

Air Force Institute of Technology

AFIT Scholar

Faculty Publications

2-2021

A Framework for Estimating the United States Depression Burden Attributable to Indoor Fine Particulate Matter Exposure

William L. Taylor

Steven J. Schuldt

Air Force Institute of Technology

Justin D. Delorit

Air Force Institute of Technology

Christopher M. Chini

Air Force Institute of Technology

Teodor T. Postolache

See next page for additional authors

Follow this and additional works at: <https://scholar.afit.edu/facpub>



Part of the [Environmental Health and Protection Commons](#), and the [Mental and Social Health Commons](#)

Recommended Citation

Taylor, W. L., Schuldt, S. J., Delorit, J. D., Chini, C. M., Postolache, T. T., Lowry, C. A., ... Hoisington, A. J. (2021). A framework for estimating the United States depression burden attributable to indoor fine particulate matter exposure. *Science of The Total Environment*, 756, 143858. <https://doi.org/10.1016/j.scitotenv.2020.143858>

This Article is brought to you for free and open access by AFIT Scholar. It has been accepted for inclusion in Faculty Publications by an authorized administrator of AFIT Scholar. For more information, please contact richard.mansfield@afit.edu.

Authors

William L. Taylor, Steven J. Schuldt, Justin D. Delorit, Christopher M. Chini, Teodor T. Postolache, Christopher A. Lowry, Lisa A. Brenner, and Andrew J. Hoisington



Contents lists available at ScienceDirect

Science of the Total Environment

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

A framework for estimating the United States depression burden attributable to indoor fine particulate matter exposure



William L. Taylor^a, Steven J. Schultdt^a, Justin D. Delorit^a, Christopher M. Chini^a, Teodor T. Postolache^{b,c,d}, Christopher A. Lowry^{b,c,e,f}, Lisa A. Brenner^{b,c,f,g}, Andrew J. Hoisington^{a,b,c,g,*}

^a Department of Systems Engineering and Management, Air Force Institute of Technology, Wright-Patterson AFB, OH 45433, USA

^b Military and Veteran Microbiome: Consortium for Research and Education (MVM-CoRE), Aurora, CO 80045, USA

^c Veterans Health Administration, Rocky Mountain Mental Illness Research Education and Clinical Center (MIRECC), Rocky Mountain Regional Veterans Affairs Medical Center (RMRVAMC), Aurora, CO 80045, USA

^d Mood and Anxiety Program, Department of Psychiatry, University of Maryland School of Medicine, Baltimore, MD 21201, USA

^e Department of Integrative Physiology, Center for Neuroscience, and Center for Microbial Exploration, University of Colorado Boulder, Boulder, CO 80309, USA

^f Departments of Physical Medicine and Rehabilitation, Psychiatry, & Neurology, University of Colorado Anschutz Medical Campus, Aurora, CO 80045, USA

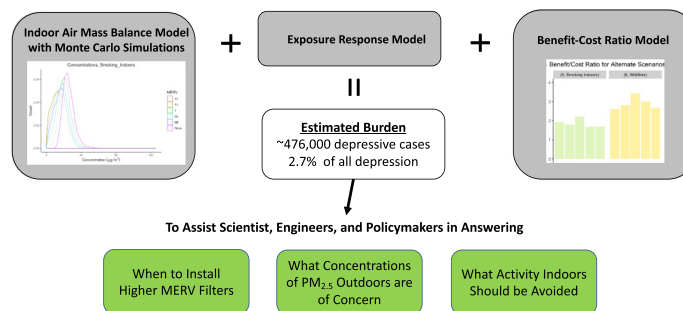
^g Department of Psychiatry and Neurology, University of Colorado Anschutz Medical Campus, Aurora, CO 80045, USA

HIGHLIGHTS

- Major depressive disorder impacted 17.7 million Americans in 2018.
- PM_{2.5} indoors may impact depression, potentially 0.07%–6.1% (2.7%) of cases.
- Increasing HVAC filter efficiency has minor reductions in depressive disorders.
- The model could estimate PM_{2.5} exposure influence on other mental illnesses.
- The model could be modified for other pollutants or building factors.

GRAPHICAL ABSTRACT

Modeling Major Depressive Disorder and Indoor Particulate Matter Exposure



ARTICLE INFO

Article history:

Received 15 June 2020

Received in revised form 11 November 2020

Accepted 19 November 2020

Available online 27 November 2020

Editor: Lidia Morawska

Keywords:

Depression

Particulate matter

Mental health

Indoor air

Epidemiology

Built environment

ABSTRACT

Recently published exploratory studies based on exposure to outdoor fine particulates, defined as particles with a nominal mean diameter less than or equal to 2.5 μm (PM_{2.5}) indicate that the pollutant may play a role in mental health conditions, such as major depressive disorder. This paper details a model that can estimate the United States (US) major depressive disorder burden attributable to indoor PM_{2.5} exposure, locally modifiable through input parameter calibrations. By utilizing concentration values in an exposure-response function, along with relative risk values derived from epidemiological studies, the model estimated the prevalence of expected cases of major depressive disorder in multiple scenarios. Model results show that exposure to indoor PM_{2.5} might contribute to 476,000 cases of major depressive disorder in the US (95% confidence interval 11,000–1,100,000), approximately 2.7% of the total number of cases reported annually. Increasing heating, ventilation, and air conditioning (HVAC) filter efficiency in a residential dwelling results in minor reductions in depressive disorders in rural or urban locations in the US. Nevertheless, a minimum efficiency reporting value (MERV) 13 filter does have a benefit/cost ratio at or near one when smoking occurs indoors; during wildfires; or in locations with elevated outdoor PM_{2.5} concentrations. The approach undertaken herein could provide a transparent strategy for investment into the built environment to improve the mental health of the occupants.

Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

* Corresponding author at: 2850 Hobson Way, Wright-Patterson AFB, OH 45419, USA.
E-mail address: Andrew.Hoisington@us.af.mil (A.J. Hoisington).

1. Introduction

The field of mental health research is expanding (ScienceDirect, n.d.), with good reason, as one in five Americans adults have a diagnosis of mental illness (Merikangas et al., 2010). One mental illness, major depressive disorder, impacted 17.7 million Americans in 2018 (2018 NSDUH Annual National Report | CBHSQ Data, n.d.) and globally was the third leading cause of disability in 2017 (Global Burden of Disease Study 2017 (GBD 2017) Burden by Risk 1990–2017 | GHDx, n.d.). Previous research has identified risk factors for mental health disorders to include genetics (Silventoinen et al., 2010), environment factors (Kendler and Baker, 2007), and social determinants (Allen et al., 2014). Another potential contributor to negative mental health outcomes might be found in the built environment (Hoisington et al., 2019). Risk of a negative health outcome is often a function of exposure time, and in the case of the built environment, Americans spend 93% of their time indoors (Leech et al., 2002) and 70% of the time in their residence (Klepeis et al., 2001).

Major depressive disorder, also colloquially known as clinical depression, is characterized by a wide variety of symptoms that cause significant distress and impairment that affects individuals for a sustained period of time (American Psychiatric Association, 2013). Symptoms may consist of a persistent sad mood, loss of pleasure derived from or interest in hobbies or routinely pleasurable activities, a poor evaluation of the past, present, and future and of oneself, decreased energy, sleep, appetite or weight changes, and reduced functioning (American Psychiatric Association, 2013). Depression can co-occur with other mental health conditions/symptoms, including anxiety and posttraumatic stress disorder (Hirschfeld, 2001; Spinhoven et al., 2014). Depressed individuals have higher odds of dying by suicide as compared to non-depressed individuals (Hawton et al., 2013).

Exposure to fine particulates, defined as particles with a nominal mean diameter less than or equal to 2.5 μm ($\text{PM}_{2.5}$), is a general health concern, providing the largest contributions to global mortality and morbidity due to air pollution (Hoek et al., 2013; Chen et al., 2008). $\text{PM}_{2.5}$ is theorized to influence depression and other mental health outcomes through two biological mechanisms, chronic inflammation and oxidative stress (Power et al., 2015). Chronic inflammation is an established contributor to mental health disorders (Anisman and Hayley, 2012; Raison et al., 2006; Bakunina et al., 2015; Rohleder, 2014; Miller and Raison, 2016), and $\text{PM}_{2.5}$ is associated with aggravation of chronic inflammation (Block and Calderón-Garcidueñas, 2009; Calderón-Garcidueñas et al., 2009). Inflammatory cytokines and other biological indicators of depression are more prevalent in individuals living in proximity to higher outdoor $\text{PM}_{2.5}$ concentrations (Block and Calderón-Garcidueñas, 2009; Calderón-Garcidueñas et al., 2009). Air pollutants such as $\text{PM}_{2.5}$ also can increase oxidative stress (Pham-Huy et al., 2008; Fournier et al., 2017). Specifically, free radicals associated with oxidative stress are highly reactive, producing harmful by-products and tissue damage (Conner and Grisham, 1996). Oxidative stress has previously been connected to mental health outcomes, including depression (Black et al., 2015). Exploratory studies between outdoor $\text{PM}_{2.5}$ concentrations and mental health outcomes, including depression, have been noted (Power et al., 2015; Pun et al., 2017; Szyszkowicz et al., 2009; Kim et al., 2010; Yue et al., 2020; Lee et al., 2019). Specifically, long-term exposure to elevated $\text{PM}_{2.5}$ concentrations outdoors may increase the risk of depression by approximately 10% (95% confidence intervals = 2.3%–18.9%) (Braithwaite et al., 2019) and contribute to an acute depressive response in select individuals (Szyszkowicz et al., 2009).

Outdoor particles enter into the built environment and become indoor $\text{PM}_{2.5}$ (MacNeill et al., 2014; Qing et al., 2005; Weisel et al., 2005; Ji and Zhao, 2015) this concept has been applied in previous prospective studies that have correlated depression with outdoor concentrations of $\text{PM}_{2.5}$ measured at central outdoor monitoring stations (Braithwaite et al., 2019) that do not have spatial resolution (Chambliss et al.,

2020). Central filtration systems can abate indoor $\text{PM}_{2.5}$ concentrations (Brown et al., 2014; Bräuner et al., 2008; Montgomery et al., 2015; Fisk, 2013; Stephens and Siegel, 2013; Azimi et al., 2014), resulting in disease-related treatment cost avoidance (Fisk and Chan, 2017a; Zhao et al., 2015; Azimi and Stephens, 2013). The purpose of this paper was to develop an epidemiological model, using a mass-balance approach for $\text{PM}_{2.5}$ concentrations, that estimates the potential magnitude of the burden of indoor $\text{PM}_{2.5}$ and depression. A secondary focus of this paper was to determine the influence that different levels of filtration had upon the estimated cases of major depressive disorder. This is the first known use of an exposure-response model to estimate cases of depression resulting from indoor $\text{PM}_{2.5}$ exposure.

2. Methodology

This paper combines an epidemiological exposure-response function and indoor mass balance models to estimate the potential major depressive disorder impacts of indoor $\text{PM}_{2.5}$ exposure within a residential setting. To account for spatial variability of model input parameters in the US, Monte Carlo simulation was used to sample from known distributions of residential housing characteristics. Calculated indoor concentrations inform an exposure-response model to estimate the number of cases of major depressive disorder. Furthermore, an economic analysis was performed to identify the tradeoffs between the cost of various minimum efficiency reporting value (MERV) filter technologies, and major depressive disorder treatment cost avoidance. A summary schematic of the process used in the present paper is shown in Fig. 1. The modeling process includes eight different scenarios, representative of a range of outdoor $\text{PM}_{2.5}$ concentrations and indoor emissions: (1) US average; (2) New York City; (3) Cincinnati; (4) Sacramento; (5) homes with indoor smokers; (6) homes near wildfires; (7) extreme case 1; and (8) extreme case 2. No parameters were changed between model runs, other than the outdoor $\text{PM}_{2.5}$ concentrations and the indoor emissions in the smoking scenario. That is, all other model parameters are characteristic of nationally averaged US housing parameters. Therefore, these different scenarios represent the estimated depressive outcomes to occur if those conditions were present in the US.

2.1. Indoor air modeling

A mass balance approach was utilized to calculate the concentration of $\text{PM}_{2.5}$ within a typical US residence (Fisk and Chan, 2017a), as shown in Eqs. (1) and (2). Air within the homes was assumed to be well-mixed, and $\text{PM}_{2.5}$ concentrations were assumed to be steady state. All homes were assumed to utilize a forced-air heating, ventilation, and air conditioning (HVAC) system, as this is currently the most widely used system in the US (Residential Energy Consumption Survey (RECS) - Analysis and Projections, n.d.).

$$C = C_o \frac{P \lambda_V}{\lambda_V + \lambda_D + \lambda_F} + \frac{E}{(\lambda_V + \lambda_D + \lambda_F)V} \quad (1)$$

where:

- C = resulting concentration of $\text{PM}_{2.5}$ ($\mu\text{g}/\text{m}^3$)
- C_o = the ambient air concentration of $\text{PM}_{2.5}$ ($\mu\text{g}/\text{m}^3$)
- P = penetration factor (unitless)
- λ_V = infiltration ventilation rate (h^{-1})
- λ_D = rate of particle removal by deposition (h^{-1})
- λ_F = rate of particle removal by filtration (h^{-1})
- E = total emissions of $\text{PM}_{2.5}$ from indoor sources ($\mu\text{g}/\text{h}$)
- V = building volume (m^3).

Discrete values for the factors in Eqs. (1) and (2) are summarized in Table 1. Ambient air concentrations were fit to lognormal distributions, calculated from mean and percentile values from 2018

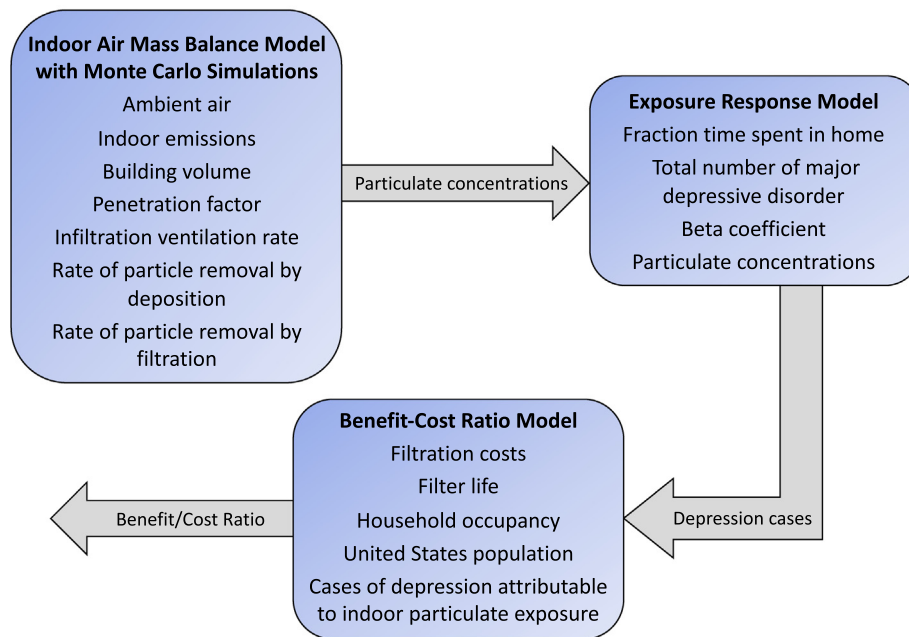


Fig. 1. Description of modeling process with input and output parameters. Blue boxes are for each major calculation, gray arrows are primary outputs.

(US EPA O, n.d.-a). The US scenarios all utilize data collected by the Environmental Protection Agency; this information as well as that about the other scenarios is referenced in the supplemental information. Cooking and smoking were the only sources of indoor emissions considered in the analysis. Cooking emissions were averaged over the course of a day in a normal distribution (Ozkaynak et al., 1996). Smoking was only considered in one of the eight case studies. Home volume was assumed to be normally distributed (Fisk and Chan, 2017a). Infiltration ventilation rate was fit to a lognormal distribution (Murray and Burmaster, 1995). Penetration factor and rate of particle removal by deposition were determined from residential studies (Ozkaynak et al., 1996; Williams et al., 2003). Penetration factor was determined using a cropped normal distribution, with an upper bound of one. The rate of particle removal by deposition was assumed to be normally distributed.

The rate of particle removal by filtration (λ_F) in the HVAC system was calculated using Eq. (2) (Fisk and Chan, 2017a). Duty cycle was a cropped normal distribution, with a minimum bound of zero (Fazli and Stephens, 2018). The flow rate through the residential HVAC

system was represented by a lognormal distribution, with distribution parameters obtained from two studies of residential housing characteristics (Jump et al., 2011; Stephens et al., 2011). Filter particle removal efficiency was assumed constant for each MERV rating (Brown et al., 2014), ignoring efficiency changes with increased dust buildup over time (Stephens and Siegel, 2011).

$$\lambda_F = DH\varepsilon_L \tag{2}$$

where:

D = duty cycle (unitless)

H = airflow rate through HVAC system, divided by indoor volume (h^{-1})

ε_L = particle removal efficiency of filter in use (unitless).

Monte Carlo simulation methods were utilized to calculate concentration values and account for variability in the parameters used in Eqs. (1) and (2). First, distributions were created from the mean and

Table 1
Input parameter values and reference sources for Eqs. (1), (2), and (3).

Parameter (variable, units)	Values (mean, SD)	Source
Outdoor air (C_o , $\mu\text{g}/\text{m}^3$)	Varies by scenario	(US EPA O, n.d.-b; Henderson et al., 2012; Sharma and Mandal, 2017; Ziková et al., 2016)
Emissions (E , $\mu\text{g}/\text{m}^3$)	2.62, 1.11	(Ozkaynak et al., 1996)
Building volume (V , m^3)	482, 28.68	(Fisk and Chan, 2017a)
Penetration Factor (P , unitless)	0.97, 0.06 ^b	(Ozkaynak et al., 1996; Williams et al., 2003)
Infiltration ventilation rate (λ_v , h^{-1})	0.53, 2.3 ^a	(Murray and Burmaster, 1995)
Rate of particle removal by deposition (λ_D , h^{-1})	0.39, 0.08	(Ozkaynak et al., 1996; Williams et al., 2003)
Rate of particle removal by filtration (λ_F , h^{-1})	Variable	(Fisk and Chan, 2017a)
Duty cycle (D , unitless)	0.153, 0.051 ^c	(Fazli and Stephens, 2018)
Airflow through residential HVAC system (Q , m^3/s)	4.36, 1.44 ^a	(Jump et al., 2011; Stephens et al., 2011)
Particle removal efficiency of filter in use (ε_L , unitless)	Variable	(Brown et al., 2014)
Percent of day spent within residence (F , unitless)	0.70	(Klepeis et al., 2001)
Annual number of major depressive disorder cases (m_0)	17,700,000	(2018 NSDUH Annual National Report CBHSQ Data, n.d.)
Coefficient of exposure-response function (β , unitless)	0.009691	(Gu et al., 2019)
Median $\text{PM}_{2.5}$ concentration of residence (Δx , $\mu\text{g}/\text{m}^3$)	Varied by scenario	Eq. (1)

Abbreviations: HVAC, heating, ventilation, and air conditioning; $\text{PM}_{2.5}$, particulate matter_{2.5}, defined as particles with a nominal mean diameter less than or equal to 2.5 μm .

^a Geometric mean and standard deviation.

^b Maximum of 1.

^c Minimum of 0.

standard deviation values for each parameter. Next, 100,000 concentrations were calculated using Eqs. (1) and (2), with random values selected from the distributions of each variable. Finally, the calculated concentrations were used to estimate major depressive disorder outcomes in the exposure-response function, detailed below. This process was replicated for each filtration system and each scenario, to understand the influence that filtration has on the estimated prevalence of major depressive disorder.

2.2. Exposure-response model

To quantify the number of major depressive disorder cases that can be attributed to indoor PM_{2.5} exposure, an exposure-response function was utilized, Eq. (3) (Boulanger et al., 2017).

$$\Delta y = F m_0 \left(1 - e^{(-\beta \cdot C)}\right) \quad (3)$$

where:

Δy = number of adults diagnosed with a major depressive disorder as a result of indoor PM_{2.5} exposure (incidences year⁻¹)

F = average percent of day that the population spends in a residence (unitless)

m_0 = the number of adults diagnosed with major depressive disorder (incidences year⁻¹)

β = coefficient of exposure-response function, selected from different epidemiology study results. $\beta = \log(RR_{10})/10$, with RR_{10} describing the relative risk for an increase of 10 $\mu\text{g}/\text{m}^3$ in PM_{2.5} concentration (unitless)

C = the median PM_{2.5} concentration of the residence, calculated using the results of Eqs. (1) and (2) ($\mu\text{g}/\text{m}^3$).

It was assumed that US adults spend 70% of their day within their residence (Klepeis et al., 2001). The number of episodes of depression in the US was based on reports for adults (over 18 years old) in 2018 (Results From the 2017 National Survey on Drug Use and Health: Detailed Tables, n.d.). Beta values were converted from odds ratio values developed from epidemiological studies, summarized in a meta-analysis (Braithwaite et al., 2019), which included long-term odds ratio of 1.102 for depression cases associated with PM_{2.5}, with a 95% confidence interval of 1.023–1.189. Many applications of an exposure-response function utilize a relative risk instead of an odds ratio. Herein the relative risk and odds ratio can be considered equivalent since the baseline prevalence for depression is low (Braithwaite et al., 2019). The median PM_{2.5} concentrations were calculated based on Eqs. (1) and (2). Some exposure-response studies utilize a baseline exposure value for concentrations, assuming that no adverse health effects occur below a select concentration (Boulanger et al., 2017; Cohen et al., 2017). However, the present analysis assumes a baseline exposure value of zero, practically meaning that any concentration could have an adverse health effect (Crouse et al., 2012; Pinault et al., 2016; Roman et al., 2008).

2.3. Economic analysis

To determine the value of indoor air filtration as a method to remove PM_{2.5} for a health benefit, major depressive disorder treatment cost avoidance was estimated. Downscaling the estimated direct and indirect cost of depressive disorders in the US to individual cases resulted in an average annual cost of \$14,926 (2017 dollars) per incidence of major depressive disorder (Greenberg et al., 2015). Multiplying the per-case cost by the estimated number of cases for each scenario yielded a total scenario cost. To determine the value of filtration, particulate matter filtration costs for filters with different efficiencies were compared to the potential cost avoidance of the reduced numbers of major depressive disorder cases, using Eq. (4). Hereafter, cost avoidance is

referred to as benefits, to conform with benefit-to-cost ratio (BCR) methodology, and to avoid confusion between costs of filtration and cost avoidance.

$$FC = \frac{F_i}{S} \quad (4)$$

where:

FC = annual cost of filter implementation (US dollars/capita)

F_i = annual operating cost of filter (US dollars)

S = average household occupancy (1.98 people over 18 years old/household) (Bureau UC, n.d.)

The total cost of filtration assumes every house in the US has the same filter. Filter operating costs were taken from (Brown et al., 2014). The treatment cost avoidance was calculated with Eq. (5).

$$B = \frac{(\$MDD - \$MDD_i)}{N} \quad (5)$$

where:

B = benefit of filtration implementation, per person

$\$MDD$ = baseline cost of major depressive disorder attributable to indoor PM_{2.5} exposure

$\$MDD_i$ = cost of major depressive disorder attributable to indoor PM_{2.5} exposure with different filtration implementations

N = US population over 18 years old (255,190,602)

Calculating both costs and benefits of filtration allows a BCR to be calculated. The baseline cost of major depressive disorder attributable to indoor PM_{2.5} exposure ($\$MDD$) assumes that the home has no filter on the HVAC system, allowing any PM_{2.5} to recirculate within the home without reduction. The baseline cost value is calculated using Eqs. (1) and (2), with the particle removal efficiency (ϵ_L) set to zero. The resulting concentration is entered into Eq. (3) to estimate the number of major depressive disorder cases, and then multiplied by the cost of each case of depression (\$14,926), ultimately representing the baseline cost of major depressive disorder attributable to indoor PM_{2.5} exposure ($\$MDD$). Repeating this process for each individual MERV rating resulted in the cost of major depressive disorder attributable to indoor PM_{2.5} exposure with different filtration implementations ($\$MDD_i$). The difference between each value and the baseline value, divided by the adult US population (N), results in a benefit value per person. All analysis was conducted in R (version 3.6.0) (R Development Core Team, 2011) and visualization was completed with the ggplot2 package (Wickham, 2011). R code used for the models and figures is provided in the supplemental information to enable further work by others in this field.

3. Results

The modeled residential PM_{2.5} concentrations were calculated using Eqs. (1) and (2), in scenarios of different MERV filter use across the US and in specific US cities (Fig. 2A). Resulting concentrations (see Supplemental Figs. 1–8) and the median levels in the present model were lower than estimated values in other studies modeling indoor PM_{2.5} (Fisk and Chan, 2017a; Azimi and Stephens, 2018), and measured concentrations in US residential environments (Qing et al., 2005; Walker et al., 2019).

The modeled concentrations for alternate scenarios (indoor smoking, wildfires, and extreme scenarios) of different MERV filters are shown in Fig. 2B. The wildfire scenario shows the highest indoor concentrations of any scenario. Measurements of PM_{2.5} emissions from wildfires vary (Henderson et al., 2012; Rittmaster et al., 2006; Van Donkelaar et al., 2011), and, notably, the selected concentrations are high. Wildfires aside from the incident modeled in this analysis may not have the same concentration levels and impact on indoor

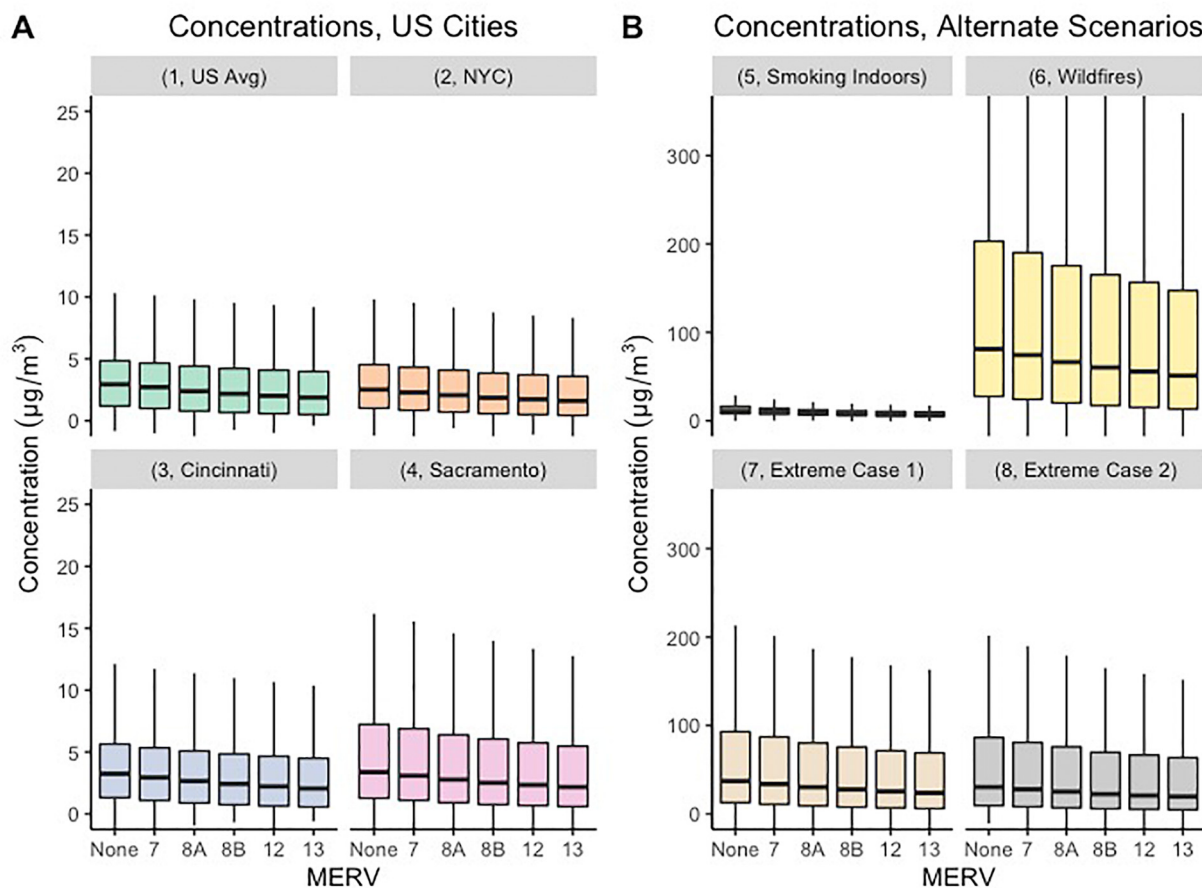


Fig. 2. Modeled indoor PM_{2.5} concentrations across filters for A) United States cities and B) indoor smoking, wildfires, and extreme cases. Abbreviations: Avg, average; MERV, minimum reporting efficiency reporting values; NYC, New York City; US, United States.

PM_{2.5} and, subsequently, health effects. The extreme case scenarios, as expected, show modeled indoor concentrations substantially higher than any of the other scenarios aside from the wildfire scenario. The extreme case scenarios use ambient PM_{2.5} concentrations from large international cities, and as such are unlikely to be representative of conditions in the US. Certain locations close to high industrial activity or vehicular traffic may experience these levels of ambient PM_{2.5}.

The use of HVAC filters reduced the indoor concentrations of PM_{2.5} in the US city scenarios from a no-filter condition by an average of approximately 8%, 18%, 24%, 31%, and 34%, for MERV 7, MERV 8A, MERV 8B, MERV 12, and MERV 13, respectively (Fig. 2A). Similar results were observed in the alternate scenarios; namely, filters reduced the modeled concentrations of PM_{2.5} in alternate scenarios by an average of approximately 9%, 18%, 22%, 26%, and 32%, for MERV 7, MERV 8A, MERV 8B, MERV 12, and MERV 13, respectively (Fig. 2B). Studies of filtration efficiency vary in estimates of PM_{2.5} removed when passing through the filter of the HVAC system (Azimi et al., 2014; Azimi et al., 2016), but they are consistent in the determination that increasing MERV ratings lowers indoor concentrations of PM_{2.5}.

Fig. 3A and B display the estimated incidences of major depressive disorder per million people, attributable to residential PM_{2.5} exposure. The estimated cases of major depressive disorder in the model of the US average scenario are approximately 2.7% of the total number of major depressive disorder cases in the US, annually. Fig. 4 highlights the results of BCR calculations for implementation of different filtration systems in each scenario. BCR was generally higher in scenarios with higher indoor PM_{2.5} values. Moreover, the filter with MERV rating 8B had the highest BCR among all scenarios, due to the balance of low price and relatively high removal efficiency.

For a direct comparison of the use of filters to impact the incidence of major depressive disorder, the same model parameters were used for each scenario. A comparison was made on the percent reduction in estimated incidence of major depressive disorder between no filter relative to MERV 7 in the US (Fig. 5A), and alternate scenarios (Fig. 5C), and then again from MERV 7 relative to MERV 13 in US (Fig. 5B), and alternate scenarios (Fig. 5D). The percent reduction in estimated incidence of major depressive disorder in the US cities scenario from zero filtration relative to a MERV 7 was independent of the outdoor concentration of PM_{2.5} in the model and the 90th percentile was at 25.7% reduction in cases of major depressive disorder. In contrast, reduction from MERV 7 to MERV 13 in US scenarios has a less skewed distribution in the percent reduction, with the 90th percentile at 68.0% reduction in cases of major depressive disorder. The alternate scenario with elevated outdoor PM_{2.5} concentrations (i.e. wildfires) did have some differences due to outdoor concentration levels.

4. Discussion

Indoor PM_{2.5} concentrations were estimated using a mass balance approach, varying building parameters with Monte Carlo simulations. The resultant concentrations then provided an estimate of expected cases of major depressive disorder in an epidemiological exposure-response function. The BCR was based on a comparison of expected treatment costs avoided and the cost of residential filters, in order to determine which filter provided the best return on investment. Finally, the percent reduction in major depressive disorder was estimated based on increased filter efficiency. The analysis provides a framework for researchers to include major depressive disorder and other mental

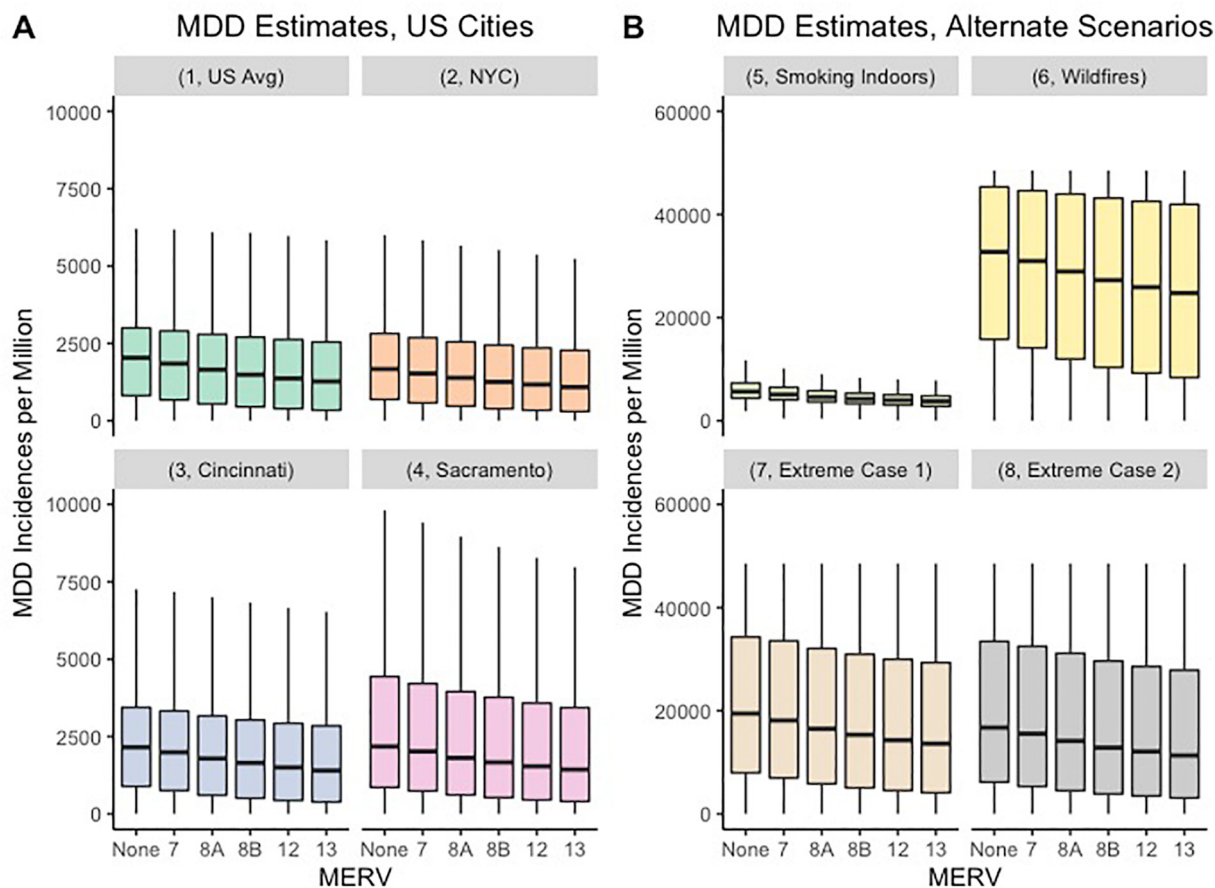


Fig. 3. Incidences per million people of major depressive disorder attributable to indoor $PM_{2.5}$ exposure across filter systems for A) United States cities and B) alternate scenarios. Abbreviations: Avg, average; MDD, major depressive disorder; MERV, minimum reporting efficiency reporting values; NYC, New York City; US, United States.

illnesses in burden of disease studies for indoor air pollutants such as $PM_{2.5}$ or other indoor air pollutants with established odds ratios.

The model estimates for concentrations of indoor $PM_{2.5}$ might be lower than previously reported, providing a conservative estimate for the incidence of major depressive disorder due to indoor pollutants in the present study. For example, the model estimates for the US average indoor $PM_{2.5}$ scenario with a MERV 7 filter calculated an indoor to outdoor (I/O) ratio of 0.37. This was lower than values reported in a meta-analysis of IO ratios (Chen and Zhao, 2011) (mean 0.92). The smoking scenario with a MERV 7 filter installed resulted in a median indoor $PM_{2.5}$ concentration of $10.33 \mu\text{g}/\text{m}^3$. Two studies measuring indoor $PM_{2.5}$ concentrations in smoking households found median concentrations of $31 \mu\text{g}/\text{m}^3$ (Semple et al., 2015) and $27.7 \mu\text{g}/\text{m}^3$ (Wallace et al., 2003). However, the estimated outdoor concentrations of $PM_{2.5}$ in the US have been declining since 2000, which might have some influence on the comparisons (US EPA O, n.d.-b).

The impact of filter efficiency on the incidence of major depressive disorder was dependent on indoor emissions. It was observed that increases in filter efficiency had a higher impact on $PM_{2.5}$ concentrations in the smoking scenario compared to other scenarios, due to the emission of indoor $PM_{2.5}$ as opposed to contamination of indoor air by outdoor air, which is reduced by the build envelope. The American Society of Heating, Refrigeration, and Air Conditioning Engineers (ASHRAE) recommends at least a MERV 7 filter in residential buildings (American Society of Heating Refrigerating and Air Conditioning Engineers, 2019). However, in 2015 ASHRAE published new recommendations for residential units to install MERV 13 filters or higher in guideline 24-2015. The model estimates presented here reinforce that guidance, suggesting a change from a MERV 7 to a MERV 13 filter

could create a meaningful difference in reducing the incidence of major depressive disorder due to elevated $PM_{2.5}$ levels in indoor air.

While it does not appear there are any other studies estimating the impact that indoor $PM_{2.5}$ has upon depressive outcomes, comparisons to morbidity and mortality studies show similar trends to what was observed in this study. Specifically, a positive relationship exists between $PM_{2.5}$ concentrations and health outcomes (Cohen et al., 2017). A recently published meta-analysis of $PM_{2.5}$ exposure and mental illness (Braithwaite et al., 2019) included a population attributable fraction (PAF) model. The model estimated that the United Kingdom's rate of depression could be reduced by 2.5%, if the ambient $PM_{2.5}$ concentration dropped from $12.8 \mu\text{g}/\text{m}^3$ to the World Health Organization's recommended limit of $10 \mu\text{g}/\text{m}^3$ (Krzyzanowski and Cohen, 2008). However, the PAF model does not account for the lower levels of $PM_{2.5}$ concentrations experienced in indoor environments, as shown in this analysis, suggesting that the 2.5% reduction could be an overestimate. The caveat to that statement is when indoor emissions of $PM_{2.5}$ are present at meaningful levels (e.g., smoking).

Although the BCRs are below 1.0 for all of the US city scenarios, this analysis does not include the benefit of filtration for the purposes of avoiding any physical diseases associated with $PM_{2.5}$, such as asthma (Brown et al., 2014), lung cancer (Zhao et al., 2015), or chronic obstructive pulmonary disease (MacIntosh et al., 2010), suggesting that these are again conservative estimates. Since these BCRs are calculated based on median concentration values, variation in actual scenarios exist, with higher BCRs in some homes, and lower BCRs in others. For sensitive individuals, alternative means of filtration, used in addition to HVAC filters, may be an effective solution. Alternative means of filtration include portable air cleaners (Fisk, 2013; Spilak et al., 2014; Cox

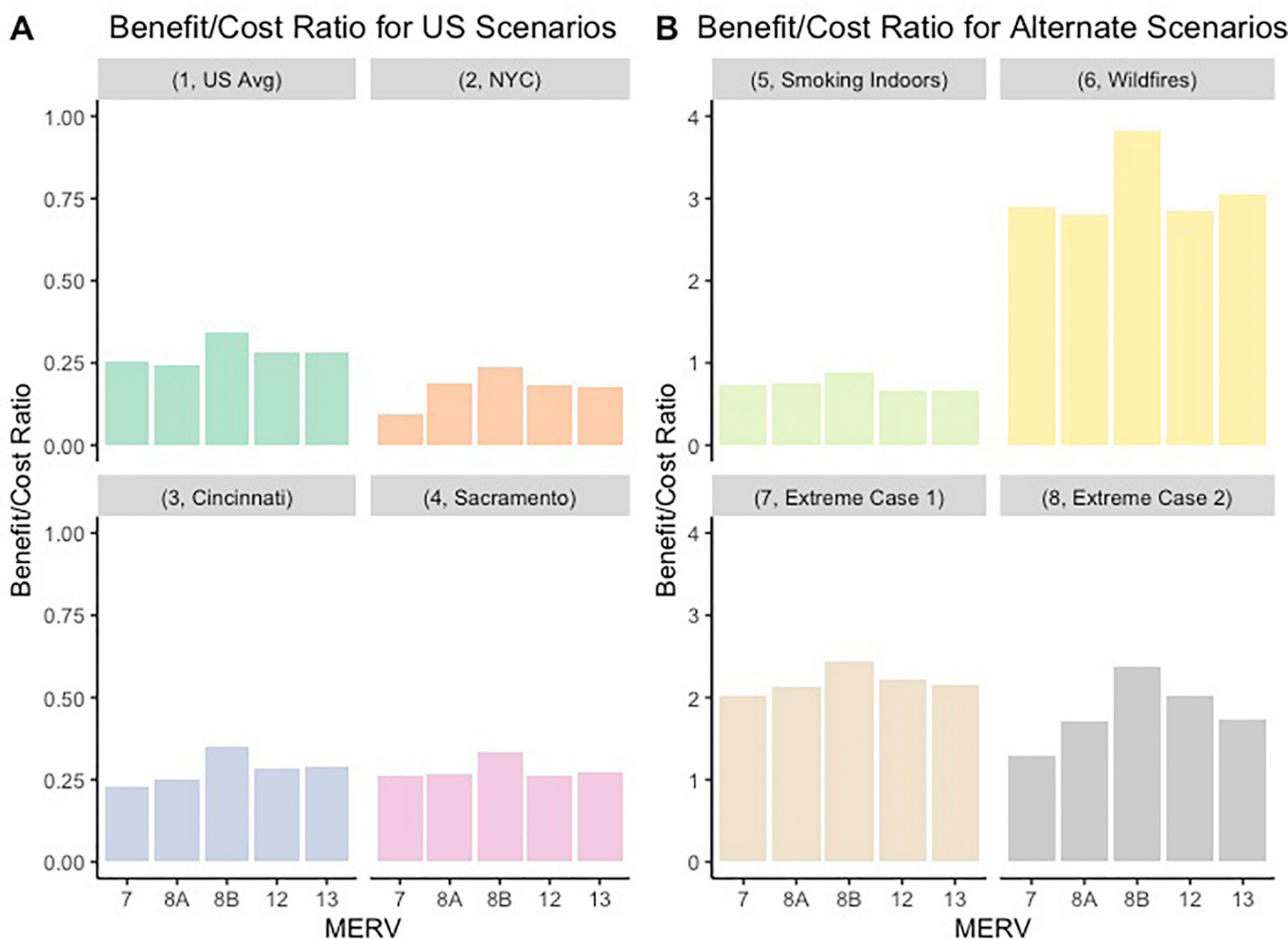


Fig. 4. Benefit/cost ratios (BCRs) for filter implementation in A) US Scenarios and B) Alternate Scenarios. Abbreviations: Avg, average; MDD, major depressive disorder; MERV = minimum reporting efficiency reporting values; NYC, New York City; US, United States.

et al., 2018), activated carbon filters (Kabrein et al., 2017; Yang et al., 2017), or even green walls (Perini et al., 2017; Pettit et al., 2017). An economic analysis of filtration methods for reducing PM_{2.5} found that portable air filters had a mean BCR between 7.7 and 13, and provided more of a reduction in expected mortality rates than just HVAC filters alone (Fisk and Chan, 2017b).

Chronic inflammation and oxidative stress are both thought to contribute to depression and other mental health outcomes, and air pollutants other than PM_{2.5}, such as volatile organic compounds and mold, are associated with both of these mechanisms (Hope, 2013; Ratnaseelan et al., 2018; Kim et al., 2011; Grešner et al., 2016). PM_{2.5} is also shown to influence gut microbiome profiles (Fitch et al., 2020), which some literature proposes are connected to mental health outcomes (Lowry et al., 2016; Hoisington et al., 2015). This introduces the possibility that poor indoor air quality could be contributing to more cases of depression than were estimated with this model. Although PM_{2.5} comprises the bulk of disease research due to poor air quality (Chen et al., 2008), it cannot be ruled out that other pollutants may increase the burden of disease. Future models estimating depressive risk due to indoor pollutants should seek to include other pollutants in addition to PM_{2.5}.

Sensitivity analysis was performed on the odds ratio, the variable parameter in the model that was not considered in the Monte Carlo simulations. Maintaining the other parameters in the exposure-response function constant, the odds ratio has a strong influence on the predicted incidence of major depressive disorder in the model. The confidence interval bounds from the odds ratio (1.023, 1.189) in average US

concentrations with a MERV 7 filter produced an estimated number of major depressive disorder cases of 122,791 and 904,718, respectively. A difference of that magnitude in the model estimates highlights the urgent need to refine the relationship between PM_{2.5} and depression in large population studies.

The model described in this paper was created to be adaptable to estimate major depressive disorder outcomes within other populations. To be as accurate as possible, mass balance input parameter distributions would need to be created for the population set to be analyzed. That is, estimates would need to be considered on parameters in Table 1 that are specific to the population of interest. Additionally, the total number of major depressive disorder cases within the region would replace the value used in this paper (17,700,000), and the population of the region would replace the value used in this paper (255,190,602). Finally, costs of residential air filters could be sourced for the area in order to create accurate BCR results.

4.1. Limitations

As this is the first known epidemiological model connecting indoor PM_{2.5} concentrations and depression, we acknowledge there are several limitations in the present study. First, the relationship between PM_{2.5} exposure and depressive outcomes is not clearly defined yet. A limited number of meta analyses of the relationship between PM_{2.5} and depression are currently published, yet have similar results in their pooling of odds ratios from the available epidemiological studies, with values of

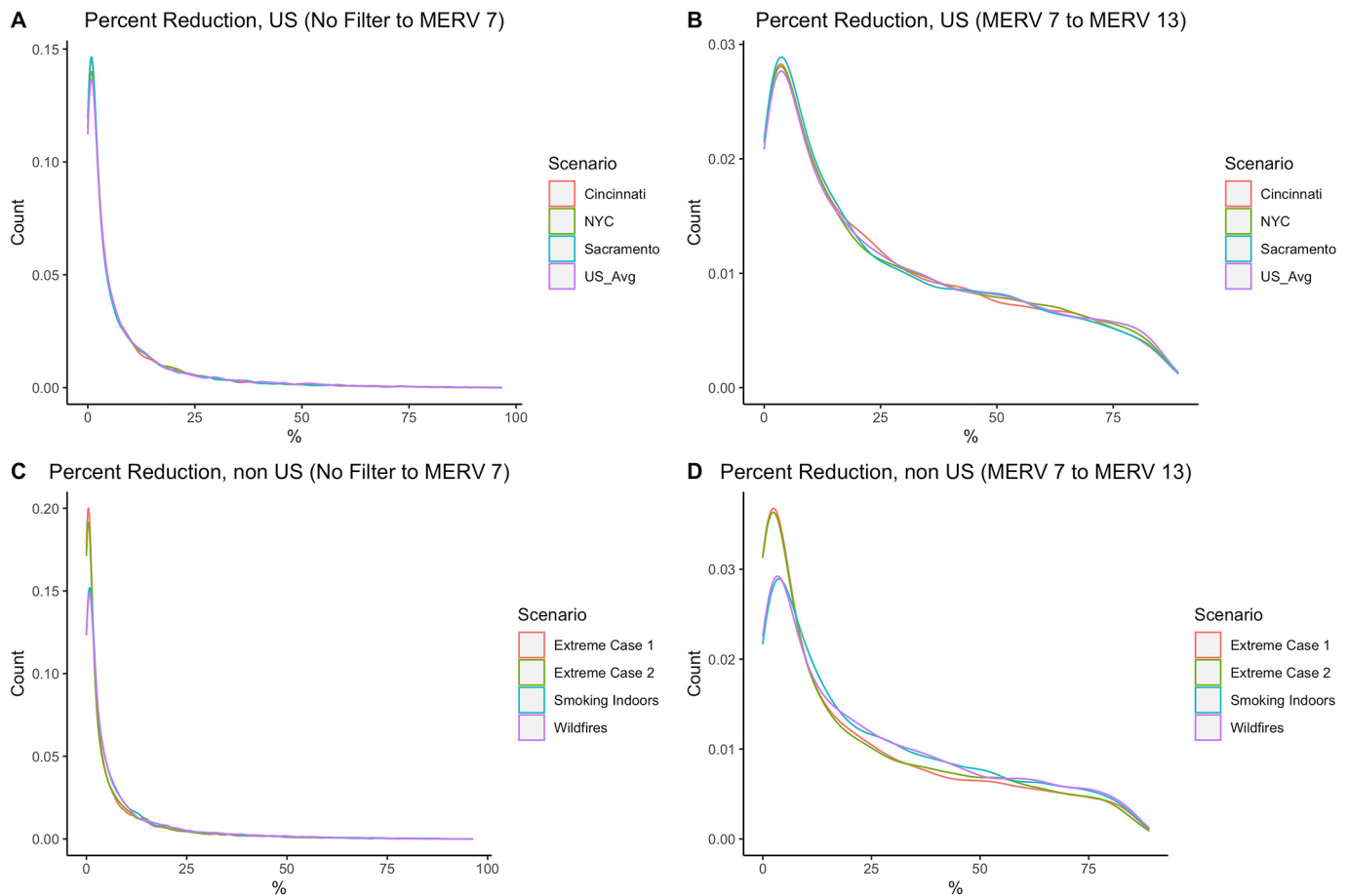


Fig. 5. Percent reduction in estimated incidence of major depressive disorder due to $PM_{2.5}$ in A) US cities, based on $PM_{2.5}$ concentrations in households with no filter relative to households using a MERV 7 filter, B) US cities, based on $PM_{2.5}$ concentrations in households with a MERV 7 filter relative to households with a MERV 13 filter, C) alternate scenarios based on $PM_{2.5}$ concentrations levels from households with no filter relative to households with a MERV 7 filter, D) alternate scenarios based on $PM_{2.5}$ concentrations in households with a MERV 7 filter relative to a MERV 13 filter. The y-axis “Count” indicates how many values of the results fall into each corresponding bin. Abbreviations: Avg, average; MDD, major depressive disorder; MERV, minimum reporting efficiency reporting values; NYC, New York City; US, United States.

1.10 (Braithwaite et al., 2019) and 1.12 (Fan et al., 2020). The mean number of studies analyzed in these meta analyses was 8.5. In comparison, a brief search of the more well-researched relationship between $PM_{2.5}$ and lung cancer mortality yielded four meta analyses, with values of 1.11 (RR) (Cui et al., 2015), 1.11 (RR) (Huang et al., 2017), 1.14 (OR) (Chen et al., 2015), and 1.09 (RR) (Hamra et al., 2014). The mean number of studies analyzed in those meta analyses was 12.25. Furthermore, differences in physiology between populations could influence the relationship between $PM_{2.5}$ and depression. At the time of this writing, no studies exist that attempted to quantify this relationship in the US population. As ORs become more established, the methods used in this paper (and code provide in the Supplementary Material) could be reanalyzed for $PM_{2.5}$ and depression, or other conditions as desired.

While the relationship between $PM_{2.5}$ and major depressive disorder may not be as robust as that between $PM_{2.5}$ and physical health, it is becoming increasingly clear there exists a relationship between the two variables. Establishing a causal relationship between $PM_{2.5}$ exposure and depressive outcomes via an exposure-response function can be accomplished through additional epidemiological studies. All $PM_{2.5}$ exposure was assumed to result in the same magnitude of depressive outcomes, regardless of source-specific $PM_{2.5}$ and evidence exists to suggest that this is a reasonable assumption (Cohen et al., 2017).

$PM_{2.5}$ levels were assumed as a snapshot in time, but it is acknowledged that while $PM_{2.5}$ concentrations have been decreasing across the US since 2000, they are increasing worldwide (Butt et al., 2017), and may remain elevated in the US due to scenarios such as proximity

to wildfires or environmental regulation changes. Approximately 90% of new homes in the US are constructed with central forced air systems, but the total number of homes with central forced air systems are lower across the entire nation (Agency UEI, 2018). The model for calculating indoor $PM_{2.5}$ concentrations will not be accurate for homes without central forced air systems, adding more uncertainty to the final estimate of the calculated depression cases. In addition, other models of indoor air quality calculate duty cycle based on site location and typical heating and cooling loads. This analysis forgoes this method and represents the variability in duty cycle values with the Monte Carlo sampling. Due to the analysis being applied to an annual period, the duty cycle was more accurately represented as a distribution. Cooking and smoking were the only sources of indoor $PM_{2.5}$ considered in this analysis, due to their well-documented emission values (Ozkaynak et al., 1996; Semple et al., 2015; Wallace et al., 2003; Hu et al., 2012). Other activities may also contribute to indoor $PM_{2.5}$ concentrations, such as cleaning or occupant movement (Ferro et al., 2004). However, these activities were considered too variable to include in this analysis. As a result, the calculated $PM_{2.5}$ concentrations and major depressive disorder estimates may be a conservative estimate, and not representative of all $PM_{2.5}$ sources potentially present in the indoor environment.

$PM_{2.5}$ composition may vary based on source apportionment (Titos et al., 2014; Mazzei et al., 2008; Pey et al., 2009), and estimates of morbidity and mortality assume that all $PM_{2.5}$ provides the same level of toxicity (Cohen et al., 2017). The model described in this paper assumes that the ambient $PM_{2.5}$ and the indoor generated $PM_{2.5}$ influence

human physiology in the same manner. Current literature suggests that there is no relationship between PM_{2.5} composition and toxicity (Stanek et al., 2011), and that magnitude of exposure is the sole predictor for health effects. However, it is possible that composition of PM_{2.5} may affect major depressive disorder outcomes in a manner different from physical mortality and morbidity, changing the estimation of the incidence of major depressive disorder described within this analysis. Microbial components and endotoxins are present in some sources of PM_{2.5} (Jalava et al., 2016), and are potentially a source of influence on major depressive disorder outcomes (De La Garza, 2005) through inflammatory mechanisms (Tonelli et al., 2008; Tonelli and Postolache, 2010). PM_{2.5} retained in the nasal passage can bypass the blood brain barrier (Tonelli and Postolache, 2010) and lead to worse depressive like behavior, brain expression of cytokines, and corticosteroid production compared to intraperitoneal transmission (Tonelli et al., 2008).

Finally, indoor PM_{2.5} concentrations were assumed to occur in a well-mixed environment. In reality, residential homes can be poorly mixed, and some areas of the home will experience higher concentrations of PM_{2.5}, while others will have lower concentrations. This variability is accounted for in the Monte Carlo simulations, via random sampling of the distributed parameters. However, select indoor activities may cause a spike in PM_{2.5} concentrations and exposure, such as cooking or resuspension of PM_{2.5} due to cleaning. These spikes in PM_{2.5} concentration may increase risk of acute depressive symptoms, but the epidemiological data do not exist to accurately model that impact. Specifically, the model described in this paper was not applied to analyze acute depressive symptoms due to indoor PM_{2.5} exposure, but evidence exists to suggest that effect may occur (Semple et al., 2015; Hiscock et al., 2012).

5. Conclusions

The results of this analysis highlight the role that PM_{2.5} has upon depressive outcome. The model described herein could be used to estimate the influence that PM_{2.5} exposure has upon other mental illnesses, provided those illnesses have established relationships (ORs or RRs) with PM_{2.5}. These results raise the question of how impactful other indoor air pollutants are on mental health outcomes. While PM_{2.5} has the highest contribution to mortality estimates of air quality (Hoek et al., 2013; Chen et al., 2008), other pollutants may have a higher degree of impact on mental health outcomes. Future research may want to include socioeconomic status, as it may represent a potential confounding factor in linking analysis of particulate matter with major depressive disorder. For example, people of lower socioeconomic status are more likely to live in areas of higher air pollution (Evans and Kantrowitz, 2002), have poor quality homes that potentially lead to higher rates of pollutant exposure (Adamkiewicz et al., 2011), and higher rates of depression (Everson et al., 2002). Moreover, smoking is a more popular activity among less affluent groups (Hiscock et al., 2012), and is associated with depression (Glassman et al., 1990; Brown et al., 1996; Fergusson et al., 2003). Additionally, socioeconomic status has an established relationship with physical morbidity (Luepker et al., 1993; Connolly et al., 2000; Ward et al., 2004), itself a risk factor for mental illness (Geerlings et al., 2000). Yet not all confounders are negative. For instance, household size is larger in areas of lower socioeconomic status (Espenshade et al., 1983), which would result in shared benefit of a higher quality filter for additional people at reduced per capita cost.

CRediT authorship contribution statement

William L. Taylor: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Steven J. Schuldt:** Formal analysis, Writing – review & editing. **Justin D. Delorit:** Validation, Formal analysis, Writing – review & editing. **Christopher M. Chini:** Software, Formal analysis, Writing –

review & editing, Visualization. **Teodor T. Postolache:** Conceptualization, Writing – review & editing. **Christopher A. Lowry:** Conceptualization, Writing – review & editing. **Lisa A. Brenner:** Conceptualization, Writing – review & editing. **Andrew J. Hoisington:** Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2020.143858>.

References

- 2018 NSDUH Annual National Report | CBHSQ Data. <http://www.samhsa.gov/data/report/2018-nsduh-annual-national-report>. (Accessed 21 December 2019).
- Adamkiewicz, G., Zota, A.R., Fabian, M.P., et al., 2011. Moving environmental justice indoors: understanding structural influences on residential exposure patterns in low-income communities. *Am. J. Public Health* (101 Suppl), S238–S245 <https://doi.org/10.2105/AJPH.2011.300119>.
- Agency UEI, 2018. *What's New in How We Use Energy at Home: Results from EIA's 2015 Residential Energy Consumption Survey (RECS)*.
- Allen, J., Balfour, R., Bell, R., Marmot, M., 2014. Social determinants of mental health. *Int. Rev. Psychiatry* 26 (4), 392–407. <https://doi.org/10.3109/09540261.2014.928270>.
- American Psychiatric Association, 2013. *Diagnostic and Statistical Manual of Mental Disorders*. 5th ed. Washington, DC.
- American Society of Heating Refrigerating and Air Conditioning Engineers, 2019n. *ANSI/ASHRAE Standard 62.2-2019, Ventilation and Acceptable Indoor Air Quality in Residential Buildings*. Atlanta, GA.
- Anisman, H., Hayley, S., 2012. Inflammatory factors contribute to depression and its comorbid conditions. *Sci. Signal*. 5 (244). <https://doi.org/10.1126/scisignal.2003579> pe45–pe45.
- Azimi, P., Stephens, B., 2013. HVAC filtration for controlling infectious airborne disease transmission in indoor environments: predicting risk reductions and operational costs. *Build. Environ.* 70 (0), 150–160. <https://doi.org/10.1016/j.buildenv.2013.08.025>.
- Azimi, P., Stephens, B., 2018. A framework for estimating the US mortality burden of fine particulate matter exposure attributable to indoor and outdoor microenvironments. *J. Expo Sci. Environ. Epidemiol.* <https://doi.org/10.1038/s41370-018-0103-4>.
- Azimi, P., Zhao, D., Stephens, B., 2014. Estimates of HVAC filtration efficiency for fine and ultrafine particles of outdoor origin. *Atmos. Environ.* 98, 337–346. <https://doi.org/10.1016/j.atmosenv.2014.09.007>.
- Azimi, P., Zhao, D., Stephens, B., 2016. Modeling the impact of residential HVAC filtration on indoor particles of outdoor origin (RP-1691). *Sci. Technol. Built Environ.* 00, 1–32. <https://doi.org/10.1080/23744731.2016.1163239>.
- Bakunina, N., Pariante, C.M., Zunszain, P.A., 2015. Immune mechanisms linked to depression via oxidative stress and neuroprogression. *Immunology* 144 (3), 365–373. <https://doi.org/10.1111/imm.12443>.
- Black, C.N., Bot, M., Scheffer, P.G., Cuijpers, P., Penninx, B.W.J.H., 2015. Is depression associated with increased oxidative stress? A systematic review and meta-analysis. *Psychoneuroendocrinology* 51, 164–175. <https://doi.org/10.1016/j.psyneuen.2014.09.025>.
- Block, M.L., Calderón-Garcidueñas, L., 2009. Air pollution: mechanisms of neuroinflammation and CNS disease. *Trends Neurosci.* 32 (9), 506–516. <https://doi.org/10.1016/j.tins.2009.05.009>.
- Boulanger, G., Bayeux, T., Mandin, C., et al., 2017. Socio-economic costs of indoor air pollution: a tentative estimation for some pollutants of health interest in France. *Environ. Int.* 104, 14–24. <https://doi.org/10.1016/j.envint.2017.03.025>.
- Braithwaite, I., Zhang, S., Kirkbride, J.B., Osborn, D.P.J., Hayes, J.F., 2019. Air pollution (particulate matter) exposure and associations with depression, anxiety, bipolar, psychosis and suicide risk: a systematic review and meta-analysis. *Environ. Health Perspect.* 127 (12), 126002. <https://doi.org/10.1289/EHP4595>.
- Bräuner, E.V., Forchhammer, L., Møller, P., et al., 2008. Indoor particles affect vascular function in the aged. *Am. J. Respir. Crit. Care Med.* 177 (4), 419–425. <https://doi.org/10.1164/rccm.200704-632OC>.
- Brown, R.A., Lewinsohn, P.M., Seeley, J.R., Wagner, E.F., 1996. Cigarette smoking, major depression, and other psychiatric disorders among adolescents. *J. Am. Acad. Child Adolesc. Psychiatry* 35 (12), 1602–1610. <https://doi.org/10.1097/00004583-199612000-00011>.
- Brown, K.W., Minegishi, T., Allen, J.G., McCarthy, J.F., Spengler, J.D., MacIntosh, D.L., 2014. Reducing patients' exposures to asthma and allergy triggers in their homes: an evaluation of effectiveness of grades of forced air ventilation filters. *J. Asthma* 51 (6), 585–594. <https://doi.org/10.3109/02770903.2014.895011>.

- Bureau UC. Historical Households Tables.
- Butt, E.W., Turnock, S.T., Rigby, R., et al., 2017. Global and regional trends in particulate air pollution and attributable health burden over the past 50 years. *Environ. Res. Lett.* 12 (10). <https://doi.org/10.1088/1748-9326/aa87be>.
- Calderón-Garcidueñas, L., Macías-Parra, M., Hoffmann, H.J., et al., 2009. Immunotoxicity and environment: immunodysregulation and systemic inflammation in children. *Toxicol. Pathol.* 37 (2), 161–169. <https://doi.org/10.1177/0192623308329340>.
- Chambliss, S.E., Preble, C.V., Caubel, J.J., et al., 2020. Comparison of mobile and fixed-site black carbon measurements for high-resolution urban pollution mapping. *Environ. Sci. Technol.* 54 (13), 7848–7857. <https://doi.org/10.1021/acs.est.0c01409>.
- Chen, C., Zhao, B., 2011. Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. *Atmos. Environ.* 45, 275–288. <https://doi.org/10.1016/j.atmosenv.2010.09.048>.
- Chen, H., Goldberg, M.S., Villeneuve, P.J., 2008. A systematic review of the relation between long-term exposure to ambient air pollution and chronic diseases. *Rev. Environ. Health* 23 (4), 243–297. <https://doi.org/10.1515/revheh.2008.23.4.243>.
- Chen, G., Wan, X., Yang, G., Zou, X., 2015. Traffic-related air pollution and lung cancer: a meta-analysis. *Thorax. Cancer* 6 (3), 307–318. <https://doi.org/10.1111/1759-7714.12185>.
- Cohen, A.J., Brauer, M., Burnett, R., et al., 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the global burden of diseases study 2015. *Lancet* 389 (10082), 1907–1918. [https://doi.org/10.1016/S0140-6736\(17\)30505-6](https://doi.org/10.1016/S0140-6736(17)30505-6).
- Conner, E.M., Grisham, M.B., 1996. Inflammation, free radicals and antioxidants. *Nutrition* 12 (4), 274–277. [https://doi.org/10.1016/S0899-9007\(96\)00000-8](https://doi.org/10.1016/S0899-9007(96)00000-8).
- Connolly, V., Unwin, N., Sherriff, P., Bilous, R., Kelly, W., 2000. Diabetes prevalence and socioeconomic status: a population based study showing increased prevalence of type 2 diabetes mellitus in deprived areas. *J. Epidemiol. Community Health* 54 (3), 173–177. <https://doi.org/10.1136/jech.54.3.173>.
- Cox, J., Isiuogo, K., Ryan, P., et al., 2018. Effectiveness of a portable air cleaner in removing aerosol particles in homes close to highways. *Indoor Air* 28 (6), 818–827. <https://doi.org/10.1111/ina.12502>.
- Crouse, D.L., Peters, P.A., van Donkelaar, A., et al., 2012. Risk of nonaccidental and cardiovascular mortality in relation to long-term exposure to low concentrations of fine particulate matter: a Canadian national-level cohort study. *Environ. Health Perspect.* 120 (5), 708–714. <https://doi.org/10.1289/ehp.1104049>.
- Cui, P., Huang, Y., Han, J., Song, F., Chen, K., 2015. Ambient particulate matter and lung cancer incidence and mortality: a meta-analysis of prospective studies. *Eur. J. Pub. Health* 25 (2), 324–329. <https://doi.org/10.1093/eurpub/cku145>.
- De La Garza, R., 2005. Endotoxin- or pro-inflammatory cytokine-induced sickness behavior as an animal model of depression: focus on anhedonia. *Neurosci. Biobehav. Rev.* 29 (4–5), 761–770. <https://doi.org/10.1016/j.neubiorev.2005.03.016>.
- Espenshade, T.J., Kamenske, G., Turchi, B.A., 1983. Family size and economic welfare. *Fam. Plan. Perspect.* 15 (6), 289–294. <https://doi.org/10.2307/2135299>.
- Evans, G.W., Kantrowitz, E., 2002. Socioeconomic status and health: the potential role of environmental risk exposure. *Annu. Rev. Public Health* 23 (1), 303–331. <https://doi.org/10.1146/annurev.pubhealth.23.1.2001.112349>.
- Everson, S.A., Maty, S.C., Lynch, J.W., Kaplan, G.A., 2002. Epidemiologic evidence for the relation between socioeconomic status and depression, obesity, and diabetes. *J. Psychosom. Res.* 53, 891–895. [https://doi.org/10.1016/S0022-3999\(02\)00303-3](https://doi.org/10.1016/S0022-3999(02)00303-3) Elsevier Inc.
- Fan, S.J., Heinrich, J., Bloom, M.S., et al., 2020. Ambient air pollution and depression: a systematic review with meta-analysis up to 2019. *Sci. Total Environ.* 701. <https://doi.org/10.1016/j.scitotenv.2019.134721>.
- Fazli, T., Stephens, B., 2018. Development of a nationally representative set of combined building energy and indoor air quality models for U.S. residences. *Build. Environ.* 136, 198–212. <https://doi.org/10.1016/j.buildenv.2018.03.047>.
- Fergusson, D.M., Goodwin, R.D., Horwood, L.J., 2003. Major depression and cigarette smoking: results of a 21-year longitudinal study. *Psychol. Med.* 33 (8), 1357–1367. <https://doi.org/10.1017/S0033291703008596>.
- Ferro, A.R., Kopperud, R.J., Hildemann, L.M., 2004. Source strengths for indoor human activities that resuspend particulate matter. *Environ. Sci. Technol.* 38 (6), 1759–1764. <https://doi.org/10.1021/es0263893>.
- Fisk, W.J., 2013. Health benefits of particle filtration. *Indoor Air* 23 (5), 357–368. <https://doi.org/10.1111/ina.12036>.
- Fisk, W.J., Chan, W.R., 2017a. Effectiveness and cost of reducing particle-related mortality with particle filtration. *Indoor Air* 27 (5), 909–920. <https://doi.org/10.1111/ina.12371>.
- Fisk, W.J., Chan, W.R., 2017b. Health benefits and costs of filtration interventions that reduce indoor exposure to PM2.5 during wildfires. *Indoor Air* 27 (1), 191–204. <https://doi.org/10.1111/ina.12285>.
- Fitch, M.N., Phillippi, D., Zhang, Y., et al., 2020. Effects of inhaled air pollution on markers of integrity, inflammation, and microbiota profiles of the intestines in Apolipoprotein E knockout mice. *Environ. Res.* 181, 108913. <https://doi.org/10.1016/j.envres.2019.108913>.
- Fournier, K., Baumont, E., Glorenne, P., Bonvallot, N., 2017. Relative toxicity for indoor semi volatile organic compounds based on neuronal death. *Toxicol. Lett.* 279. <https://doi.org/10.1016/j.toxlet.2017.07.875i>.
- Geerlings, S.W., Beekman, A.T.F., Deeg, D.J.H., Van Tilburg, W., 2000. Physical health and the onset and persistence of depression in older adults: an eight-wave prospective community-based study. *Psychol. Med.* 30, 369–380.
- Glassman, A.H., Helzer, J.E., Covey, L.S., et al., 1990. Smoking, smoking cessation, and major depression. *JAMA J. Am. Med. Assoc.* 264 (12), 1546–1549. <https://doi.org/10.1001/jama.1990.03450120058029>.
- Global Burden of Disease Study 2017 (GBD 2017) Burden by Risk 1990–2017 | GHDx. <http://ghdx.healthdata.org/record/ihme-data/gbd-2017-burden-risk-1990-2017>. (Accessed 31 December 2019).
- Greenberg, P.E., Fournier, A.-A., Sisitsky, T., Pike, C.T., Kessler, R.C., 2015. The economic burden of adults with major depressive disorder in the United States (2005 and 2010). *J. Clin. Psychiatry* 76 (2), 155–162. <https://doi.org/10.4088/JCP.14m09298>.
- Grešner, P., Świercz, R., Wąsowicz, W., Gromadzińska, J., 2016. Faster health deterioration among nail technicians occupationally exposed to low levels of volatile organic compounds. *Int. J. Occup. Med. Environ. Health* 30 (3), 469–483. <https://doi.org/10.13075/ijomh.1896.00854>.
- Gu, X., Liu, Q., Deng, F., et al., 2019. Association between particulate matter air pollution and risk of depression and suicide: systematic review and meta-analysis. *Br. J. Psychiatry* 215 (2), 456–467. <https://doi.org/10.1192/bjp.2018.295>.
- Hamra, G.B., Guha, N., Cohen, A., et al., 2014. Outdoor particulate matter exposure and lung cancer: a systematic review and meta-analysis. *Environ. Health Perspect.* 122 (9), 906–911. <https://doi.org/10.1289/ehp.1408092>.
- Hawton, K., Casañas I Comabella, C., Haw, C., Saunders, K., 2013. Risk factors for suicide in individuals with depression: a systematic review. *J. Affect. Disord.* 147 (1–3), 17–28. <https://doi.org/10.1016/j.jad.2013.01.004>.
- Henderson, D.E., Milford, J.B., Miller, S.L., 2012. Prescribed burns and wildfires in Colorado: impacts of mitigation measures on indoor air particulate matter. *J. Air Waste Manage. Assoc.* 55 (10), 1516–1526. <https://doi.org/10.1080/10473289.2005.10464746>.
- Hirschfeld, R.M.A., 2001. The comorbidity of major depression and anxiety disorders. *Prim Care Compan. J. Clin. Psychiatry* 03 (06), 244–254. <https://doi.org/10.4088/pcc.v03n0609>.
- Hiscock, R., Bauld, L., Amos, A., Fidler, J.A., Munafò, M., Munafò, M., 2012. Socioeconomic status and smoking: a review. *Ann. N. Y. Acad. Sci.* 1248, 107–123. <https://doi.org/10.1111/j.1749-6632.2011.06202.x>.
- Hoek, G., Krishnan, R.M., Beelen, R., et al., 2013. Long-term air pollution exposure and cardio-respiratory mortality: a review. *Environ. Health* 12 (1), 43. <https://doi.org/10.1186/1476-069X-12-43>.
- Hoisington, A.J., Brenner, L.A., Kinney, K.A., Postolache, T.T., Lowry, C.A., 2015. The microbiome of the built environment and mental health. *Microbiome* 3 (1). <https://doi.org/10.1186/s40168-015-0127-0>.
- Hoisington, A.J., Stearns-Yoder, K.A., Schuldt, S.J., et al., 2019. Ten questions concerning the built environment and mental health. *Build. Environ.* 155 (March), 58–69. <https://doi.org/10.1016/j.buildenv.2019.03.036>.
- Hope, J., 2013. A review of the mechanism of injury and treatment approaches for illness resulting from exposure to water-damaged buildings, mold, and mycotoxins. *Sci. World J.* 2013. <https://doi.org/10.1155/2013/767482>.
- Hu, T., Singer, B.C., Logue, J.M., 2012. Compilation of Published PM2.5 Emission Rates for Cooking, Candles and Incense for Use in Modeling of Exposures in Residences. Berkeley, CA (United States). <https://doi.org/10.2172/1172959>.
- Huang, F., Pan, B., Wu, J., Chen, E., Chen, L., 2017. Relationship between exposure to PM2.5 and lung cancer incidence and mortality: a meta-analysis. *Oncotarget* 8 (26), 43322–43331. <https://doi.org/10.18632/oncotarget.17313>.
- Jalava, P.I., Happonen, M.S., Huttunen, K., et al., 2016. Chemical and microbial components of urban air PM cause seasonal variation of toxicological activity. *Environ. Toxicol. Pharmacol.* 40 (2), 375–387. <https://doi.org/10.1016/j.etap.2015.06.023>.
- Ji, W., Zhao, B., 2015. Estimating mortality derived from indoor exposure to particles of outdoor origin. *Sun Q. ed. PLoS One* 10 (4), e0124238. <https://doi.org/10.1371/journal.pone.0124238>.
- Jump, D.A., Walker, I.S., Modera, M.P., 2011. Title Field Measurements of Efficiency and Duct Effectiveness in Residential Forced Air Distributions Systems.
- Kabrejn, H., Harii, A., Leman, A.M., NMR, Noraini, Yusof, M.Z.M., Afandi, A., 2017. Impact of the air filtration on indoor particle concentration by using combination filters in offices building. IOP Conference Series: Materials Science and Engineering, vol 243. Institute of Physics Publishing. <https://doi.org/10.1088/1757-899X/243/1/012051>.
- Kendler, K.S., Baker, J.H., 2007. Genetic influences on measures of the environment: a systematic review. *Psychol. Med.* 37 (5), 615–626. <https://doi.org/10.1017/S0033291706009524>.
- Kim, C., Jung, S.H., Kang, D.R., et al., 2010. Ambient particulate matter as a risk factor for suicide. *Am. J. Psychiatry* 167 (9), 1100–1107. <https://doi.org/10.1176/appi.ajp.2010.09050706>.
- Kim, J.H., Moon, J.Y., Park, E.-Y., Lee, K.-H., Hong, Y.-C., 2011. Changes in oxidative stress biomarker and gene expression levels in workers exposed to volatile organic compounds. *Ind. Health* 49 (1), 8–14.
- Klepeis, N.E., Nelson, W.C., Ott, W.R., et al., 2001. The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. *J. Expo. Anal. Environ. Epidemiol.* 11 (3), 231–252. <https://doi.org/10.1038/sj.jea.7500165>.
- Krzyżanowski, M., Cohen, A., 2008. Update of WHO air quality guidelines. *Air Qual. Atmos. Health* 1 (1), 7–13. <https://doi.org/10.1007/s11869-008-0008-9>.
- Lee, S., Lee, W., Kim, D., et al., 2019. Short-term PM2.5 exposure and emergency hospital admissions for mental disease. *Environ. Res.* 171, 313–320. <https://doi.org/10.1016/j.envres.2019.01.036>.
- Leech, J.A., Nelson, W.C., Burnett, R.T., Aaron, S., Raizenne, M.E., 2002. It's about time: a comparison of Canadian and American time-activity patterns. *J. Expo Sci. Environ. Epidemiol.* 12 (6), 427–432. <https://doi.org/10.1038/sj.jea.7500244>.
- Lowry, C.A., Smith, D.G., Siebler, P.H., et al., 2016. The microbiota, immunoregulation, and mental health: implications for public health. *Curr. Environ. Health Rep.* 3 (3), 270–286. <https://doi.org/10.1007/s40572-016-0100-5>.
- Luepker, R.V., Rosamond, W.D., Murphy, R., et al., 1993. Socioeconomic status and coronary heart disease risk factor trends: the Minnesota heart survey. *Circulation* 88 (5), 2172–2179. <https://doi.org/10.1161/01.CIR.88.5.2172>.

- MacIntosh, D.L., Minegishi, T., Kaufman, M., et al., 2010. The benefits of whole-house in-duct air cleaning in reducing exposures to fine particulate matter of outdoor origin: a modeling analysis. *J. Expo. Sci. Environ. Epidemiol.* 20 (2), 213–224. <https://doi.org/10.1038/jes.2009.16>.
- MacNeill, M., Kearney, J., Wallace, L., et al., 2014. Quantifying the contribution of ambient and indoor-generated fine particles to indoor air in residential environments. *Indoor Air* 24 (4), 362–375. <https://doi.org/10.1111/ina.12084>.
- Mazzei, F., D'Alessandro, A., Lucarelli, F., et al., 2008. Characterization of particulate matter sources in an urban environment. *Sci. Total Environ.* 401 (1–3), 81–89. <https://doi.org/10.1016/j.scitotenv.2008.03.008>.
- Merikangas, K.R., He, J.-P., Burstein, M., et al., 2010. Lifetime prevalence of mental disorders in U.S. adolescents: results from the National Comorbidity Survey Replication–Adolescent Supplement (NCS-A). *J. Am. Acad. Child Adolesc. Psychiatry* 49 (10), 980–989. <https://doi.org/10.1016/j.jaac.2010.05.017>.
- Miller, A.H., Raison, C.L., 2016. The role of inflammation in depression: from evolutionary imperative to modern treatment target. *Nat. Rev. Immunol.* 16 (1), 22–34. <https://doi.org/10.1038/nri.2015.5>.
- Montgomery, J.F., Reynolds, C.C., Rogak, S.N., Green, S.J., 2015. Financial implications of modifications to building filtration systems. *Build. Environ.* 85, 17–28. <https://doi.org/10.1016/j.buildenv.2014.11.005>.
- Murray, D.M., Burmaster, D.E., 1995. Residential air exchange rates in the United States: empirical and estimated parametric distributions by season and climatic region. *Risk Anal.* 15 (4), 459–465. <https://doi.org/10.1111/j.1539-6924.1995.tb00338.x>.
- Ozkaynak, H., Xue, J., Spengler, J., Wallace, L., Pellizzari, E., Jenkins, A.P., 1996. *Personal Exposure to Airborne Particles and Metals: Results From the Particle TEAM Study in Riverside, California*. vol 6.
- Perini, K., Ottele, M., Giuliani, S., Magliocco, A., Rocciotello, E., 2017. Quantification of fine dust deposition on different plant species in a vertical greening system. *Ecol. Eng.* 100, 268–276. <https://doi.org/10.1016/j.ecoleng.2016.12.032>.
- Pettit, T., Irga, P.J., Abdo, P., Torpy, F.R., 2017. Do the plants in functional green walls contribute to their ability to filter particulate matter? *Build. Environ.* 125, 299–307. <https://doi.org/10.1016/j.buildenv.2017.09.004>.
- Pey, J., Querol, X., Alastuey, A., Rodríguez, S., Philippe Putaud, J., Van Dingenen, R., 2009. Source apportionment of urban fine and ultra-fine particle number concentration in a Western Mediterranean city. *Atmos. Environ.* 43 (29), 4407–4415. <https://doi.org/10.1016/j.atmosenv.2009.05.024>.
- Pham-Huy, L.A., He, H., Pham-Huy, C., 2008. Free radicals, antioxidants in disease and health. *Int. J. Biomed. Sci.* 4 (2), 89–96.
- Pinault, L., Tjepkema, M., Crouse, D.L., et al., 2016. Risk estimates of mortality attributed to low concentrations of ambient fine particulate matter in the Canadian community health survey cohort. *Environ. Health A Glob. Access Sci. Source* 15 (1). <https://doi.org/10.1186/s12940-016-0111-6>.
- Power, M.C., Kioumourtoglou, M.-A., Hart, J.E., Okereke, O.J., Laden, F., Weiskopf, M.G., 2015. The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study. *BMJ* 350, h1111. <https://doi.org/10.1136/bmj.H1111>.
- Pun, V.C., Manjourides, J., Suh, H., 2017. Association of ambient air pollution with depressive and anxiety symptoms in older adults: results from the NSHAP study. *Environ. Health Perspect.* 125 (3), 342–348. <https://doi.org/10.1289/EHP494>.
- Qing, Y.M., Turpin, B.J., Korn, L., et al., 2005. Influence of ambient (outdoor) sources on residential indoor and personal PM2.5 concentrations: analyses of RIOPA data. *J. Expo. Anal. Environ. Epidemiol.* 15 (1), 17–28. <https://doi.org/10.1038/sj.jea.7500378>.
- R Development Core Team, 2011. *R: A Language and Environment for Statistical Computing*. <https://doi.org/10.1007/978-3-540-74686-7>.
- Raison, C.L., Capuron, L., Miller, A.H., 2006. Cytokines sing the blues: inflammation and the pathogenesis of depression. *Trends Immunol.* 27 (1), 24–31. <https://doi.org/10.1016/j.it.2005.11.006>.
- Ratnaselan, A.M., Tsilioni, I., Theoharides, T.C., 2018. Effects of mycotoxins on neuropsychiatric symptoms and immune processes. *Clin. Ther.* 40 (6), 903–917. <https://doi.org/10.1016/j.clinthera.2018.05.004>.
- Residential Energy Consumption Survey (RECS) - Analysis & Projections - U.S. Energy Information Administration (EIA).
- Results From the 2017 National Survey on Drug Use and Health: Detailed Tables, SAMHSA, CBHSQ.
- Rittmaster, R., Adamowicz, W.L., Amiro, B., Pelletier, R.T., 2006. Economic analysis of health effects from forest fires. *Can. J. For. Res.* 36 (4), 4. <https://doi.org/10.1139/X05-293>.
- Rohleder, N., 2014. Stimulation of systemic low-grade inflammation by psychosocial stress. *Psychosom. Med.* 76 (3), 181–189. <https://doi.org/10.1097/PSY.0000000000000049>.
- Roman, H.A., Walker, K.D., Walsh, T.L., et al., 2008. Expert judgment assessment of the mortality impact of changes in ambient fine particulate matter in the U.S. *Environ. Sci. Technol.* 42 (7), 2268–2274. <https://doi.org/10.1021/es0713882>.
- ScienceDirect, d. Search results - keywords (mental health) - ScienceDirect. <https://www.sciencedirect.com/search/advanced?qs=mentalhealth>. (Accessed 2 February 2020).
- Semple, S., Apsley, A., Azmina Ibrahim, T., Turner, S.W., Cherrie, J.W., 2015. Fine particulate matter concentrations in smoking households: just how much secondhand smoke do you breathe in if you live with a smoker who smokes indoors? *Tob. Control.* 24, 205–211. <https://doi.org/10.1136/tobaccocontrol>.
- Sharma, S.K., Mandal, T.K., 2017. Chemical composition of fine mode particulate matter (PM 2.5) in an urban area of Delhi, India and its source apportionment. *Urban Clim.* 21, 106–122. <https://doi.org/10.1016/j.uclim.2017.05.009>.
- Silventoinen, K., Rokholm, B., Kaprio, J., Sørensen, T.I.A., 2010. The genetic and environmental influences on childhood obesity: a systematic review of twin and adoption studies. *Int. J. Obes.* 34 (1), 29–40. <https://doi.org/10.1038/ijo.2009.177>.
- Spilak, M.P., Karottki, G.D., Frederiksen, M., Loft, S., Gunnarsen, L., 2014. Evaluation of building characteristics in 27 dwellings in Denmark and the effect of using particle filtration units on PM2.5 concentrations. *Build. Environ.* 73, 55–63. <https://doi.org/10.1016/j.buildenv.2013.11.020>.
- Spinhoven, P., Penninx, B.W., Van Hemert, A.M., De Rooij, M., Elzinga, B.M., 2014. Comorbidity of PTSD in anxiety and depressive disorders: prevalence and shared risk factors. *Child Abuse Negl.* 38, 1320–1330. <https://doi.org/10.1016/j.chiabu.2014.01.017>.
- Staneik, L.W., Sacks, J.D., Dutton, S.J., Dubois, J.J.B., 2011. Attributing health effects to apportioned components and sources of particulate matter: an evaluation of collective results. *Atmos. Environ.* 45 (32), 5655–5663. <https://doi.org/10.1016/j.atmosenv.2011.07.023>.
- Stephens, B., Siegel, J.A., 2011. Comparison of test methods for determining the particle removal efficiency of filters in residential and light-commercial central HVAC systems. *Aerosol Sci. Technol.* 46 (5), 504–513. <https://doi.org/10.1080/02786826.2011.642825>.
- Stephens, B., Siegel, J.A., 2013. Ultrafine particle removal by residential heating, ventilating, and air-conditioning filters. *Indoor Air* 23 (6), 488–497. <https://doi.org/10.1111/ina.12045>.
- Stephens, B., Siegel, J.A., Novoselac, A., 2011. Operational characteristics of residential and light-commercial air-conditioning systems in a hot and humid climate zone. *Build. Environ.* 46 (10), 1972–1983. <https://doi.org/10.1016/j.buildenv.2011.04.005>.
- Szyszkowicz, M., Rowe, B.H., Colman, I., 2009. Air pollution and daily emergency department visits for depression. *Int. J. Occup. Med. Environ. Health* 22 (4), 355–362. <https://doi.org/10.2478/v10001-009-0031-6>.
- Titos, G., Lyamani, H., Pandolfi, M., Alastuey, A., Alados-Arboledas, L., 2014. Identification of fine (PM 1) and coarse (PM 10-1) sources of particulate matter in an urban environment. *Atmos. Environ.* 89 (July 2018), 593–602. <https://doi.org/10.1016/j.atmosenv.2014.03.001>.
- Tonelli, L.H., Postolache, T., 2010. Airborne inflammatory factors: “from the nose to the brain”. *Front. Biosci.* 2, 135–152. <https://doi.org/10.2741/s52>.
- Tonelli, L.H., Holmes, A., Postolache, T.T., 2008. Intranasal immune challenge induces sex-dependent depressive-like behavior and cytokine expression in the brain. *Neuropsychopharmacology* 33 (5), 1038–1048. <https://doi.org/10.1038/sj.npp.1301488>.
- US EPA O. Air Quality - Cities and Counties.
- US EPA O. Particulate Matter (PM2.5) Trends.
- Van Donkelaar, A., Martin, R.V., Levy, R.C., et al., 2011. Satellite-based Estimates of Ground-level Fine Particulate Matter during Extreme Events: A Case Study of the Moscow Fires in 2010. <https://doi.org/10.1016/j.atmosenv.2011.07.068>.
- Walker, I., Singer, B., Chan, R., 2019. *Ventilation and Measured Indoor Air Quality in New US Homes*.
- Wallace, L.A., Mitchell, H., O'Connor, G.T., et al., 2003. Particle concentrations in inner-city homes of children with asthma: the effect of smoking, cooking, and outdoor pollution. *Environ. Health Perspect.* 111 (9), 1265–1272. <https://doi.org/10.1289/ehp.6135>.
- Ward, E., Jemal, A., Cokkinides, V., et al., 2004. Cancer disparities by race/ethnicity and socioeconomic status. *CA Cancer J. Clin.* 54 (2), 78–93. <https://doi.org/10.3322/canjclin.54.2.78>.
- Weisel, C.P., Zhang, J., Turpin, B.J., et al., 2005. Relationship of indoor, outdoor and personal air (RIOPA) study: study design, methods and quality assurance/control results. *J. Expo. Anal. Environ. Epidemiol.* 15 (2), 123–137. <https://doi.org/10.1038/sj.jea.7500379>.
- Wickham, H., 2011. *ggplot2*. Wiley Interdiscip. Rev. Comput. Stat. <https://doi.org/10.1002/wics.147>.
- Williams, R., Suggs, J., Rea, A., Sheldon, L., Rodes, C., Thornburg, J., 2003. The Research Triangle Park particulate matter panel study: modeling ambient source contribution to personal and residential PM mass concentrations. *Atmos. Environ.* 37 (38), 5365–5378. <https://doi.org/10.1016/j.atmosenv.2003.09.010>.
- Yang, S., Zhu, Z., Wei, F., Yang, X., 2017. Carbon nanotubes/activated carbon fiber based air filter media for simultaneous removal of particulate matter and ozone. *Build. Environ.* 125, 60–66. <https://doi.org/10.1016/j.buildenv.2017.08.040>.
- Yue, J.L., Liu, H., Li, H., et al., 2020. Association between ambient particulate matter and hospitalization for anxiety in China: a multicity case-crossover study. *Int. J. Hyg. Environ. Health* 223 (1), 171–178. <https://doi.org/10.1016/j.ijheh.2019.09.006>.
- Zhao, D., Azimi, P., Stephens, B., 2015. Evaluating the long-term health and economic impacts of central residential air filtration for reducing premature mortality associated with indoor fine particulate matter (PM2.5) of outdoor origin. *Int. J. Environ. Res. Public Health* 12 (7), 8448–8479. <https://doi.org/10.3390/ijerph12078448>.
- Ziková, N., Wang, Y., Yang, F., Li, X., Tian, M., Hopke, P.K., 2016. On the source contribution to Beijing PM2.5 concentrations. *Atmos. Environ.* 134, 84–95. <https://doi.org/10.1016/j.atmosenv.2016.03.047>.