243 | 137,429 | 12.4% | 2,926,324 | 3,046,355 | 4.1% | 733,638 | 727,993 | -0.8% |
| Kansas | 105,939 | 124,563 | 17.6% | 2,688,418 | 2,853,118 | 6.1% | 712,993 | 726,939 | 2.0% |
| Kentucky | 81,447 | 91,035 | 11.8% | 4,041,769 | 4,339,367 | 7.4% | 994,818 | 1,023,371 | 2.9% |
| Louisiana | 87,812 | 100,666 | 14.6% | 4,468,976 | 4,533,372 | 1.4% | 1,219,799 | 1,118,015 | -8.3% |
| Maine | 33,013 | 34,604 | 4.8% | 1,274,923 | 1,328,361 | 4.2% | 301,238 | 274,533 | -8.9% |
| Maryland | 60,164 | 80,944 | 34.5% | 5,296,486 | 5,773,552 | 9.0% | 1,356,172 | 1,352,964 | -0.2% |
| Massachusetts | 88,315 | 96,334 | 9.1% | 6,349,097 | 6,547,629 | 3.1% | 1,500,064 | 1,418,923 | -5.4% |
| Michigan | 190,827 | 207,522 | 8.8% | 9,938,444 | 9,883,640 | -0.6% | 2,595,767 | 2,344,068 | -9.7% |
| Minnesota | 133,531 | 151,983 | 13.8% | 4,919,479 | 5,303,925 | 7.8% | 1,286,894 | 1,284,063 | -0.2% |
| Mississippi | 82,279 | 84,750 | 3.0% | 2,844,658 | 2,967,297 | 4.3% | 775,187 | 755,555 | -2.5% |
| Missouri | 156,435 | 184,400 | 17.9% | 5,595,211 | 5,988,927 | 7.0% | 1,427,692 | 1,425,436 | -0.2% |
| Montana | 38,505 | 47,433 | 23.2% | 902,195 | 989,415 | 9.7% | 230,062 | 223,563 | -2.8% |
| Nebraska | 79,867 | 97,030 | 21.5% | 1,711,263 | 1,826,341 | 6.7% | 450,242 | 459,221 | 2.0% |
| Nevada | 26,209 | 35,617 | 35.9% | 1,998,257 | 2,700,551 | 35.1% | 511,799 | 665,008 | 29.9% |
| New Hampshire | 24,797 | 28,880 | 16.5% | 1,235,786 | 1,316,470 | 6.5% | 309,562 | 287,234 | -7.2% |
| New Jersey | 112,186 | 118,654 | 5.8% | 8,414,350 | 8,791,894 | 4.5% | 2,087,558 | 2,065,214 | -1.1% |
| New Mexico | 48,883 | 60,810 | 24.4% | 1,819,046 | 2,059,179 | 13.2% | 508,574 | 518,672 | 2.0% |
| New York | 225,167 | 242,807 | 7.8% | 18,976,457 | 19,378,102 | 2.1% | 4,690,107 | 4,324,929 | -7.8% |
| North Carolina | 157,641 | 185,219 | 17.5% | 8,049,313 | 9,535,483 | 18.5% | 1,964,047 | 2,281,635 | 16.2% |
| North Dakota | 39,145 | 47,559 | 21.5% | 642,200 | 672,591 | 4.7% | 160,849 | 149,871 | -6.8% |
| Ohio | 211,111 | 243,021 | 15.1% | 11,353,140 | 11,536,504 | 1.6% | 2,888,339 | 2,730,751 | -5.5% |
| Oklahoma | 111,022 | 135,561 | 22.1% | 3,450,654 | 3,751,351 | 8.7% | 892,360 | 929,666 | 4.2% |
| Oregon | 72,756 | 85,922 | 18.1% | 3,421,399 | 3,831,074 | 12.0% | 846,526 | 866,453 | 2.4% |
| Pennsylvania | 251,525 | 292,143 | 16.1% | 12,281,054 | 12,702,379 | 3.4% | 2,922,221 | 2,792,155 | -4.5% |
| Rhode Island | 17,196 | 17,644 | 2.6% | 1,048,319 | 1,052,567 | 0.4% | 247,822 | 223,956 | -9.6% |
| South Carolina | 95,667 | 108,669 | 13.6% | 4,012,012 | 4,625,364 | 15.3% | 1,009,641 | 1,080,474 | 7.0% |
| South Dakota | 42,094 | 45,168 | 7.3% | 754,844 | 814,180 | 7.9% | 202,649 | 202,797 | 0.1% |
| Tennessee | 122,059 | 143,319 | 17.4% | 5,689,283 | 6,346,105 | 11.5% | 1,398,521 | 1,496,001 | 7.0% |
| Texas | 388,643 | 454,658 | 17.0% | 20,851,820 | 25,145,561 | 20.6% | 5,886,759 | 6,865,824 | 16.6% |
| Utah | 36,375 | 45,558 | 25.2% | 2,233,169 | 2,763,885 | 23.8% | 718,698 | 871,027 | 21.2% |
| Vermont | 16,105 | 17,541 | 8.9% | 608,827 | 625,741 | 2.8% | 147,523 | 129,233 | -12.4% |
| Virginia | 101,285 | 145,045 | 43.2% | 7,078,515 | 8,001,024 | 13.0% | 1,738,262 | 1,853,677 | 6.6% |
| Washington | 100,263 | 118,774 | 18.5% | 5,894,121 | 6,724,540 | 14.1% | 1,513,843 | 1,581,354 | 4.5% |
| West Virginia | 49,101 | 66,728 | 35.9% | 1,808,344 | 1,852,994 | 2.5% | 402,393 | 387,418 | -3.7% |
| Wisconsin | 139,546 | 152,756 | 9.5% | 5,363,675 | 5,686,986 | 6.0% | 1,368,756 | 1,339,492 | -2.1% |
| Wyoming | 20,190 | 25,633 | 27.0% | 493,782 | 563,626 | 14.1% | 128,873 | 135,402 | 5.1% |

Table 3. Incident cases

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | **Incident Cases** | | |
|  | | 2000 | 2010 | Change (%) |
| **Total** |  | 786,300 | 794,900 | 1% |
| **Living Location** | Urbanized area | 537,200 | 571,000 | 6% |
| Urban cluster | 81,600 | 75,500 | -7% |
| Rural | 167,600 | 148,500 | -11% |
| **Median Household Income** | Not defined | 0 | 100 | NA |
| <$20,000 | 44,400 | 28,200 | -36% |
| $20,000 to <$35,000 | 226,600 | 137,800 | -39% |
| $35,000 to <$50,000 | 240,600 | 200,400 | -17% |
| $50,000 to <$75,000 | 190,000 | 236,800 | 25% |
| >=$75,000 | 84,700 | 191,600 | 126% |

Table 4. Air pollution concentrations

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | | **Concentration (µg/m3)** | | |
|  | | **2000** | **2010** | **Change (%)** |
| **NO2** | |  | | |
| **Total** |  | 20.6 | 13.2 | -36% |
| **Living Location** | Urbanized area | 29.7 | 18.4 | -38% |
| Urban cluster | 18.7 | 12 | -36% |
| Rural | 12.4 | 8 | -35% |
| **Median Household Income** | Not defined | NA | 16 |  |
| <$20,000 | 24.2 | 16.1 | -33% |
| $20,000 to <$35,000 | 18.3 | 13.2 | -28% |
| $35,000 to <$50,000 | 19.1 | 11.8 | -38% |
| $50,000 to <$75,000 | 24.3 | 12.8 | -47% |
| >=$75,000 | 28.8 | 16.5 | -43% |
| **PM10** | |  | | |
| **Total** |  | 21.5 | 17.9 | -17% |
| **Living Location** | Urbanized area | 23.4 | 19.1 | -18% |
| Urban cluster | 21.5 | 19.1 | -11% |
| Rural | 19.5 | 16.3 | -16% |
| **Median Household Income** | Not defined | NA | 18.2 |  |
| <$20,000 | 23.4 | 19.2 | -18% |
| $20,000 to <$35,000 | 21.5 | 18.2 | -15% |
| $35,000 to <$50,000 | 21.2 | 17.8 | -16% |
| $50,000 to <$75,000 | 21.6 | 18 | -17% |
| >=$75,000 | 21.1 | 17.7 | -16% |
| **PM2.5** | |  | | |
| **Total** |  | 12.1 | 9 | -26% |
| **Living Location** | Urbanized area | 13.3 | 9.7 | -27% |
| Urban cluster | 11.9 | 9.4 | -21% |
| Rural | 10.9 | 8.1 | -26% |
| **Median Household Income** | Not defined | NA | 8.8 |  |
| <$20,000 | 13.3 | 10.3 | -23% |
| $20,000 to <$35,000 | 11.9 | 9.5 | -20% |
| $35,000 to <$50,000 | 11.9 | 8.9 | -25% |
| $50,000 to <$75,000 | 12.4 | 8.7 | -30% |
| >=$75,000 | 12.7 | 8.7 | -31% |

Table S2. Air pollution concentrations by state

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **NO2** | | | **PM10** | | | **PM2.5** | | |
| **State** | **2000** | **2010** | **Change (%)** | **2000** | **2010** | **Change (%)** | **2000** | **2010** | **Change (%)** |
| Alabama | 16.2 | 10.3 | -36% | 23.4 | 17 | -27% | 15.6 | 10.3 | -34% |
| Arizona | 27.8 | 17 | -39% | 31.5 | 22.6 | -28% | 8.8 | 5.7 | -35% |
| Arkansas | 13.2 | 9.3 | -30% | 20.5 | 17.3 | -16% | 12.4 | 10.2 | -18% |
| California | 35.9 | 21.1 | -41% | 28.6 | 20.2 | -29% | 14.5 | 8.6 | -41% |
| Colorado | 26.5 | 18.1 | -32% | 19.4 | 18.6 | -4% | 6.8 | 5.6 | -18% |
| Connecticut | 26.3 | 15.6 | -41% | 15.6 | 13.4 | -14% | 11.4 | 7.9 | -31% |
| Delaware | 20.4 | 13.2 | -35% | 18.2 | 17.9 | -2% | 13.8 | 9.7 | -30% |
| District of Columbia | 38.2 | 26.3 | -31% | 21.8 | 18.1 | -17% | 15.7 | 11 | -30% |
| Florida | 19.7 | 10.7 | -46% | 20.5 | 15.9 | -22% | 11 | 7.8 | -29% |
| Georgia | 16.6 | 10.8 | -35% | 21.6 | 15.9 | -26% | 15.7 | 10.8 | -31% |
| Idaho | 15.3 | 9.8 | -36% | 22.8 | 14.9 | -35% | 7.5 | 5.3 | -29% |
| Illinois | 25.6 | 19 | -26% | 24.2 | 22.1 | -9% | 14.4 | 11.3 | -22% |
| Indiana | 24.8 | 15.4 | -38% | 22 | 22 | 0% | 14.9 | 12 | -19% |
| Iowa | 11.9 | 9.1 | -24% | 23.7 | 23 | -3% | 9.9 | 9.4 | -5% |
| Kansas | 13.4 | 9.7 | -28% | 23.8 | 21 | -12% | 10 | 8.2 | -18% |
| Kentucky | 19.7 | 12.4 | -37% | 22.9 | 17.4 | -24% | 15.3 | 11.3 | -26% |
| Louisiana | 15.8 | 9.6 | -39% | 19.9 | 18.2 | -9% | 12.7 | 9.6 | -24% |
| Maine | 10.8 | 6.3 | -42% | 12 | 10.1 | -16% | 7.3 | 5 | -32% |
| Maryland | 24.1 | 16.1 | -33% | 18.8 | 16.5 | -12% | 14.6 | 9.8 | -33% |
| Massachusetts | 23.9 | 14.1 | -41% | 16.2 | 12.4 | -23% | 10.6 | 7.7 | -27% |
| Michigan | 19.8 | 12.9 | -35% | 18.9 | 15.9 | -16% | 12 | 8.3 | -31% |
| Minnesota | 14.1 | 9.9 | -30% | 19.3 | 20.5 | 6% | 9.7 | 7.7 | -21% |
| Mississippi | 12.4 | 8.3 | -33% | 17.1 | 15.2 | -11% | 12.8 | 9.3 | -27% |
| Missouri | 13.1 | 9.3 | -29% | 22.8 | 19.5 | -14% | 12.2 | 10.1 | -17% |
| Montana | 9.6 | 6.2 | -35% | 19 | 15.1 | -21% | 8.2 | 5.5 | -33% |
| Nebraska | 12.3 | 8.6 | -30% | 25.3 | 22.4 | -11% | 8.5 | 7.6 | -11% |
| Nevada | 22.5 | 15.9 | -29% | 26 | 17.8 | -32% | 7.3 | 5.4 | -26% |
| New Hampshire | 16.4 | 9.1 | -45% | 10.4 | 9.4 | -10% | 7.9 | 6 | -24% |
| New Jersey | 34.4 | 21 | -39% | 20.6 | 19.3 | -6% | 13 | 9.2 | -29% |
| New Mexico | 16 | 12.1 | -24% | 17.5 | 15.9 | -9% | 5.5 | 4.5 | -18% |
| New York | 28.8 | 16.6 | -42% | 18 | 15.5 | -14% | 11.2 | 8.1 | -28% |
| North Carolina | 17.1 | 11 | -36% | 20.2 | 14.9 | -26% | 14.2 | 9.8 | -31% |
| North Dakota | 6.8 | 5.4 | -21% | 17 | 18.2 | 7% | 6.5 | 6.9 | 6% |
| Ohio | 23.6 | 14.3 | -39% | 22.8 | 20.8 | -9% | 15.6 | 11.8 | -24% |
| Oklahoma | 14.8 | 10.4 | -30% | 23.7 | 19.6 | -17% | 10.1 | 9.2 | -9% |
| Oregon | 18.1 | 11.1 | -39% | 16.9 | 11.9 | -30% | 7.8 | 5.4 | -31% |
| Pennsylvania | 27.6 | 16.6 | -40% | 21.2 | 17 | -20% | 14 | 10.1 | -28% |
| Rhode Island | 23.6 | 13.8 | -42% | 18.1 | 13.1 | -28% | 11 | 7.8 | -29% |
| South Carolina | 14.2 | 9.4 | -34% | 21.5 | 14.7 | -32% | 14.3 | 9.9 | -31% |
| South Dakota | 7.6 | 5.2 | -32% | 18.9 | 18.7 | -1% | 7.1 | 7.2 | 1% |
| Tennessee | 19.4 | 12.7 | -35% | 24.6 | 16.9 | -31% | 15.3 | 10.5 | -31% |
| Texas | 16.2 | 11.5 | -29% | 22.4 | 18.8 | -16% | 10.7 | 9.2 | -14% |
| Utah | 25.5 | 17 | -33% | 23.8 | 19.8 | -17% | 8.2 | 7.4 | -10% |
| Vermont | 14 | 8.3 | -41% | 11.3 | 9.4 | -17% | 6.8 | 5.7 | -16% |
| Virginia | 21 | 13.5 | -36% | 19 | 14.7 | -23% | 13.4 | 9.5 | -29% |
| Washington | 20.9 | 14.9 | -29% | 17.9 | 13.2 | -26% | 8.7 | 5.8 | -33% |
| West Virginia | 19.9 | 12.7 | -36% | 19.7 | 17.8 | -10% | 14.4 | 10.8 | -25% |
| Wisconsin | 15.9 | 10.6 | -33% | 18.5 | 18.8 | 2% | 10.6 | 9.1 | -14% |
| Wyoming | 12.3 | 7.6 | -38% | 18.3 | 15.4 | -16% | 6.6 | 4.8 | -27% |

Table 5. Burden estimates

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | **Attributable Cases** | | | **Attributable Fraction** | | |
|  | | **2000** | **2010** | **Change (%)** | **2000** | **2010** | **Change (%)** |
| **NO2** | |  | | | | | |
| **Total** |  | 209,100 | 141,900 | -32% | 27% | 18% | -33% |
| **Living Location** | Urbanized area | 168,400 | 117,600 | -30% | 31% | 21% | -32% |
| Urban cluster | 16,100 | 9,800 | -39% | 20% | 13% | -35% |
| Rural | 24,600 | 14,500 | -41% | 15% | 10% | -33% |
|  | Not defined | 0 | <100 | NA | NA | NA | NA |
| **Median Household Income** | <$20,000 | 13,700 | 5,900 | -57% | 31% | 21% | -32% |
| $20,000 to <$35,000 | 59,600 | 25,800 | -57% | 26% | 19% | -27% |
| $35,000 to <$50,000 | 60,700 | 34,500 | -43% | 25% | 17% | -32% |
| $50,000 to <$75,000 | 50,900 | 40,500 | -20% | 27% | 17% | -37% |
| >=$75,000 | 24,100 | 35,100 | 46% | 28% | 18% | -36% |
| **PM10** | |  | | | | | |
| **Total** |  | 379,400 | 331,600 | -13% | 48% | 42% | -13% |
| **Living Location** | Urbanized area | 271,100 | 246,600 | -9% | 50% | 43% | -14% |
| Urban cluster | 37,600 | 31,800 | -15% | 46% | 42% | -9% |
| Rural | 70,600 | 53,300 | -25% | 42% | 36% | -14% |
|  | Not defined | 0 | 100 | NA | NA | NA | NA |
| **Median Household Income** | <$20,000 | 22,600 | 12,400 | -45% | 51% | 44% | -14% |
| $20,000 to <$35,000 | 112,300 | 59,200 | -47% | 50% | 43% | -14% |
| $35,000 to <$50,000 | 115,500 | 83,600 | -28% | 48% | 42% | -13% |
| $50,000 to <$75,000 | 90,200 | 98,400 | 9% | 47% | 42% | -11% |
| >=$75,000 | 38,800 | 78,000 | 101% | 46% | 41% | -11% |
| **PM2.5** | |  | | | | | |
| **Total** |  | 247,100 | 190,200 | -23% | 31% | 24% | -23% |
| **Living Location** | Urbanized area | 176,400 | 140,400 | -20% | 33% | 25% | -24% |
| Urban cluster | 23,700 | 17,700 | -25% | 29% | 23% | -21% |
| Rural | 47,000 | 32,000 | -32% | 28% | 22% | -21% |
|  | Not defined | 0 | <100 | NA | NA | NA | NA |
| **Median Household Income** | <$20,000 | 14,600 | 7,400 | -49% | 33% | 26% | -21% |
| $20,000 to <$35,000 | 71,600 | 34,600 | -52% | 32% | 25% | -22% |
| $35,000 to <$50,000 | 74,900 | 48,300 | -36% | 31% | 24% | -23% |
| $50,000 to <$75,000 | 59,400 | 55,700 | -6% | 31% | 24% | -23% |
| >=$75,000 | 26,700 | 44,100 | 65% | 32% | 23% | -28% |

Table S3. Incident cases by state

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Incident Cases** | | |
| **STATE** | **2000** | **2010** | **Change (%)** |
| Alabama | 12,300 | 12,200 | -1% |
| Arizona | 15,000 | 17,600 | 17% |
| Arkansas | 7,500 | 7,700 | 3% |
| California | 101,300 | 100,300 | -1% |
| Colorado | 12,100 | 13,200 | 9% |
| Connecticut | 9,200 | 8,800 | -4% |
| Delaware | 2,100 | 2,200 | 5% |
| District of Columbia | 1,300 | 1,100 | -15% |
| Florida | 39,900 | 43,200 | 8% |
| Georgia | 23,800 | 26,900 | 13% |
| Idaho | 4,000 | 4,600 | 15% |
| Illinois | 35,500 | 33,800 | -5% |
| Indiana | 17,200 | 17,300 | 1% |
| Iowa | 8,000 | 7,900 | -1% |
| Kansas | 7,800 | 7,800 | 0% |
| Kentucky | 10,900 | 11,000 | 1% |
| Louisiana | 13,400 | 12,100 | -10% |
| Maine | 3,300 | 3,000 | -9% |
| Maryland | 14,900 | 14,600 | -2% |
| Massachusetts | 16,400 | 15,300 | -7% |
| Michigan | 28,400 | 25,300 | -11% |
| Minnesota | 14,100 | 13,900 | -1% |
| Mississippi | 8,500 | 8,200 | -4% |
| Missouri | 15,600 | 15,400 | -1% |
| Montana | 2,500 | 2,400 | -4% |
| Nebraska | 4,900 | 5,000 | 2% |
| Nevada | 5,600 | 7,200 | 29% |
| New Hampshire | 3,400 | 3,100 | -9% |
| New Jersey | 22,900 | 22,300 | -3% |
| New Mexico | 5,600 | 5,600 | 0% |
| New York | 51,400 | 46,700 | -9% |
| North Carolina | 21,500 | 24,600 | 14% |
| North Dakota | 1,800 | 1,600 | -11% |
| Ohio | 31,600 | 29,500 | -7% |
| Oklahoma | 9,800 | 10,000 | 2% |
| Oregon | 9,300 | 9,300 | 0% |
| Pennsylvania | 32,000 | 30,100 | -6% |
| Rhode Island | 2,700 | 2,400 | -11% |
| South Carolina | 11,100 | 11,700 | 5% |
| South Dakota | 2,200 | 2,200 | 0% |
| Tennessee | 15,300 | 16,100 | 5% |
| Texas | 64,500 | 74,100 | 15% |
| Utah | 7,900 | 9,400 | 19% |
| Vermont | 1,600 | 1,400 | -13% |
| Virginia | 19,000 | 20,000 | 5% |
| Washington | 16,600 | 17,100 | 3% |
| West Virginia | 4,400 | 4,200 | -5% |
| Wisconsin | 15,000 | 14,400 | -4% |
| Wyoming | 1,400 | 1,500 | 7% |

Table S4. Burden estimates due to NO2 by state

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **NO2** | **Attributable Cases** | | | **Attributable Fraction** | | |
| **STATE** | **2000** | **2010** | **Change (%)** | **2000** | **2010** | **Change (%)** |
| Alabama | 2,300 | 1,400 | -39% | 19% | 11% | -42% |
| Arizona | 4,900 | 3,800 | -22% | 33% | 22% | -33% |
| Arkansas | 1,200 | 900 | -25% | 16% | 12% | -25% |
| California | 39,300 | 25,400 | -35% | 39% | 25% | -36% |
| Colorado | 3,800 | 3,100 | -18% | 31% | 23% | -26% |
| Connecticut | 2,600 | 1,600 | -38% | 28% | 18% | -36% |
| Delaware | 500 | 400 | -20% | 24% | 18% | -25% |
| District Of Columbia | 500 | 300 | -40% | 38% | 27% | -29% |
| Florida | 8,700 | 5,500 | -37% | 22% | 13% | -41% |
| Georgia | 5,000 | 3,900 | -22% | 21% | 14% | -33% |
| Idaho | 700 | 600 | -14% | 18% | 13% | -28% |
| Illinois | 12,000 | 8,300 | -31% | 34% | 25% | -26% |
| Indiana | 4,800 | 3,100 | -35% | 28% | 18% | -36% |
| Iowa | 1,300 | 1,000 | -23% | 16% | 13% | -19% |
| Kansas | 1,400 | 1,100 | -21% | 18% | 14% | -22% |
| Kentucky | 2,500 | 1,600 | -36% | 23% | 15% | -35% |
| Louisiana | 2,500 | 1,400 | -44% | 19% | 12% | -37% |
| Maine | 400 | 200 | -50% | 12% | 7% | -42% |
| Maryland | 4,000 | 2,800 | -30% | 27% | 19% | -30% |
| Massachusetts | 4,300 | 2,500 | -42% | 26% | 16% | -38% |
| Michigan | 7,000 | 4,200 | -40% | 25% | 17% | -32% |
| Minnesota | 2,900 | 2,100 | -28% | 21% | 15% | -29% |
| Mississippi | 1,300 | 800 | -38% | 15% | 10% | -33% |
| Missouri | 2,700 | 1,800 | -33% | 17% | 12% | -29% |
| Montana | 300 | 200 | -33% | 12% | 8% | -33% |
| Nebraska | 900 | 600 | -33% | 18% | 12% | -33% |
| Nevada | 1,500 | 1,400 | -7% | 27% | 19% | -30% |
| New Hampshire | 600 | 300 | -50% | 18% | 10% | -44% |
| New Jersey | 8,200 | 5,400 | -34% | 36% | 24% | -33% |
| New Mexico | 1,100 | 900 | -18% | 20% | 16% | -20% |
| New York | 19,400 | 11,800 | -39% | 38% | 25% | -34% |
| North Carolina | 4,100 | 3,200 | -22% | 19% | 13% | -32% |
| North Dakota | 200 | 100 | -50% | 11% | 6% | -45% |
| Ohio | 8,400 | 5,000 | -40% | 27% | 17% | -37% |
| Oklahoma | 1,800 | 1,300 | -28% | 18% | 13% | -28% |
| Oregon | 2,000 | 1,300 | -35% | 22% | 14% | -36% |
| Pennsylvania | 9,600 | 6,000 | -38% | 30% | 20% | -33% |
| Rhode Island | 700 | 400 | -43% | 26% | 17% | -35% |
| South Carolina | 1,800 | 1,300 | -28% | 16% | 11% | -31% |
| South Dakota | 200 | 200 | 0% | 9% | 9% | 0% |
| Tennessee | 3,400 | 2,500 | -26% | 22% | 16% | -27% |
| Texas | 12,900 | 10,700 | -17% | 20% | 14% | -30% |
| Utah | 2,300 | 1,900 | -17% | 29% | 20% | -31% |
| Vermont | 300 | 100 | -67% | 19% | 7% | -63% |
| Virginia | 4,600 | 3,400 | -26% | 24% | 17% | -29% |
| Washington | 3,900 | 3,000 | -23% | 23% | 18% | -22% |
| West Virginia | 900 | 600 | -33% | 20% | 14% | -30% |
| Wisconsin | 3,100 | 2,100 | -32% | 21% | 15% | -29% |
| Wyoming | 200 | 100 | -50% | 14% | 7% | -50% |

Table S5. Burden estimates due to PM10 by state

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **PM10** | **Attributable Cases** | | | **Attributable Fraction** | | |
| **STATE** | **2000** | **2010** | **Change (%)** | **2000** | **2010** | **Change (%)** |
| Alabama | 6,100 | 4,800 | -21% | 50% | 39% | -22% |
| Arizona | 9,500 | 9,200 | -3% | 63% | 52% | -17% |
| Arkansas | 3,400 | 3,100 | -9% | 45% | 40% | -11% |
| California | 59,700 | 47,400 | -21% | 59% | 47% | -20% |
| Colorado | 5,300 | 5,800 | 9% | 44% | 44% | 0% |
| Connecticut | 3,500 | 2,900 | -17% | 38% | 33% | -13% |
| Delaware | 900 | 900 | 0% | 43% | 41% | -5% |
| District of Columbia | 600 | 400 | -33% | 46% | 36% | -22% |
| Florida | 17,900 | 16,300 | -9% | 45% | 38% | -16% |
| Georgia | 11,100 | 10,300 | -7% | 47% | 38% | -19% |
| Idaho | 2,000 | 1,700 | -15% | 50% | 37% | -26% |
| Illinois | 18,600 | 16,200 | -13% | 52% | 48% | -8% |
| Indiana | 8,100 | 8,200 | 1% | 47% | 47% | 0% |
| Iowa | 4,000 | 3,800 | -5% | 50% | 48% | -4% |
| Kansas | 3,900 | 3,700 | -5% | 50% | 47% | -6% |
| Kentucky | 5,400 | 4,400 | -19% | 50% | 40% | -20% |
| Louisiana | 6,000 | 5,000 | -17% | 45% | 41% | -9% |
| Maine | 1,000 | 800 | -20% | 30% | 27% | -10% |
| Maryland | 6,300 | 5,600 | -11% | 42% | 38% | -10% |
| Massachusetts | 6,300 | 4,700 | -25% | 38% | 31% | -18% |
| Michigan | 12,700 | 9,600 | -24% | 45% | 38% | -16% |
| Minnesota | 6,400 | 6,400 | 0% | 45% | 46% | 2% |
| Mississippi | 3,400 | 3,000 | -12% | 40% | 37% | -8% |
| Missouri | 7,600 | 6,800 | -11% | 49% | 44% | -10% |
| Montana | 1,100 | 900 | -18% | 44% | 38% | -14% |
| Nebraska | 2,700 | 2,500 | -7% | 55% | 50% | -9% |
| Nevada | 3,200 | 3,000 | -6% | 57% | 42% | -26% |
| New Hampshire | 900 | 800 | -11% | 26% | 26% | 0% |
| New Jersey | 10,600 | 9,700 | -8% | 46% | 43% | -7% |
| New Mexico | 2,300 | 2,200 | -4% | 41% | 39% | -5% |
| New York | 24,100 | 18,800 | -22% | 47% | 40% | -15% |
| North Carolina | 9,700 | 8,800 | -9% | 45% | 36% | -20% |
| North Dakota | 700 | 700 | 0% | 39% | 44% | 13% |
| Ohio | 15,400 | 13,300 | -14% | 49% | 45% | -8% |
| Oklahoma | 4,900 | 4,500 | -8% | 50% | 45% | -10% |
| Oregon | 3,700 | 2,900 | -22% | 40% | 31% | -23% |
| Pennsylvania | 15,200 | 11,900 | -22% | 48% | 40% | -17% |
| Rhode Island | 1,100 | 800 | -27% | 41% | 33% | -20% |
| South Carolina | 5,100 | 4,100 | -20% | 46% | 35% | -24% |
| South Dakota | 900 | 900 | 0% | 41% | 41% | 0% |
| Tennessee | 7,800 | 6,400 | -18% | 51% | 40% | -22% |
| Texas | 32,000 | 32,400 | 1% | 50% | 44% | -12% |
| Utah | 4,100 | 4,400 | 7% | 52% | 47% | -10% |
| Vermont | 500 | 300 | -40% | 31% | 21% | -32% |
| Virginia | 8,000 | 7,300 | -9% | 42% | 36% | -14% |
| Washington | 6,700 | 5,400 | -19% | 40% | 32% | -20% |
| West Virginia | 1,900 | 1,700 | -11% | 43% | 40% | -7% |
| Wisconsin | 6,500 | 6,300 | -3% | 43% | 44% | 2% |
| Wyoming | 600 | 500 | -17% | 43% | 33% | -23% |

Table S6. Burden estimates due to PM2.5 by state

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **PM2.5** | **Attributable Cases** | | | **Attributable Fraction** | | |
| **STATE** | **2000** | **2010** | **Change (%)** | **2000** | **2010** | **Change (%)** |
| Alabama | 4,500 | 3,200 | -29% | 37% | 26% | -30% |
| Arizona | 3,600 | 3,000 | -17% | 24% | 17% | -29% |
| Arkansas | 2,300 | 2,100 | -9% | 31% | 27% | -13% |
| California | 37,700 | 24,400 | -35% | 37% | 24% | -35% |
| Colorado | 2,300 | 2,200 | -4% | 19% | 17% | -11% |
| Connecticut | 2,700 | 1,900 | -30% | 29% | 22% | -24% |
| Delaware | 700 | 600 | -14% | 33% | 27% | -18% |
| District Of Columbia | 500 | 300 | -40% | 38% | 27% | -29% |
| Florida | 11,000 | 8,700 | -21% | 28% | 20% | -29% |
| Georgia | 9,000 | 7,600 | -16% | 38% | 28% | -26% |
| Idaho | 800 | 700 | -13% | 20% | 15% | -25% |
| Illinois | 12,800 | 9,700 | -24% | 36% | 29% | -19% |
| Indiana | 6,200 | 5,200 | -16% | 36% | 30% | -17% |
| Iowa | 2,100 | 2,000 | -5% | 26% | 25% | -4% |
| Kansas | 2,100 | 1,800 | -14% | 27% | 23% | -15% |
| Kentucky | 4,000 | 3,200 | -20% | 37% | 29% | -22% |
| Louisiana | 4,200 | 3,000 | -29% | 31% | 25% | -19% |
| Maine | 700 | 400 | -43% | 21% | 13% | -38% |
| Maryland | 5,200 | 3,700 | -29% | 35% | 25% | -29% |
| Massachusetts | 4,500 | 3,200 | -29% | 27% | 21% | -22% |
| Michigan | 9,000 | 5,700 | -37% | 32% | 23% | -28% |
| Minnesota | 3,800 | 3,000 | -21% | 27% | 22% | -19% |
| Mississippi | 2,700 | 2,000 | -26% | 32% | 24% | -25% |
| Missouri | 4,900 | 4,100 | -16% | 31% | 27% | -13% |
| Montana | 600 | 400 | -33% | 24% | 17% | -29% |
| Nebraska | 1,200 | 1,100 | -8% | 24% | 22% | -8% |
| Nevada | 1,100 | 1,100 | 0% | 20% | 15% | -25% |
| New Hampshire | 700 | 500 | -29% | 21% | 16% | -24% |
| New Jersey | 7,400 | 5,300 | -28% | 32% | 24% | -25% |
| New Mexico | 800 | 700 | -13% | 14% | 12% | -14% |
| New York | 16,200 | 10,900 | -33% | 32% | 23% | -28% |
| North Carolina | 7,400 | 6,200 | -16% | 34% | 25% | -26% |
| North Dakota | 300 | 300 | 0% | 17% | 19% | 12% |
| Ohio | 11,700 | 8,800 | -25% | 37% | 30% | -19% |
| Oklahoma | 2,600 | 2,400 | -8% | 27% | 24% | -11% |
| Oregon | 2,000 | 1,500 | -25% | 22% | 16% | -27% |
| Pennsylvania | 11,000 | 7,800 | -29% | 34% | 26% | -24% |
| Rhode Island | 800 | 500 | -38% | 30% | 21% | -30% |
| South Carolina | 3,800 | 3,000 | -21% | 34% | 26% | -24% |
| South Dakota | 400 | 400 | 0% | 18% | 18% | 0% |
| Tennessee | 5,600 | 4,400 | -21% | 37% | 27% | -27% |
| Texas | 18,100 | 18,300 | 1% | 28% | 25% | -11% |
| Utah | 1,800 | 2,000 | 11% | 23% | 21% | -9% |
| Vermont | 300 | 200 | -33% | 19% | 14% | -26% |
| Virginia | 6,300 | 5,000 | -21% | 33% | 25% | -24% |
| Washington | 3,900 | 2,700 | -31% | 23% | 16% | -30% |
| West Virginia | 1,500 | 1,100 | -27% | 34% | 26% | -24% |
| Wisconsin | 4,200 | 3,600 | -14% | 28% | 25% | -11% |
| Wyoming | 200 | 200 | 0% | 14% | 13% | -7% |

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