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Impact of regional versus local resolution air quality modeling on particulate matter exposure health impact assessment

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Abstract

As much of the population lives in close proximity to high-traffic roads, there is the potential for health impact assessments based on regional air quality modeling to underpredict health impacts. We compare the estimated health impacts from fine particulate matter ($PM_{2.5}$) using local (0.04 × 0.04 km upscaled to census block group resolution) compared to regional (12 × 12 km resolution) modeled concentrations for three locations in Connecticut: Hartford, New Haven, and Willimantic. We use concentration estimates from the Comprehensive Air Quality Model with Extensions (CAMx) regional model and a hybrid model combining CAMx with a near road model (HYCAMR) in the Environmental Benefits Mapping and Analysis Program—Community Edition (BenMAP-CE) to calculate the difference in estimated human health impacts using different resolution air quality estimates from $PM_{2.5}$ exposure including mortality, emergency room visits, hospitalizations, and asthma exacerbation. This provides an estimate of the potential underprediction of health impacts resulting from not accounting for the sharp concentration gradients in near road environments in urban areas. The fine-scale estimates capture the elevated concentrations near the roadways leading to increased estimates of overall mortality and morbidity in the population. We find an increase in the estimated likelihood of emergency department visits and mortality in the urban core. We also compare the impact of model resolution on the health impact estimates for different demographic groups. Of the locations investigated, we see the largest differences between demographic groups in Willimantic, CT. Our results indicate that using regional air pollutant concentrations may lead to an underprediction of human health impacts from air pollution exposure.

Keywords Air pollution exposure assessment · $PM_{2.5}$ · Air pollution modeling · Grid resolution · Health impact analysis

Introduction

Ground-level particulate matter ($PM_{2.5}$ or particles with aerodynamic diameter < 2.5 μm) has negative impacts on human health including premature death, increases in hospital admissions for respiratory and cardiovascular diseases, and asthma exacerbation (Pope et al. 2006; Krewski et al. 2009; Ostro et al. 2001). As economic growth and technological advancements continue, an increasing number of people live near heavily trafficked roadways and industrial areas (Adar and Kaufman 2007; Salam et al. 2008). While vehicular emissions factor may have decreased over time, there is still the question of the impacts on environmental equality. Fann et al. (2013) found that mobile sources were the second highest contributor to the total $PM_{2.5}$ exposure-related premature deaths in the USA. Although estimates of the impact of $PM_{2.5}$ on human health are available based on regional-scale (> 1 km) modeling (Parvez et al. 2017; Abel et al. 2018; Lu et al. 2018), estimates based on local-scale (< 1 km) modeling are still sparse. Several studies have demonstrated the impact of air quality model grid resolution on health impact assessment, particularly mortality, but have focused on resolutions at the regional and global scales (Kheirbek et al. 2013; Punger and West 2013; Thompson et al. 2014; Li et al. 2016). As pollutant concentrations from mobile sources rapidly (< 0.4 km) reach background levels, regional-scale modeling approaches cannot effectively capture these areas of elevated near road concentrations. To adequately estimate the health

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burden from local sources, like mobile emissions, researchers and policymakers must employ concentration estimates on appropriate spatial scales.

The US EPA has developed BenMAP-CE (Environmental Benefits Mapping and Analysis Program—Community Edition), an environmental benefits mapping and analysis program, to aid policymakers in accounting for health impacts and their associated economic burden in policy decisions (US EPA 2018). BenMAP-CE allows users to estimate health and economic impacts resulting from changes in air quality using either modeled or monitored air quality data. For instance, Fann et al. (2013) used BenMAP (an older version of BenMAP-CE) with modeled air quality estimates to quantify the number of premature deaths and cases of chronic and acute illness resulting from $PM_{2.5}$ and ozone exposure between the years 2005 and 2016 for different emission sectors in the USA. Although this study was able to quantify the contribution of individual sectors to the health burden, these estimates were based on regional (12 km) resolution estimates of air pollutant concentrations. This level of resolution does not adequately account for exposure in the near road environments encountered by individuals in many urban areas. Carvour et al. (2018) completed a local health impact assessment on ozone changes in a ten county non-attainment area in the Dallas-Fort Worth region of Texas for the years 2008, 2011, and 2013 using both incremental rollback and rollback-to-a-standard ambient level scenario of BenMAP-CE. This study suggested that BenMAP-CE can provide timely, evidence-based estimates of health impacts and economic consequences of potential policy changes. Studies on the relative impacts or benefits of changes in air quality for different demographic groups are sparse.

In this work, we pair BenMAP-CE with two air quality models, the Comprehensive Air Quality Model with Extensions (CAMx) at 12 × 12 km resolution and a hybrid fine-scale model accounting for near road and regional contributions to air quality (HYCAMR) at 0.04 × 0.04 km resolution (Parvez and Wagstrom 2019), to evaluate the impact of fine-scale versus regional-scale modeling on the estimated health burden from $PM_{2.5}$ exposure in three locations in Connecticut: Hartford, New Haven, and Willimantic. We use the built-in concentration-response functions available in BenMAP-CE to calculate the difference in estimated premature deaths, cases of asthma exacerbation, hospital admissions due to respiratory illness, hospital admissions due to cardiovascular illness, and emergency room visits given using regional- versus fine-scale modeled concentrations to determine the impact of model resolution on estimated health impact. We also compare the impact of model resolution on the health impact estimates for different demographic groups.

Methodology

Our objective in this study is to compare the estimated mortality and morbidity rates associated with $PM_{2.5}$ exposure using supplied $PM_{2.5}$ concentrations at coarse (12 × 12 km) and fine (0.04 × 0.04 km) model resolution. We evaluate the estimated health burden between three locations and different demographic groups using BenMAP-CE. BenMAP-CE is typically used to estimate the benefits resulting from the implementation of a new control system or policy. We apply BenMAP-CE in a slightly different way to compare the difference in predicted heath outcomes resulting from a change in modeling scale, including the influence on health disparities between demographic groups. For our health impact analysis, we apply the "porch potato" assumption, meaning we assume all members of the population are exposed to the outdoor concentrations at their place of residence all day whether than accounting for specific activity patterns. In "Coarse resolution air quality modeling" and "Fine resolution air quality modeling" sections, we provide an overview of the coarse (CAMx) and fine (HYCAMR) scale $PM_{2.5}$ modeling approaches, respectively. In "Health impact analysis" section, we provide a detailed description of the health impacts assessment model (BenMAP-CE).

Coarse resolution air quality modeling

To evaluate the impact of model resolution on health burden, we estimate $PM_{2.5}$ concentrations using two different modeling approaches: coarse and fine. For the coarse scale, we use the Comprehensive Air Quality Model with Extensions (CAMx version 6.0) to estimate $PM_{2.5}$ concentrations in the Northeastern US at 12 km × 12 km resolution as described in Parvez and Wagstrom (2019). CAMx is one of two models typically used by US EPA for regulatory analysis. CAMx uses first principles to simulate emissions, wet and dry deposition, gas- and aqueous-phase chemistry, and secondary particulate matter formation (Environ 2013). We use emissions based on the 2011 National Emissions Inventory (NEI) developed by the US EPA processed using the Sparse Matrix Operator Kernel Emissions (SMOKE) (CMAS 2013) model. These emissions inputs were included as part of the United States EPA's Ozone Regulatory Reanalysis, including model evaluation (US EPA 2014). For gas phase chemistry, we use CAMx mechanism 7. This mechanism is based on the Carbon Bond version 6 (CB-6) (Yarwood et al. 2010) mechanism and includes 16 aerosol species and a total of 218 reactions for 77 gaseous species. We create hourly boundary conditions for the New England domain from full year CAMx modeling for the continental US using the same inputs. We use meteorological inputs predicted by the Weather Research and Forecasting model WRF (version 3.4) (Skamarock et al. 2008), also from EPA's Ozone Regulatory Reanalysis. Additional details,

including model evaluation, are available in Parvez and Wagstrom (2019) and Parvez et al. (2017).

Fine resolution air quality modeling

For the fine scale, we employ a newly developed hybrid modeling framework, HYCAMR (Parvez and Wagstrom 2019). HYCAMR is capable of estimating combined $PM_{2.5}$ concentrations from onroad and regional sources at fine resolution (0.04 km × 0.04 km). HYCAMR combines a regional-scale model, CAMx, and a local scale dispersion model, R-LINE. The details and evaluation of this modeling framework and the modeled concentrations used in this study are available in Parvez and Wagstrom (2019). For consistency, the regional model component in HYCAMR is based on the same CAMx modeling described above for the coarse resolution. For this study, we use $PM_{2.5}$ concentrations estimated using HYCAMR for three locations in Connecticut: New Haven, Hartford, and Willimantic. We then up-scale the concentration estimates to census block group resolution for the year 2011. We then use annual average concentrations in the health impact analysis. Upscaling HYCAMR estimated concentrations results in the loss of some of the fine resolution; however, this is necessary due to the lack of population data on as fine a scale as HYCAMR. We have evaluated this new modeling framework against available satellite measurements and other high resolution concentration estimates in Parvez and Wagstrom (2019).

Health impact analysis

We use BenMAP-CE (version 1.3) to estimate the health impacts associated with the difference in estimated $PM_{2.5}$ exposure between the course and fine resolution model estimates. BenMAP-CE is commonly used by regulatory agencies to quantify and monetize potential health impacts associated with changes in air quality. BenMAP-CE relates changes in concentration to changes in health outcomes using built-in or imported concentration-response functions (CRF); multiple groups have used BenMAP-CE to conduct human health risk assessments (Abel et al. 2018; Kheirbek et al. 2016; Ravi et al. 2018). The general concentration-response function used by BenMAP-CE is shown in Eq. 1.

$$\Delta Y = Y_0\left(1-e^{-\beta\Delta PM}\right) \times Pop \quad (1)$$

In Eq. 1, ΔY is the change in health outcome, Y_0 is the baseline incident rate for a specified health outcome, β is the estimated effect coefficient drawn from epidemiology studies for each specified health outcome, ΔPM is the difference between two estimates of concentration (typically a base case and control scenario), and *Pop* is the population. The specific effect coefficients and baseline incidence rates can be found in BenMAP-CE.

We use a slightly modified approach for implementing BenMAP-CE; we define our baseline as the HYCAMR predicted fine resolution (0.04 km × 0.04 km upscaled to census block group) $PM_{2.5}$ concentration estimates and our control as the CAMx predicted coarse resolution (12 km × 12 km) $PM_{2.5}$ concentration estimates. We calculate these estimates at each of the census block groups within each location. Figure 1 shows an overview of our implementation for this BenMAP-CE analysis.

We assume all demographic groups experience the same health impacts when exposed to the same $PM_{2.5}$ concentrations. We use the existing CRF in BenMAP-CE which is based on published studies incorporating different assumptions of potential thresholds and observed slopes between changes in concentrations and changes in health outcomes (von Stackelberg et al. 2013). For each selected CRF, BenMAP-CE uses the mean estimate of the regression coefficient (β) and standard error to calculate a distribution of point estimates in each census block group. In addition to concentration-response functions, BenMAP-CE also contains census-based population and demographic data, baseline mortality and morbidity rates, and baseline incident and prevalence data for the contiguous USA. We use population data at the census block group level for the year 2010 (US Census Bureau 2010) for five different demographic groups: Hispanic white, Hispanic black, non-Hispanic white, non-Hispanic black, and non-Hispanic Asian. For baseline mortality incident rate, we use the US mortality incident rate for the year 2015 on a 36-km grid resolution which is built into BenMAP-CE. For other incident and prevalence rates, we use year 2014 and 2008 estimates, respectively, which are also available in BenMAP-CE.

Mortality

We include mortality rate impacts based on the CRF from two studies, Lepeule et al. (2012) and Krewski et al. (2009), based on two commonly used cohort studies: Harvard Six Cities and the American Cancer Society (respectively). Lepeule et al. (2012) (referred to as the Lepeule CRF) and Krewski et al. (2009) (referred to as the Krewski CRF) report an approximate 1.3 and 0.6% increase in all-cause mortality risk rate for each 1 $\mu g/m^3$ $PM_{2.5}$ concentration increase, respectively. The EPA Advisory Committee on Clean Air Act Compliance Analysis recommends developing a distribution using estimates from both the Krewski CRF (age 30–99) and Lepeule CRF (age 25–99) at the 25th and 75th percentiles, respectively (von Stackelberg et al. 2013). This is consistent with an expert elicitation completed by the EPA Science Advisory Board (US EPA Advisory Council on the CCA 2010). As already mentioned, we use the mortality incident rates for the year

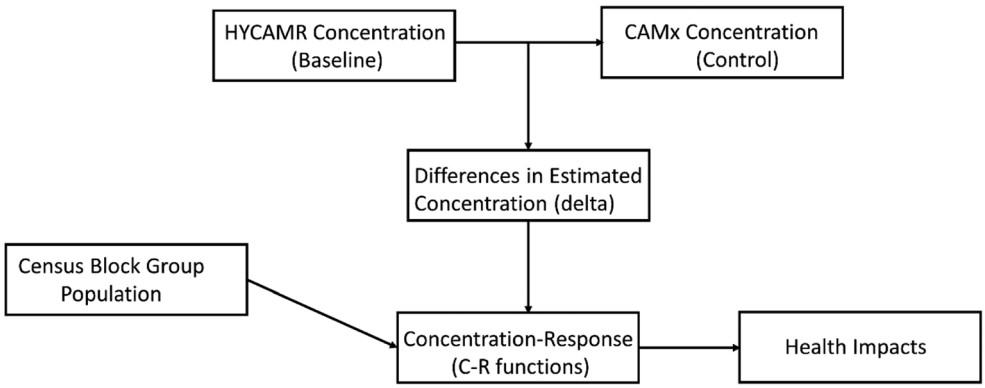

Fig. 1 BenMAP-CE analysis flow diagram

2015 that are built into BenMAP-CE to estimate the difference in premature mortality rate based on model resolution for each census block group.

Other health impacts

In addition to differences in estimated mortality rate, we also estimate the impact of model resolution on other health outcomes including asthma exacerbation, hospital admission due to cardiovascular illness, hospital admission due to respiratory illness, and emergency room visits. For asthma exacerbation, we include CRFs from two studies, Ostro et al. (2001) (Ostro CRF) and Mar et al. (2004) (Mar CRF), which both suggest a positive correlation between $PM_{2.5}$ concentration and asthma in children age 6 to 18 years. We use these two studies to quantify pooled incidents (cough, wheezing, and shortness of breath) within this age group. We consider another CRF from Mar et al. (2010) to estimate the difference in total emergency room visits for individuals age 0 to 99 years. For hospital admission due to cardiovascular problems, we consider four CRFs for individuals age 18 to 99 years: Bell et al. (2008); Moolgavkar (2000). Similarly, for hospital admission due to respiratory problem, we consider the CRF based on the work in Babin et al. (2007), Moolgavkar (2000), and Zanobetti et al. (2009) for individuals age 0 to 99 years. When using multiple CRFs, we report an average between the results.

Results and discussions

HYCAMR estimated concentrations and exposure

Figures 2 and S.1 show the HYCAMR estimated annual average $PM_{2.5}$ concentrations in New Haven, Hartford, and Willimantic at census block group resolution. The HYCAMR estimates show a maximum value of 15.3, 12.7, and 21.7 μg/m^3 for New Haven, Hartford, and Willimantic, respectively. HYCAMR is able to capture sharp concentration gradients near roads to better estimate differences in

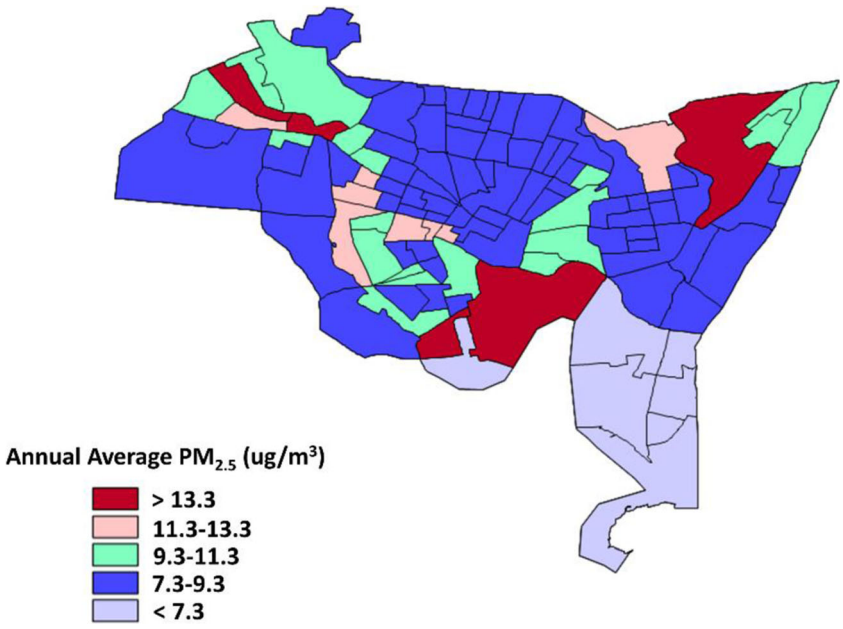

Fig. 2 Annual average $PM_{2.5}$ concentrations (μg/m^3) in New Haven, CT at census block resolution for the year 2011

concentrations between census block groups. In these cities, the differences in $PM_{2.5}$ concentrations between census block groups mostly result from differences in traffic volume.

The population density of each demographic group differs in each census block group. We compare the average exposure for different demographic groups for each location as a first comparison of the air pollution burden faced by different demographic groups. We use population data from the 2010 US Census (US Census Bureau 2010) and Eq. 2 to estimate the average exposure for each demographic group.

$$C_{pop,j} = \frac{\sum_i^N C_i \times P_{i,j}}{\sum_i^N P_{i,j}} \quad (2)$$

In Eq. 2, $C_{pop,j}$ is the average exposure for demographic group j, C_i and $P_{i,j}$ are the concentration and population of demographic group j in census block group i, respectively, and N is the total number of census block groups in the location. Figure 3 shows the difference in estimated average exposure between the fine and coarse resolution modeled $PM_{2.5}$ concentrations. We find that the differences in estimated average exposure for each demographic group in New Haven and Hartford are similar; however, we see a substantial variation in the differences in estimated average exposure for demographic groups in Willimantic. There are two possible explanations for this difference: (1) Hartford and New Haven have more census block groups than Willimantic making the non-uniformity between the demographic groups more pronounced in Willimantic; (2) the difference in estimated concentrations between the census block groups in Willimantic is more substantial than in Hartford or New Haven. It is also important to note that in each city, we are investigating the city itself, not the full metropolitan area. We have similarly quantified the difference in the average exposure between different income groups (Fig. S.2) and find no significant distinction in the difference in estimated exposures between income groups.

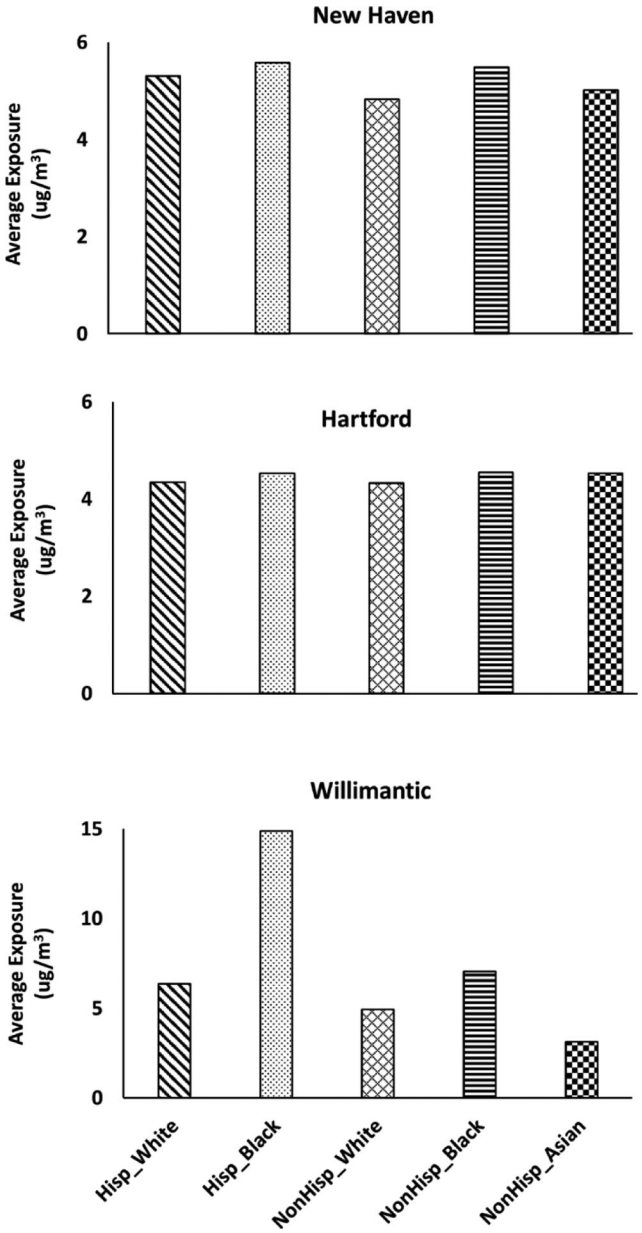

Fig. 3 Difference in estimated average $PM_{2.5}$ exposure between CAMx and HYCAMR for each demographic group in New Haven, Hartford, and Willimantic for the year 2011. We consider five different demographic groups: Hispanic white (Hisp_White), Hispanic black (Hisp_Black), non-Hispanic white (NonHisp_White), non-Hispanic black (NonHisp_Black), and Asian (Nonhispanic_Asian)

BenMAP-CE estimated health impact

We present the BenMAP-CE estimated difference in the number of annual deaths (mortality) and cases of asthma exacerbation for each location in Table 1. According to the risk estimated using the Krewski CRF, we find an increase in the estimated number of deaths in New Haven, Hartford, and Willimantic of 16, 13, and 2, respectively, for the population age 30 to 99 resulting from a change in resolution of the $PM_{2.5}$ concentration estimates. This corresponds to an increase in estimated mortality rate of 2 deaths per 10,000 people. Although the population density varies substantially between the locations, the change in estimated mortality rate is not substantially different. This results from the high concentrations in some of the most populated census block groups in Willimantic where people live in close proximity to roads. Compared to the estimates using the Krewski CRF, those using the Lepeule CRF are higher, partially because the Lepeule CRF included ages 25 to 99 while the Krewski CRF only includes those 30 to 99. In addition, these studies were also based on different study populations. We find a substantial increase in estimated cases of asthma exacerbation in all three cities when using the higher resolution concentration predictions (Table 1). Like differences in estimates of mortality, differences in estimated asthma exacerbation also

Table 1 Difference in the estimated number of death and cases of asthma exacerbation in each city using the fine resolution estimates of $PM_{2.5}$ concentrations compared to coarse resolution estimates

		New Haven		Hartford		Willimantic	
Health indicator	CRF	Population at risk (age group)	Difference in outcomes	Population at risk (age group)	Difference in outcomes	Population at risk (age group)	Difference in outcomes
All-cause mortality	Krewski et al. 2009 (Krewski CRF)	91,645 (30–99)	16	87,332 (30–99)	13	12,677 (30–99)	2
	Lepeule et al. 2012 (Lepeule CRF)	98,192 (25–99)	35	93,570 (25–99)	28	13,583 (25–99)	5
Asthma exacerbation	Ostro et al. 2001 (Ostro CRF)	17,020 (6–18)	1300	16,219 (6–18)	1000	2354 (6–18)	190
	Mar et al. 2004 (Mar CRF)	17,020 (6–18)	6900	16,219 (6–18)	5600	2355 (6–18)	980

vary between the two CRF which were developed based on different study populations. For other health impact such as emergency room visit, hospital visit cardiovascular, and hospital visit respiratory, we also find some differences associated with model resolution change (Table S.1).

Figures 4 and S.3-S.4 show the difference in the estimated mortality rate per 10,000 people using each CRF. We see the greatest impact in the most populated census block groups for both CRFs in New Haven. We find noticeable differences in estimated cases of asthma exacerbation between census block groups depending on whether we apply the Ostro CRF or Mar CRF (Fig. 5) and the overall differences in estimated cases of exacerbation vary greatly between the two CRFs. Although the difference in estimated mortality rate is not as significant as that for asthma exacerbation, we still see a difference in the estimated total number of deaths in each city. According to our estimates, mortality and asthma exacerbation show the biggest sensitivity to the model resolution. Although the average exposure is higher in Willimantic than the other two cities, the difference in estimated absolute health impacts is lower in Willimantic due to the lower population; however, the difference in estimated mortality rate in Willimantic is higher (Fig. S.4) meaning the fine resolution concentration estimates have more impact on health estimates in Willimantic.

In Fig. 6, we present the distribution of the differences in the estimated health outcomes between demographic groups. This is not an estimate of absolute health burden or even percent health burden from $PM_{2.5}$ exposure, but rather the

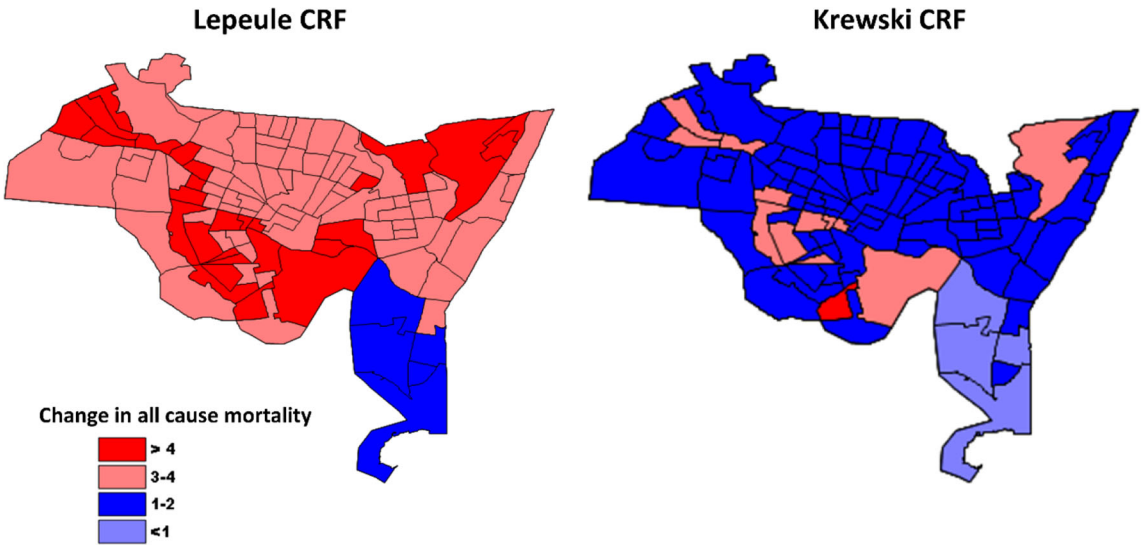

Fig. 4 Differences in estimated all-cause mortality from $PM_{2.5}$ exposure due to differences in the resolution of the $PM_{2.5}$ concentration estimates in New Haven

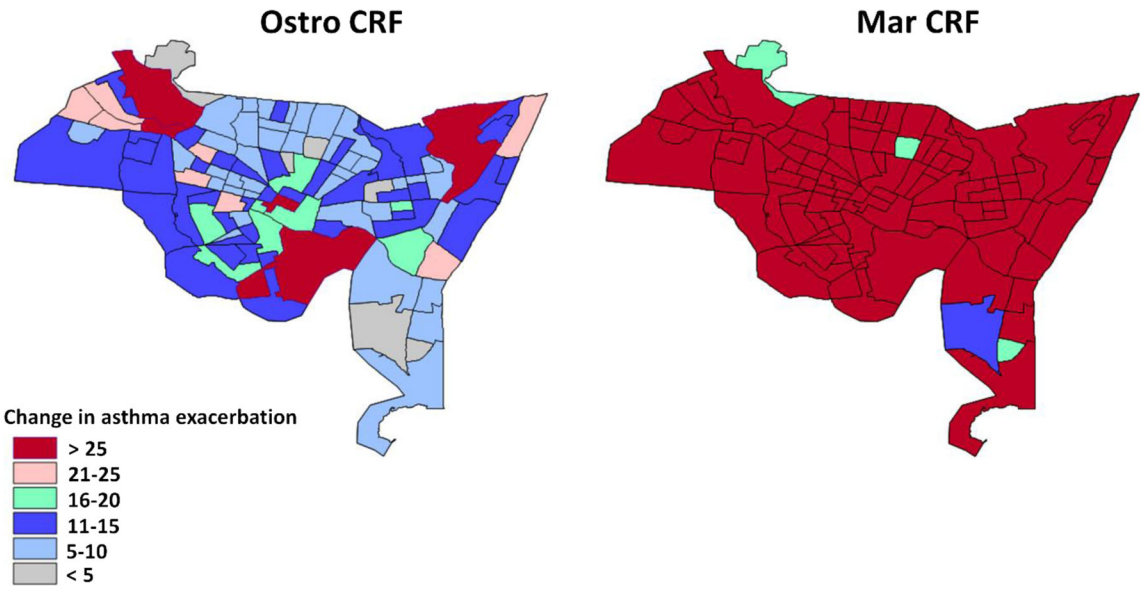

Fig. 5 Difference in the estimated number of cases of asthma exacerbation from $PM_{2.5}$ exposure due to differences in the resolution of the $PM_{2.5}$ concentration estimates in New Haven

difference in estimated health burden when we account for higher resolution estimates of concentrations. The demographic breakdown of the population is also included in Fig. 6 for reference. According to our estimates, we mainly see similar distributions between demographic groups in differences in health impacts as the distribution among demographic groups in the population with a few exceptions. Overall the impact of model resolution on health risk estimation affects all sectors of the population similarly in New Haven. In Hartford, we find a disproportionate higher increase in estimated hospitalizations for respiratory issues and emergency room visits for Hispanic black and non-Hispanic black members of the population, respectively, while we find a disproportionate lower increase in the estimated number of cases for non-Hispanic white members of the population see. In Willimantic, we find a disproportionate higher increase in estimated emergency room visits for the Hispanic black members of the population and a disproportionate slightly higher increase in estimated overall health outcomes for the Hispanic white members of the population.

Conclusions

As seen in past work (Parvez and Wagstrom 2019), the estimated air pollution exposure to populations differs greatly depending on the resolution of the air quality model. In this work, we use BenMAP-CE to estimate how these differences in estimated exposure may translate to differences in estimated health burden among different demographic groups. Our study constitutes one of the few attempts (Kheirbek et al. 2013; Punger and West 2013; Thompson et al. 2014; Li et al. 2016) to quantify the differences in estimated health impacts resulting from differences in the resolution of air quality estimates. As with these past studies looking at impacts at the regional and global scales, our results show that the model resolution can influence the health risk assessment at local scales and higher resolution estimates may lead to higher predicted health outcomes, particularly for some demographic groups. Our results show that using coarse resolution air quality concentrations may lead to an underprediction of the number of deaths and other health impacts in urban populations. Although BenMAP-CE is widely used for conducting health impact assessment, these results should be interpreted with caution considering the uncertainties and limitations. One limitation of this study is that we maintained the baseline incidents at county scale already available in BenMAP-CE. As the goal of this study was to compare the impact of differences in air quality estimate resolution on predicted health outcomes, this assumption should have little overall impact on the findings. In addition, this analysis is limited by the use of epidemiological studies developed based on air monitoring network data rather than concentrations measurements on the resolutions used here. This could impact the applicability of these concentration-response functions to high resolution concentration estimates. This work is partially motivated by the potential for future, high resolution estimates of air pollutant concentrations to enable the development of more refined concentration-response functions. Finally, the exposures estimated here are limited and based on the location of an individual's residence and do not account for activity. These findings provide policy makers another perspective and potential motivation to consider fine-scale estimates of air pollutant concentrations when estimating potential health impacts and developing policies to safeguard human health.

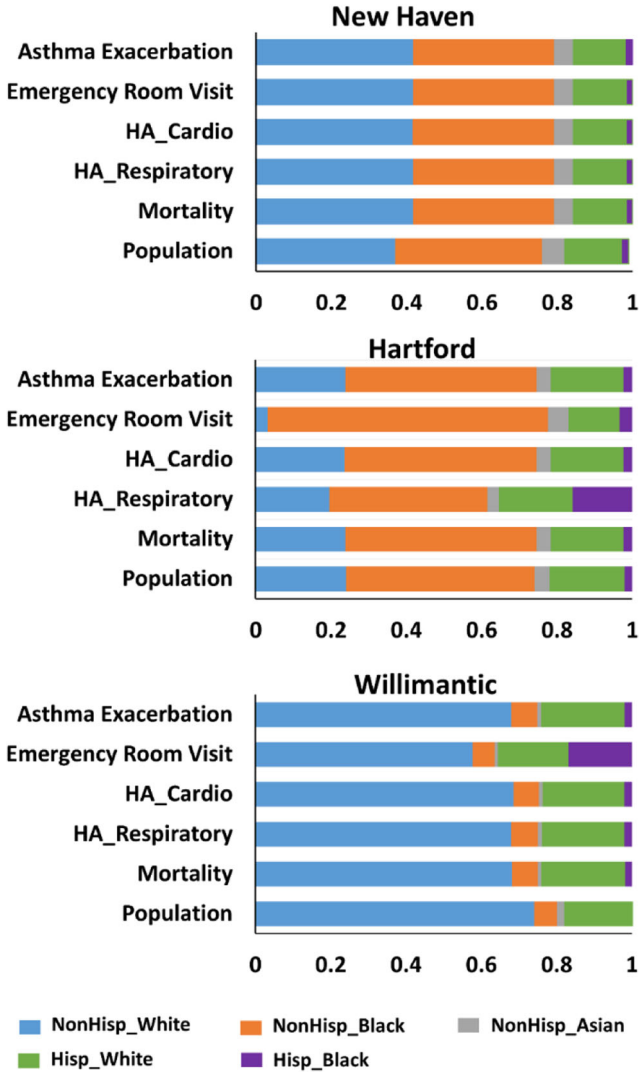

Fig. 6 The distribution among demographic groups of the differences in estimated health impacts resulting from using fine-scale estimates of $PM_{2.5}$ concentration instead of regional estimates

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References

Abel D, Holloway T, Harkey M, Rrushaj A, Brinkman G, Duran P, Janssen M, Denholm P (2018) Potential air quality benefits from increased solar photovoltaic electricity generation in the eastern United States. Atmos Environ 175:65–74. https://doi.org/10.1016/j.atmosenv.2017.11.049

Adar SD, Kaufman JD (2007) Cardiovascular disease and air pollutants: evaluating and improving epidemiological data implicating traffic exposure. Inhal Toxicol 19:135–149. https://doi.org/10.1080/08958370701496012

Babin SM, Burkom HS, Holtry NR, Tabernero NR, Stokes LD, Davies-Cole JO, DeHaan K, Lee DH (2007) Pediatric patient asthma-related emergency department visits and admissions in Washington, DC, from 2001-2004, and associations with air quality, socio-economic status and age gap. Environ Health 6:9

Bell ML, Ebisu K, Peng RD, Walker J, Samet JM, Zeger SL, Dominici F (2008) Seasonal and regional short-term effects of fine particles on hospital admissions in 202 US counties, 1999-2005. Am J Epidemiol 168(11):1301–1310. https://doi.org/10.1093/aje/kwn252

Carvour ML, Hughes AE, Fann N, Haley RW (2018) Estimating the health and economic impacts of changes in local air quality. Am J Public Health 108(S2):S151–S157. https://doi.org/10.2105/AJPH.2017.304252

Community Modeling and Analysis System (CMAS), University of North Carolina (2013) SMOKE v3.6.5 User's Mannual. Retrieved from https://www.cmascenter.org/smoke/documentation/3.6.5/html/ch01s02.html

EPA U.S. Advisory Council of the Clean Air Act, Health Effects Subcommittee (HES) of the Council (2010) Review of the EPA's draft health benefits of the Second Section 812 prospective study of the Clean Air Act. https://yosemite.epa.gov/sab/sabproduct.nsf/0/72D4EFA39E48CDB28525774500738776/$File/EPA-COUNCIL-10-001-unsigned.pdf

Environ International Corporation (2013) User's guide comprehensive air quality model with extensions version 6.0. http://www.camx.com/files/camxusersguide_v6-00.pdf

EPA, US (2014) Regulatory impact analysis for the proposed revisions to the national ambient air quality standards for particulate matter. U.S. Environ. Prot. Agency, EPA-452/P-14-006

EPA, US (2018) Environmentals benefits mapping and analysis program community edition (BenMAP-CE) user's manual. https://www.epa.gov/benmap

Fann N, Fulcher CM, Baker K (2013) The recent and future health burden of air pollution apportioned across U.S. sectors. Environ Sci Technol 47(8):3580–3589. https://doi.org/10.1021/es304831q

Kheirbek I, Wheeler K, Walters S, Kass D, Matte T (2013) $PM_{2.5}$ and ozone health impacts and disparities in New York City: sensitivity to spatial and temporal resolution. Air Qual Atmos Health 6:473–486. https://doi.org/10.1007/s11869-0185-4

Kheirbek I, Haney J, Douglas S, Ito K, Matte T (2016) The contribution of motor vehicle emissions to ambient fine particulate matter public health impacts in New York City: a health burden assessment. Environ Health 15(1). https://doi.org/10.1186/s12940-016-0172-6

Krewski D, Jerrett M, Burnett RT, Ma R, Hughes E, Shi Y, Turner MC, Pope A III, Thurston G, Calle EE, Thun MJ, Beckerman B, DeLuca P, Finnkelstein N, Ito K, Moore DK, Newbold KB, Ramsay T, Ross Z, Shin H, Tempalski B (2009) Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality. Res Rep Health Eff Inst 140:5–36 Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/19627030

Lepeule J, Laden F, Dockery D, Schwartz J (2012) Chronic exposure to fine particles and mortality: an extended follow-up of the Harvard Six Cities Study from 1974 to 2009. Environ Health Perspect 120(7):965–970. https://doi.org/10.1289/ehp.1104660

Li Y, Hanze D, Jack D, Kinney P (2016) The influence of air quality model resolution on health impact assessment for fine particulate matter and its components. Air Qual Atmos Health 9:51–68. https://doi.org/10.1007/s11869-015-0321-z

Lu X, Lin C, Li W, Chen Y, Huang Y, Fung JCH, Lau AKH (2018) Analysis of the adverse health effects of PM2.5 from 2001 to 2017 in China and the role of urbanization in aggravating the health burden. Sci Total Environ 652:683–695

Mar TF, Koenig JQ, Primomo J (2004) An analysis of the association between respiratory symptoms in subjects with asthma and daily air pollution in Spokane, Washington. Inhal Toxicol 16:809–815

Mar TF, Koenig JQ, Primomo J (2010) Associations between asthma emergency visits and particulate matter sources, including diesel emissions from stationary generators in Tacoma, Washington. Inhal Toxicol 22(6):445–448

Moolgavkar SH (2000) Air pollution and hospital admissions for chronic obstructive pulmonary disease in three metropolitan areas in the United States. Inhal Toxicol 12(Supl 4):75–90. https://doi.org/10.1016/S0300-2896(10)70060-0

Ostro B, Lipsett M, Mann J, Braxton-Owens H, White M (2001) Air pollution and exacerbation of asthma in African-American children in Los Angeles. Epidemiology 12(2):200–208. https://doi.org/10.1097/00001648-200103000-00012

Parvez F, Lamancusa C, Wagstrom K (2017) Primary and secondary particulate matter intake fraction from different height emission sources. Atmos Environ 165:1–11. https://doi.org/10.1016/j.atmosenv.2017.06.011

Parvez F, Wagstrom K (2019) A hybrid modeling framework to estimate pollutant concentrations and exposures in near road environments. Sci Total Environ 663:144–153

Pope CA, Muhlestein JB, May HT, Renlund DG, Anderson JL, Horne BD (2006) Ischemic heart disease events triggered by short-term exposure to fine particulate air pollution. Circulation 114(23):2443–2448. https://doi.org/10.1161/CIRCULATIONAHA.106.636977

Punger E, West J (2013) The effect of grid resolution on estimates of the burden of ozone and fine particulate matter on premature mortality in the USA. Air Qual Atmos Health 6:563–573. https://doi.org/10.1007/s11869-013-0197-8

Ravi V, Gao AH, Martinkus NB, Wolcott MP, Lamb BK (2018) Air quality and health impacts of an aviation biofuel supply chain using forest residue in the northwestern United States. Environ Sci Technol 52(7):4154–4162. https://doi.org/10.1021/acs.est.7b04860

Salam MT, Islam T, Gilliland FD (2008) Recent evidence for adverse effects of residential proximity to traffic sources on asthma. Curr Opin Pulm Med 14:3–8

Skamarock WC, Klemp JB, Dudhi J, Gill DO, Barker DM, Duda MG et al (2008) A description of the advanced research WRF version 3. Tech Rep (June):113. https://doi.org/10.5065/D6DZ069T

Thompson TM, Saari RK, Selin NE (2014) Air quality resolution for health impact assessment: influence of regional characteristics. Atmos Chem Phys 14:969–978. https://doi.org/10.5194/acp-14-969-2014

United States Census Bureau (2010) http://www.census.gov/topics/population/data.html

Yarwood G, Jung J, Whitten GZ, Heo G, Melberg J Estes M (2010) Updates to the carbon bond mechanism for version 6 (CB6). Presented at the 9th Annual CMAS Conference, Chapel Hill, NC, October 11–13, 6(415), pp.1–4

Von Stackelberg K, Buonocore J, Bhave PV, Schwartz JA (2013) Public health impacts of secondary particulate formation from aromatic hydrocarbons in gasoline. Environ Health 12(1):1–13. https://doi.org/10.1186/1476-069X-12-19

Zanobetti A, Franklin M, Koutrakis P, Schwartz J (2009) Fine particulate air pollution and its components in association with cause-specific emergency admissions. Environ Health 8(58):1–8. https://doi.org/10.1186/1476-069X-8-58