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Residential Proximity to Biorefinery Sources of Air Pollution and Respiratory Diseases in New York State

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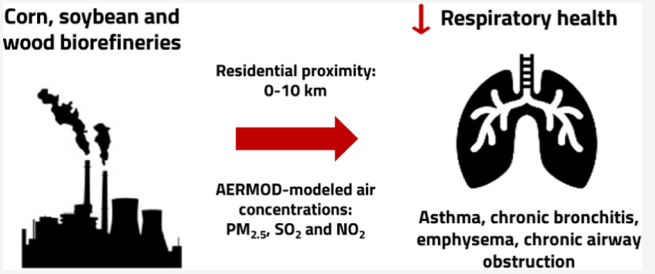
ABSTRACT: Understanding potential health risks associated with biofuel production is critical to sustainably combating energy insecurity and climate change. However, the specific health impacts associated with biorefinery-related emissions are not yet well characterized. We evaluated the relationship between respiratory emergency department (ED) visits (2011−2015) and residential exposure to biorefineries by comparing 15 biorefinery sites to 15 control areas across New York (NY) State. We further examined these associations by biorefinery types (e.g., corn, wood, or soybean), seasons, and lower respiratory disease subtypes. We measured biorefinery exposure using residential proximity in a cross-sectional study and estimation of biorefinery emission via AERMOD-simulated modeling. After controlling for multiple confounders, we consistently found that respiratory ED visit rates among residents living within 10 km of biorefineries were significantly higher (rate ratios (RRs) range from 1.03 to 3.64) than those in control areas across our two types of exposure indices. This relationship held across biorefinery types (higher in corn and soybean biorefineries), seasons (higher in spring and winter), air pollutant types (highest for NO_2), and respiratory subtypes (highest for emphysema). Further research is needed to confirm our findings.



KEYWORDS: *biorefineries, respiratory health, residential exposure, air pollution, cleaner energy, exposure measurement*

1. INTRODUCTION

To combat energy insecurity and climate change, biofuels have been promoted as alternative energy sources to traditional fossil fuels. Currently, a range of national and regional policies are mandating biofuels and encouraging the rapid growth of the biofuel industry. For example, the national Renewable Fuel Standard (RFS2) has requested that ∼36 billion gallons of biofuels should be produced by 2022.[1] As a result of such policies, biorefineries have expanded by almost 3.8 times over the last 2 decades (1997−2017), increasing from 56 to 211 facilities throughout the United States.[2] However, the burgeoning biorefineries emit fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2),[3,4] which may cause local increases of air pollution exposure and contribute to adverse respiratory outcomes for nearby residents. Therefore, to achieve energy security and climate adaptation in a sustainable manner, it is critical to understand the potential respiratory health impacts associated with biorefineries.

To date, little is known about the health risks associated with biorefinery-derived air pollutants. Recent studies suggest that biofuels generate higher amounts of $PM_{2.5}$ than fossil fuels.[5,6] For example, Hill et al.[5] and Sengupta et al.[6] found that county-level health costs and impacts from exposure to air pollutants derived from the biorefineries were much higher compared to those health impacts related to gasoline production. In addition, numerous mechanistic studies[7−13] indicate that criteria air pollutants, including $PM_{2.5}$, SO_2, and NO_2, which are also emitted from biorefinery facilities and other sources of pollution, are significantly associated with respiratory diseases. The possible biological mechanisms include irritating effect causing damages to the lung epithelial cells and pulmonary inflammation; damages to the tissues causing oxidative stress; and impairment of mucociliary clearance, which serves as defense mechanisms to environmental insults, causing bronchoconstriction.[11−13] Although these valuable studies began to shed light on the health impacts of biorefineries, significant knowledge gaps remain. First, the effect of residential proximity to biorefineries on respiratory health is unknown. Second, the seasonality of biorefinery-related air emissions and their associations with residential respiratory health have not been investigated. Additionally, the effect of biomass types on the associations between

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biorefinery-related air emissions and residential respiratory health is unknown.

To address these knowledge gaps, we examined the associations between the rates of respiratory diseases and exposure to biorefineries by utilizing two distinct and complementary exposure approaches, i.e., residential proximity to biorefineries and air dispersion-modeled concentrations of multiple pollutants ($PM_{2.5}$, SO_2, and NO_2). We also further assessed whether these relationships varied by biomass types, seasons, and respiratory subtypes.

2. MATERIALS AND METHODS

2.1. Study Population and Study Areas. This study population included all emergency department (ED) visits due to lower respiratory diseases among New York State (NYS) residents aged 1−85 living within 20 km from the biorefinery facilities and the control areas between 2011 and 2015. We excluded infants of age less than 1 because of the difficulties of differentiating asthma with bronchiolitis, viral infections, and other conditions at such early stages after birth.[14−16] Moreover, adults aged over 85 were not included in the study for the following reasons: (1) substantial increase in comorbidities and/or multimorbidities is observed among adults aged over 85, when compared to that among adults aged 65−85 based on the literature;[17−19] (2) changes in daily activity patterns (e.g., use of wheelchairs) and significant decrease in regular activities (e.g., less physical activity, less time spent outdoors) are notably evident among adults aged over 85;[20,21] and (3) within our study population, we found that the percentage of adults aged >85 comprised 1.48% of the total cases.

The study areas included 15 representative biorefinery sites in NYS. These 15 biorefinery facilities in NYS included two corn biorefineries, two soybean biorefineries, and 11 wood biorefineries. We obtained their production capacity, location, and building characteristics from the Renewable Fuel Association (RFA), EPA's National Air Pollutants Emissions Inventory Trends database and biorefinery websites.[2,22] These sites were defined as "biorefinery sites". The 15 selected biorefineries' production capacities ranged from 5.4 to 108.9 million gallons of biofuels per year (MGY). Detailed information on the biorefinery facilities and capacities is described in Table S1.

We selected 15 control areas within NYS matched to the 15 biorefinery sites by similar median income (<10% difference), age distribution (1−85 years), and % of African-Americans (<10% difference) at the census tract level. The control areas were selected ensuring that these areas do not overlap with any biorefinery sites or other control areas, as depicted in Figure S1. We also matched the number of the control areas with the number of biorefinery sites both in New York City (NYC) (1:1) and in the rest of the NYS (14:14) to account for differences in sociodemographic characteristics and exposure sources between NYC and the rest of the state.

2.2. Outcome Definition and Measurement. Information on respiratory hospital ED visits was retrieved from the NYS Department of Health Statewide Planning and Research Cooperative System (SPARCS) database. SPARCS data are NY state's widely used and legislatively mandated collection of health data information on hospital admissions and discharge data, covering ∼95% of all hospitals (excluding federal and psychiatric facilities) in NYS.[23] SPARCS data include information on principal diagnoses of 24 comorbidities, hospital admissions and discharge dates, sources of payment, date of birth, sex, race/ethnicity, length of stay, and street address. SPARCS data have been widely used in previous studies examining similar respiratory outcomes.[24−27]

The lower respiratory diseases (N = 1 285 163 ED visits) in this study include hospital ED visits from January 1, 2011 through December 31, 2015 due to four subtypes with primary diagnosis using the International Classification of Diseases (ICD), 9th and 10th versions.[28] We included the most common types of COPDs, i.e., chronic bronchitis (ICD 491), emphysema (ICD 492), and chronic airway obstruction (ICD 496) rather than other less common subtypes (ICD 490, 494, and 495), in addition to asthma (ICD 493). These respiratory diseases were chosen due to well-established associations previously examined among residents living near industrial areas.[29−32]

We defined the outcome as the number of these cases during the period from 2011 to 2015, overall and aggregated by sex, race, age groups (1−17, 18−44, 45−64, 65−85 years), and distances (0−5, >5−10, >10−15, >15−20 km) of residential proximity to biorefinery facilities and control areas. We obtained 5 year estimates of demographics data from the American Community Survey (ACS) for the years 2011−2015 by census tract.[33] Ethical approval was obtained from the Institutional Review Board of the University at Albany, State University of New York.

2.3. Exposure Definition and Assessment. As it is challenging to measure exposure directly, two complementary approaches were used to assess residential exposure to biorefineries: (1) based on straight-line distances (km) measured between the centroid of each biorefinery site or control area, which was further divided by four distance groups as a dichotomous variable, as described in Section 2.3.1; and (2) air dispersion-modeled concentrations of each air pollutant, including $PM_{2.5}$, SO_2, and NO_2 generated from AERMOD model (described in Section 2.3.2).

We chose to include residents living up to 20 km from the biorefineries since previous studies examining air pollutants from point sources of pollution or industries have demonstrated environmental health impacts on residents up to this distance.[34−37] To identify a threshold cutoff distance of increased risk for respiratory ED visits, the areas surrounding each of the 30 sites (15 biorefinery centroids and 15 census tract centroids) were divided into four distance groups according to the distance to each centroid (0−5, >5−10, >10−15, or >15−20 km). We first examined the range to 20 km and then refined our analyses when we identified 10 km as the possible threshold of health risks. Therefore, most of the analyses were conducted within 10 km (Figure S1).

2.3.1. Residential Proximity to Biorefinery Facilities and Control Areas. All residential addresses of cases and the locations of biorefinery facilities and control areas were geocoded to the street level using ArcGIS (version 10.4, ESRI, Redlands, CA).[38] Residential proximity was measured based on straight-line distances (in km) from the center of each biorefinery facility to the households of cases for the biorefinery sites and from the census tract centroids to the households of cases for the "control areas". Cases were then assigned to the census tracts of the residences to calculate the aggregate number of cases by distance groups (e.g., 0−5 km) (Figure S1). Analyzing the data at a finer geographic scale was not possible due to the lack of availability of census demographics at smaller units (such as census block groups

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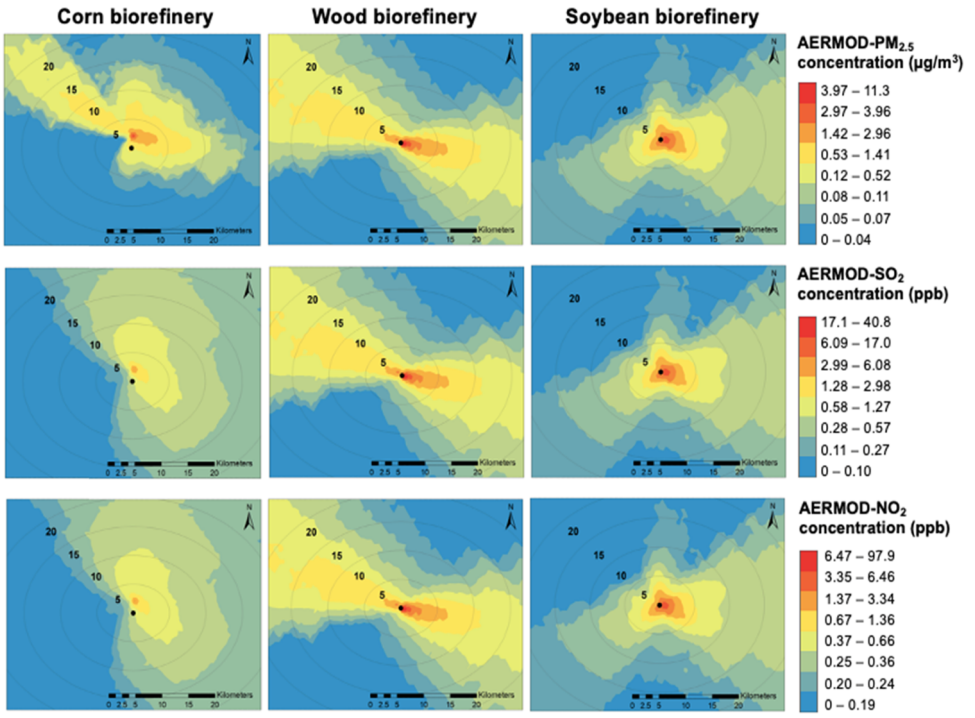

Figure 1. Heat maps showing the dispersion of AERMOD-modeled air pollutants of $PM_{2.5}$, SO_2, and NO_2 by sources of emission (corn, soybean, and wood biorefineries). Black dots represent biorefinery facilities and the gray circles represent distances, and the numbers indicate the distances from the biorefinery facilities (up to 20 km).

or blocks) and the rare occurrences of our outcomes of interest in the data set.

2.3.2. AERMOD Modeling Air Concentrations. The daily air concentrations of fine particulate matter ($PM_{2.5}$, $\mu g/m^3$), sulfur dioxide (SO_2, ppb), and nitrogen dioxide (NO_2, ppb) up to 20 km radii from each of the biorefineries were quantified using the American Meteorological Society and the U.S. EPA (AMS/EPA) Regulatory Model (AERMOD) over a 5 year period (2011−2015). AERMOD-modeled air pollutants were simulated in biorefinery sites only. The selected air pollutants ($PM_{2.5}$, SO_2, and NO_2) are common and major air pollutants from the operational processes[39] in biorefineries.[4,40]

The AERMOD dispersion model, which was approved and preferred by the U.S. EPA for regulatory purposes, is one of the well-recognized air dispersion models for simulating air concentrations from stationary point sources.[41] Several studies applied AERMOD simulations to examine the health impacts associated with residential exposure to air pollution among residents living near industrial sites.[32,42,43] The AERMOD dispersion model was chosen due to its high accuracy and reliability in estimating stationary point sources of air concentrations.[41,44−46] In addition, the AERMOD model simulations have previously been validated against several field site measurements in Canada,[47] Thailand,[48] and several parts of the United States.[49,50]

The AERMOD model is composed of three preprocessors: (1) the AERMOD Meteorological Preprocessor (AERMET), (2) the AERMOD Terrain Preprocessor (AERMAP), and, (3) the Building Profile Input Program for PRIME (BPIPPRM) (for details, see Figure S2 and Table S2).[51,52] Based on the processed outputs from the three preprocessors, we processed AERMOD (v.18081) to obtain the daily air concentrations of $PM_{2.5}$ ($\mu g/m^3$), SO_2 (ppb), and NO_2 (ppb) from 2011 to 2015 at the grid level (1 km × 1 km), yielding a total of 505−541 receptor points within 20 km from each biorefinery facility (Figure 1).[53]

2.4. Covariates. Covariates in this study included (1) the individual patients' age, race, and sex obtained from the SPARCS database;[23] (2) county-level smoking rates (2011−2012) acquired from the Global Health Exchange[54] (Figure S3); (3) meteorological variables (seasonal mean temperature and relative humidity measured from the closest weather station) obtained from the U.S. EPA;[55] and (4) annual mean air pollutant concentrations of $PM_{2.5}$, SO_2, and NO_2 of the nearest air monitors from the biorefinery facilities and control areas for years 2011−2015 obtained from the U.S. EPA.[55] The confounding variables were selected based on evidence in the existing literature on well-established risk factors for respiratory diseases,[56,57] especially those factors related to both respiratory diseases and air pollution exposure or proximity to industrial facilities,[58−62] as well as by consulting subject experts and considering biological plausibility.

2.5. Statistical Analysis. Using Poisson regression models, we regressed the aggregate number of ED visits due to respiratory diseases per distance areas (e.g., 0−5 km) on either the residential proximity to biorefineries or the AERMOD-modeled air concentrations of $PM_{2.5}$, SO_2, and NO_2 while controlling for multiple confounders. We ran separate models by distance groups (e.g., 0−5 km), biorefinery types (e.g., corn biorefinery sites), seasons (e.g., spring), as well as for the different outcomes of different respiratory subtypes (e.g., asthma). For example, for the 0−5 km category for the 30 locations (15 around biorefinery and 15 around control areas), we ran a model as follows (eq 1)

$$\ln(\text{case}) \sim \text{exposure}_{(\text{site/area})} + \text{sex} + \text{age} + \text{race} + \text{smoking} + \text{offset}_{(\text{population})} + \text{other confounders} \quad (1)$$

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Table 1. Adjusted Rate Ratios (RRs) and 95% Confidence Intervals of the Associations between Respiratory Morbidity[a]

		adjusted RR (95% CI)[d]			
	all respiratory (N = 547 437)	asthma (N = 507 066)	chronic bronchitis (N = 27 832)	emphysema (N = 1638)	chronic airway obstruction (N = 10 901)
(A) Residential Proximity to Biorefineries (in km)[b]					
0−5	3.64 (3.47, 3.81)	3.46 (3.29, 3.64)	4.95 (4.01, 6.13)	18.2 (4.35, 75.9)	5.29 (4.35, 6.42)
>5−10	1.50 (1.44, 1.56)	1.42 (1.36, 1.49)	3.02 (2.46, 3.71)	0.17 (0.01, 1.57)	2.06 (1.71, 2.49)
>10−15	0.69 (0.66, 0.72)	0.69 (0.66, 0.72)	0.68 (0.55, 0.85)	0.95 (0.31. 2.92)	0.59 (0.38, 0.94)
>15−20	0.55 (0.52, 0.58)	0.56 (0.53, 0.59)	0.38 (0.29, 0.48)	0.27 (0.07, 0.99)	0.39 (0.23, 0.68)
(B) AERMOD Modeling Air Pollutants (in km)[b,c]					
$PM_{2.5}$ ($\mu g/m^3$)					
0−5	1.15 (1.11, 1.20)	1.10 (1.09, 1.10)	1.13 (1.13, 1.15)	1.25 (1.12, 1.39)	1.14 (1.12, 1.15)
>5−10	1.00 (0.99, 1.01)	1.01 (1.01, 1.01)	1.02 (1.02, 1.03)	0.97 (0.93, 1.01)	1.01 (1.01, 1.02)
>10−15	1.00 (0.99, 1.00)	0.99 (0.99, 0.99)	0.99 (0.99, 0.99)	0.99 (0.98, 1.02)	0.99 (0.98, 0.99)
>15−20	0.99 (0.99, 1.00)	0.99 (0.99, 0.99)	0.99 (0.99, 0.99)	0.99 (0.98, 1.00)	0.99 (0.98, 0.99)
SO_2 (ppb)					
0−5	2.07 (1.68, 2.68)	1.59 (1.57, 1.63)	1.83 (1.69, 1.98)	2.98 (1.74, 5.12)	1.87 (1.74, 2.02)
>5−10	1.02 (0.97, 1.07)	1.03 (1.03, 1.04)	1.11 (1.09, 1.13)	0.85 (0.69, 1.04)	1.07 (1.05, 1.08)
>10−15	0.97 (0.94, 1.01)	0.97 (0.97, 0.97)	0.97 (0.95, 0.99)	0.99 (0.91, 1.09)	0.96 (0.93, 0.99)
>15−20	0.95 (0.93, 0.98)	0.97 (0.97, 0.97)	0.96 (0.94, 0.97)	0.92 (0.85, 0.99)	0.96 (0.93, 0.98)
NO_2 (ppb)					
0−5	2.17 (1.74, 2.87)	1.64 (1.61, 1.68)	1.89 (1.74, 2.07)	3.19 (1.80, 5.65)	1.95 (1.80, 2.10)
>5−10	1.02 (0.96, 1.10)	1.04 (1.04, 1.04)	1.14 (1.12, 1.17)	0.81 (0.62, 1.06)	1.09 (1.07, 1.12)
>10−15	0.97 (0.93, 1.01)	0.97 (0.96, 0.97)	0.97 (0.95, 0.99)	0.99 (0.89, 1.12)	0.95 (0.91, 0.99)
>15−20	0.96 (0.92, 0.98)	0.96 (0.96, 0.97)	0.94 (0.93, 0.96)	0.99 (0.85, 0.99)	0.95 (0.95, 0.98)

[a](A) Residential proximity to biorefineries (0−20 km) and (B) AERMOD-modeled air pollutants of $PM_{2.5}$, SO_2, and NO_2 (0-20 km) from 15 biorefinery facilities in NYS, 2011−2015. Abbreviations: RR, rate ratio; CI, confidence intervals. [b]All models were adjusted for sex, age, race, county-level smoking rate, temperature, relative humidity, and background air pollutants of $PM_{2.5}$, SO_2, and NO_2. [c]RRs were estimated based on $e^{\beta \times IQR}$. [d]All values were statistically significant with p-values <0.05.

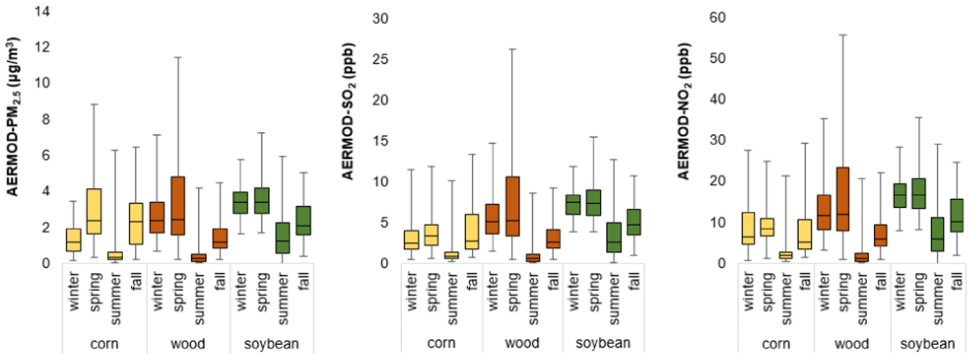

Figure 2. Seasonal estimates of AERMOD-modeled air concentrations of $PM_{2.5}$, SO_2, and NO_2 by biorefinery type (corn, wood, and soybean) within 10 km from biorefinery facilities in NYS, 2011−2015. The box plots show the median and interquartile range (IQR) values, and the error bars represent the minimum and maximum values.

where case represents the number of ED visits aggregated by sex (males and females), age groups (1−17, 18−44, 45−64, 64−85), and race (Whites, Black or African-Americans, Native Americans, Asians, Native Hawaiians or Pacific Islanders, and other races) analyzed within the designated distances (e.g., 0−5 km) or locations (e.g., corn biorefinery sites); exposure was either a dichotomous variable indicating (a) biorefinery site or control area or (b) the annual mean concentrations of $PM_{2.5}$, SO_2, or NO_2 simulated using the AERMOD model or control area; sex, age, and race were indicators of corresponding groups; smoking represents the smoking rate of the county where the study population was located in; and offset represents the 2011−2015 number of population of the corresponding distance groups retrieved from the American Community Survey (ACS).[33] Additionally, we adjusted for other confounders as listed in Section 2.4.

We obtained the rate ratios (RRs) of respiratory diseases from the models and subsequently identified a distance (0−5, >5−10, >10−15, or >15−20 km) at which no associations were observed (Table 1). Once identified, the affected areas were further divided and analyzed every 2 km (i.e., 0−2, >2−4, >4−6, >6−8, and >8−10 km) since, in this study, we identified 10 km as the cutoff point for posing health risks based on the previous step. We chose to analyze in 2 km intervals as opposed to 1 km due to the small sample size within 1 km intervals. All of the analyses were stratified by distances, biorefinery types, seasons, pollutant types, and disease subtypes.

For models with the mean concentration of air pollutants as the major exposure, RRs were scaled to each interquartile range (IQR) increase in the concentrations. Each pollutant was evaluated individually as separate exposures, but a multi-

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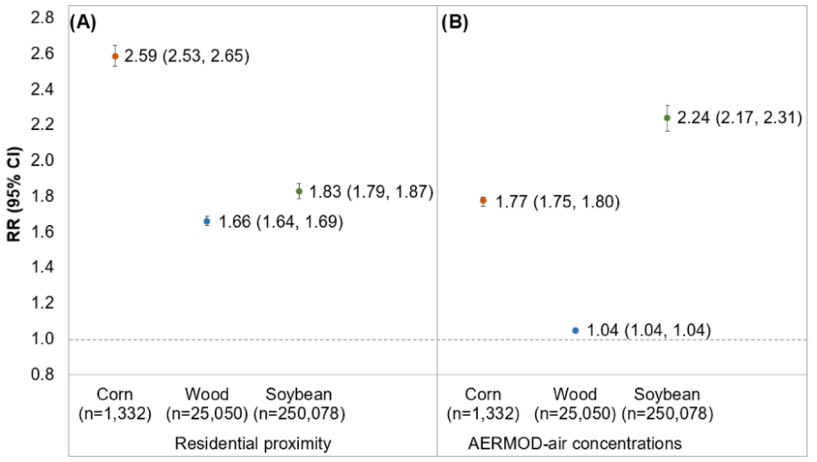

Figure 3. Adjusted rate ratios (RRs) and 95% confidence intervals of the associations between respiratory diseases. (A) Residential proximity to biorefineries and (B) AERMOD-modeled air concentrations by biorefinery type within 10 km from 15 biorefinery facilities (biorefinery sites) compared to the control areas in NYS, 2011−2015. All models were adjusted for age, race, sex, county-level smoking rate, seasonal mean temperature and relative humidity, and background air pollutants of $PM_{2.5}$, SO_2, and NO_2.

pollutant model was used to adjust for the concentrations of $PM_{2.5}$, NO_2, and SO_2 simultaneously. Two-tailed p-values of <0.05 were considered statistically significant. Estimated rate ratios in relation to the exposure were reported with their respective 95% confidence intervals.[63] All statistical analyses were performed using SAS software version 9.4.[64]

3. RESULTS

3.1. Spatial−Temporal Variations of the Modeled Air Pollutants. AERMOD-modeled $PM_{2.5}$, SO_2, and NO_2 mean concentrations decreased with increasing distance from the biorefinery facilities (Figure 1). The modeled concentrations observed within 10 km from the biorefineries were 8−10 times higher compared to the air concentrations beyond 10 km (Table S3). The mean values of AERMOD-modeled air concentrations within 10 km from the biorefinery facilities were 0.39 $\mu g/m^3$, 0.75 ppb, and 0.45 ppb for $PM_{2.5}$, SO_2, and NO_2, respectively, whereas the AERMOD-modeled air concentrations farther away from the biorefinery facilities (i.e., >10 km) were lower, with mean values of 0.05 $\mu g/m^3$, 0.08 ppb, and 0.05 ppb for $PM_{2.5}$, SO_2, and NO_2, respectively.

Moreover, the present study showed substantial seasonal variability in AERMOD-modeled air pollutants across the 5 year period of the study (2011−2015) and by biorefinery types (Figure 2). The median AERMOD-modeled $PM_{2.5}$, SO_2, and NO_2 levels were, in general, higher during the spring and winter seasons (except for $PM_{2.5}$ levels from corn biorefineries that were higher during fall than other seasons) compared to those of other seasons (i.e., summer and fall).

3.2. Residential Proximity to Biorefineries and Respiratory Health (Overall and Respiratory Subtypes). Table 1 describes the association between biorefinery exposures and respiratory health based on two exposure indicators. Based on residential proximity, we found that living within 5 km from biorefinery facilities was significantly and positively associated with overall respiratory ED visit rates (RR: 3.64, 95% CI: 3.47, 3.81), when compared to those in control areas (Figure S4A). The likelihood of visiting ED among those living between >5 and 10 km from biorefinery facilities was 50% higher (95% CI: 1.44, 1.56) compared to those in control areas. However, we found protective effects of exposure on lower respiratory diseases (RRs ranging from 0.55 to 0.69) among residents living beyond 10 km (10−20 km) from the biorefineries compared to those of their control area counterparts. In this study, we also observed particularly high ED visit rates due to emphysema (RR: 18.2, 95% CI: 4.35, 75.9) among residents living within 5 km from a biorefinery facility, followed by asthma (RR: 3.46, 95% CI: 3.29, 3.64), chronic bronchitis (RR: 4.95, 95% CI: 4.01, 6.13), and chronic airway obstruction (RR: 5.29, 95% CI: 4.35, 6.42). In contrast, we observed a 5−83% decreased likelihood of visiting ED due to emphysema for residents living beyond 5 km from biorefinery facilities (>5−20 km) compared to those in control areas. For all other respiratory subtypes (i.e., chronic bronchitis, asthma, chronic airway obstruction), we found consistently increased ED visit rates among residents living within 10 km from the biorefinery facilities (RRs ranging from 1.42 to 5.29), while we found 5−73% decreased ED visit rates among those living beyond 10 km from biorefinery facilities.

When we examined the associations based on AERMOD-modeled pollutants, we observed similar trends, where higher likelihood of visiting ED due to emphysema was observed among residents living within 5 km from biorefinery facilities (RR: 1.25, 95% CI: 1.12, 1.39). For all other respiratory diseases (i.e., chronic bronchitis, asthma, chronic airway obstruction), we found increased ED visit rates for those living within 10 km from the biorefinery facilities (RRs ranging from 1.01 to 1.95). These associations varied significantly depending on where residents lived (near corn, soybean, or wood biorefineries), as described in Section 3.3. Results based on modeled pollutants also revealed the strongest associations with overall lower respiratory diseases among those residing within 5 km from a biorefinery facility (RR: 1.44, 95% CI: 1.43, 1.46), followed by residents living farther away (>5−10 km) (RR: 1.03, 95% CI: 1.03, 1.04) (Figure S4B). Furthermore, when we examined the trends of respiratory risks among residents living within 10 km from biorefinery facilities, we found decreasing associations of modeled air pollutants and respiratory health with increasing distance from the biorefineries (Table S4). However, these decreasing trends were nonexistent when examined based on residential proximity.

3.3. Variation in the Associations among Biorefinery Types. This study found that the likelihood of having respiratory diseases was higher among residents living near

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corn biorefineries (RR: 2.59, 95% CI: 2.53, 2.65), followed by soybean (RR: 1.83, 95% CI: 1.79, 1.87) and wood biorefineries (RR: 1.66, 95% CI: 1.64, 1.69) (Figure 3A). When we examined the associations based on the modeled air pollutants, we found the strongest associations among those living in close proximity to soybean (RR: 2.24, 95% CI: 2.17, 2.31), followed by corn (RR: 1.77, 95% CI: 1.75, 1.79) and wood biorefineries (RR: 1.04, 95% CI: 1.04, 1.04) (Figure 3B).

The associations between residential proximity to biorefineries and respiratory outcomes varied by types of air pollutants examined ($PM_{2.5}$ vs SO_2 vs NO_2) (Table S5). Exposure to the modeled pollutants of NO_2 (RR: 3.63, 95% CI: 3.46, 3.80) and SO_2 (RR: 1.71, 95% CI: 1.68, 1.74) was strongly associated with respiratory-related ED visits in soybean biorefinery areas compared to those in control areas, whereas these associations in these sites were lower for $PM_{2.5}$ exposures (RR: 1.38, 95% CI: 1.36, 1.39). We found similar patterns among residents living near wood biorefineries, where we observed stronger associations due to exposure to NO_2 (RR: 1.06; 95% CI: 1.05, 1.06) and SO_2 (RR: 1.07, 95% CI: 1.07, 1.07), relative to $PM_{2.5}$ (RR: 1.003, 95% CI: 1.003−1.003) compared to control areas. However, among residents living near corn biorefinery facilities, we found that the associations were stronger for the modeled $PM_{2.5}$ (RR: 2.05, 95% CI: 2.01, 2.08) relative to NO_2 (RR: 1.92, 95% CI: 1.89, 1.95) and SO_2 exposures (RR: 1.35, 95% CI: 1.34, 1.36) compared to control sites.

3.4. Seasonal Variation in the Associations between Residential Proximity to Biorefineries and Respiratory Health. Results from this study revealed seasonal variation in the associations between respiratory morbidity and residential proximity to biorefineries and biorefinery-emitted air pollutants (Figure S5). Based on residential proximity, we observed moderate seasonal variability in the associations of biorefinery exposures and lower respiratory diseases, with RRs ranging from 1.32 to 1.39 (Figure S6A). When we examined the associations based on the modeled pollutants of $PM_{2.5}$, SO_2, or NO_2 individually from all three types of biorefineries, the likelihood of visiting ED due to lower respiratory diseases for those living within 10 km from the biorefineries was the strongest during spring (RR: 6.22, 95% CI: 5.75, 6.74), followed by winter (RR: 5.24, 95% CI: 4.89, 5.64) and the lowest during the summer (RR: 3.42, 95% CI: 3.24, 3.60) (Figure S6B).

4. DISCUSSION

4.1. Residential Proximity to Biorefineries and Respiratory Health. In this study, we observed a 3−50% increase in respiratory ED visits among residents living within 10 km of biorefinery facilities compared to that of their counterparts living in control areas. However, these relationships were not evident among residents living beyond 10 km from the biorefineries. Although there is no literature available regarding the health effects associated with residential proximity to biorefinery facilities, our findings were consistent with the findings from previous epidemiological studies conducted in industrial areas in several countries.[32,37,65,66] For example, an Italian study based on five wood factories and two chipboard industries also showed significantly increased odds of respiratory ED visits among children living within 2 km from at least one chipboard industry.[35] This study also observed a decreasing trend of respiratory diseases with increasing distance from the biorefinery facilities, which was consistent by using both exposure indices. In fact, our results reflect a possible protective relationship beyond 10 km distance. This could be due to some uncontrolled confounders such as local unknown exposure sources, greenness coverage, residual socioeconomic confounders, or any of a host of unknown factors within this large spatial distance. Further evaluation of this finding in future work may help explain it.

4.2. Associations Using AERMOD-Modeled Air Pollutants. The present study revealed that residential proximity to biorefineries (<10 km) was significantly associated with all three air pollutants (NO_2, SO_2, and $PM_{2.5}$) emitted from the biorefinery facilities, with the strongest association observed with NO_2. A cross-sectional study[67] based on children in five German communities also found that increases in NO_2 levels by 10−70 $\mu g/m^3$ were associated with a 28% increase in obstructive bronchitis cases, which corroborates the findings of the present study. Additionally, mechanistic studies[11,13] have shown that NO_2 suppresses alveolar macrophages, which are the white blood cells responsible for the initiation of an immune response against foreign organisms.

Moreover, several epidemiological and toxicological studies have supported that exposure to SO_2 is associated with several respiratory symptoms.[32,60,68] Potential biological mechanisms that may explain the increased risk of respiratory symptoms due to SO_2 include the following: (1) the oxidizing and irritating effect of SO_2 causing damage to the lung epithelial cells and pulmonary inflammation[12] and (2) the impairment of mucociliary clearance, which serves as the respiratory system's defense against environmental insults, causing bronchoconstriction.[69]

The modeled $PM_{2.5}$ also showed significant relationship with lower respiratory symptoms as $PM_{2.5}$ are largely known to cause adverse health effects from oxidative stress and damages to respiratory tract cells and alveolar macrophages[7−10] due to their microscopic size and composition of both inorganic and organic materials.[70,71] However, the magnitude of this association was lower compared to the associations with SO_2 or NO_2. This is likely due to the amount of $PM_{2.5}$ (mean emission rates: 1.93 g/s) emitted from the biorefineries, which was roughly 8−13 times lower than the amounts of SO_2 or NO_2 levels (mean emission rates: 24.5 and 15.7 g/s, respectively). Results from this study highlight the importance of including SO_2 and NO_2 air pollutants in future studies due to the demonstrated high risks of their contribution to respiratory ED visits.

4.3. Associations by Respiratory Subtypes. This study found that, among residents living within 5 km from biorefinery facilities, all respiratory subtypes of ED visit rates were statistically associated with biorefinery exposures. Among them, the risk of emphysema was the highest. Findings from this study corroborate with several prior studies showing evidence that residential proximity to industrial facilities, which emit similar air pollutants to biorefineries (i.e., fine particulates, NO_2 and SO_2), was associated with increased risks of developing emphysema.[31,72] For example, a cross-sectional study[31] in South Korea found that the odds of having emphysema were 2.9 times higher among residents living within 1 km from a cement plant compared to those living ≥5 km away from that same plant. Similarly, the multiethnic study of atherosclerosis (MESA) cohort study[72] conducted in six regions of the United States observed that the percentage of emphysema in adults (aged 45−64) increased by 0.11 and 0.06 for every 2 $\mu g/m^3$ and 10 ppb-unit increases in $PM_{2.5}$ and NO_x,

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respectively. The magnitudes of the RRs for each respiratory subtype related to biorefinery exposures found in this study (significant RRs ranged from 3.46 to 18.2) are substantially higher than the risks associated with exposure to any other sources of ambient pollutants, such as from cement plants (OR: 1.68, 95% CI: 0.98, 2.90), industrial facilities (OR: 2.24, 95% CI: 1.27, 3.95), and coal mining sites (OR: 1.03, 95% CI: 0.8, 1.2).[31,36,73]

4.4. Association Differences by Biorefinery Types and Exposure Disparities. This study found that the elevated emergency department visit rates for respiratory diseases significantly associated with residential proximity to all three types of biorefineries: corn, wood, and soybean biorefineries. This finding was consistent across two exposure assessment measures. The health risks appear to be higher with exposure to corn and soybean biorefineries compared to that of wood biorefinery facilities. We also found that the average $PM_{2.5}$ and NO_2 emission rates (g/s) from corn and soybean biorefineries were 1.5−3 times higher than the average $PM_{2.5}$ and NO_2 emission rates from wood biorefineries, which may explain the higher health risks among the residents living proximity to corn and soybean biorefinery sites. The higher emission rates from corn and soybean biorefinery facilities are likely due to the multiple processes associated with converting solid feedstocks to liquid biofuels.[4,74,75] Unfortunately, there is no literature available to compare the health risks among the three biorefinery types. For comparing other sources emitting pollutants, a study conducted by Hill et al.[5] found that producing corn ethanol resulted in emitting higher $PM_{2.5}$ concentrations (average $PM_{2.5}$: 1.32−4.70 $\mu g/m^3$) vs producing cellulosic ethanol (average $PM_{2.5}$: 1.00−1.06 $\mu g/m^3$) or gasoline (average $PM_{2.5}$: 0.55 $\mu g/m^3$).[5] Their study showed that the associated health costs were higher for corn ethanol production ($270−610 million) vs cellulosic ethanol ($102−176 million) or gasoline ($223 million). Moreover, Sengupta et al.[6] found that the health impacts linked to exposure to pollutants from ethanol production were 4−10 times higher than those associated with criteria air pollutants from gasoline production. Additionally, the discrepancies observed in the associations by biorefinery types based on different exposure measurements (i.e., higher among residents near soybean biorefineries based on residential proximity vs higher for corn biorefineries based on modeled pollutants) are likely due to the differences in the biological responses to the specific modeled air pollutants in the latter, compared to the mere effects of living nearby biorefinery facilities of the former, where neighborhood factors may play a greater role in explaining the higher risks.

We also found substantial racial and socioeconomic disparities among all study participants when compared to those of the entire NYS. The median income among the study population in biorefinery sites was 2.7 times lower than that in NYS (median income in NYS: $65,323). Additionally, the percentage of African-Americans in biorefinery sites was 3.4 times higher (54.1%) compared to 15.9% statewide, far exceeding the state's average percentage of African-Americans. Corn and soybean biorefineries were also located in highly populated counties of 1 million residents or more, with a high percentage (9.3−26.2%) of uninsured population.[76] Therefore, this study observed that biorefineries were located in areas where disproportionate percentages of African-Americans and households of lower income resided, a relationship similarly found in previous studies,[77−80] and a point worth further exploration in future research to mitigate potential environmental health disparities that may result from this. Additionally, emerging research shows that government-sponsored historical discriminatory housing policies set in place in the 1930s, namely, "redlining", where some of the biorefineries in this study were located, are significant drivers of modern health inequities. Such historical context, which lies beyond the scope of this paper, may provide additional explanation for the underlying cause of health inequities observed in the present study.[81,82]

4.5. Seasonal Difference in the Biorefineries-Health Associations. We found statistically significant and positive associations between residential exposure to biorefinery facilities and lower respiratory ED visits in all four seasons. Specifically, we observed higher biorefinery-respiratory health associations during the spring and winter compared to those during fall and summer (with the lowest risk). Temperature inversions resulting in air pollutants stagnating in the lower boundary layer during cold temperatures may explain the higher air pollution concentrations during cold seasons.[83−85] Additionally, a decrease in atmospheric temperatures lowers photochemical decomposition rates of air pollutants (gas phase-oxidation/photochemistry), thereby increasing air pollution concentration levels during cold seasons (spring−winter).[86] Furthermore, seasonal variation in air pollutants, i.e., higher average modeled $PM_{2.5}$, SO_2, and NO_2 levels during cold seasons (spring to winter) compared to those during summer seasons reported in another study,[87] is consistent with our finding.

In terms of possible biological mechanisms, respiratory symptoms observed during the cold seasons potentially resulted from (1) higher attachment of influenza viruses to particulate matter affecting the overall respiratory system,[88] particularly affecting children during the school year,[89] and those with compromised immune system due to higher generation of oxidative stress and enhanced attachment of influenza viruses to nasal and bronchial epithelial cells as shown in animal-based studies;[90−92] (2) cold outdoor air triggering bronchoconstriction particularly among people with pre-existing asthma symptoms;[93] and (3) tree and grass pollen triggering asthma during the spring season.[94]

4.6. Strengths and Limitations. To the best of our knowledge, this is the first epidemiological study assessing potential relationships between residential proximity to biorefineries or biorefinery-related air pollutants and respiratory morbidity. This study was based on NY state's legislatively mandated hospital data, which is more accurate than self-reported data due to the cases being reported by physicians' diagnosis. Additionally, this study included a large sample size (N = >500 000 respiratory cases), increasing the statistical power of this analysis. Unlike past studies, this study used two proxies of exposure measurements, i.e., residential proximity to biorefineries and AERMOD-modeled estimates of biorefinery-emitted air pollutants to validate the findings. Multiple air pollutant levels ($PM_{2.5}$, SO_2, and NO_2) based on an air dispersion model, with the capability of capturing location-, time- and source-specific exposures at finer spatial resolutions (1 km × 1 km), were linked to individual cases of respiratory morbidity reduced exposure misclassification in a cross-sectional study. Another strength of this study is the use of AERMOD to compare and validate the findings from our residential proximity models. While the residential proximity in the cross-sectional study is commonly used for hypothesis

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generating, AERMOD modeling is capable of quantifying dispersion of individual air pollutants from biorefineries at daily scale, which minimizes the temporality limitations associated with a cross-sectional study design. Finally, a major strength was that we examined multiple biorefinery sites (corn, wood, and soybean) to identify specific sources of exposure and distances of threshold for potential intervention.

Notwithstanding, we recognize that there are also some limitations to this study. First, since respiratory cases were based on ED hospital data only, this potentially caught the severe cases only rather than mild cases, which likely underestimate the total impact of biorefinery on respiratory health. On the other hand, hospital ED data are more objective and valid than self-reported symptoms from questionnaires, which helped us to minimize the reporting biases that limited many prior studies. Moreover, selection bias might have increased due to the specific geographical locations of the study population. Housing costs near biorefinery industrial areas tend to be lower, which potentially increased the number of nearby residents of lower socioeconomic status (SES), a segment of population that have been found to have higher respiratory ED visits, especially asthma, compared to those with high SES.[78] This potential selection bias might distort the associations we examined. To address this issue, we matched residents in biorefinery areas with those in nonbiorefinery areas based on similar median income, percentage of African-Americans, and age distribution in the study design to ensure that the SES and racial composition are comparable between the biorefinery and control areas. In addition, we also controlled for residual confounders such as individual levels of age, race, and sex, county-level smoking rate, temperature, relative humidity, and local background air levels (e.g., auto vehicles, industrial facilities, and other sources) in the stage of statistical analyses.

We also recognize that unmeasured confounders such as indoor exposures (e.g., indoor chemicals, pets) and activity pattern may have introduced confounding bias. To address this concern, we have controlled for many potential confounders including individual levels of age, sex, and race and community-level smoking rate, temperature, relative humidity, and air pollution levels in the statistical analysis in addition to the matching of sites by income and race described above. In addition, some industrial facilities located in some of the study areas potentially introduce confounding effects. To address this issue, the background level of air pollution sources from transportation, industrial facilities or agriculture, the environmental factors (e.g., elevation, land use), and weather factors (e.g., temperature, precipitation, wind speed) have been automatically controlled through the AERMOD. Finally, due to the nature of the ecological and cross-sectional design of the study, the results might be prone to ecological fallacy and present difficulties for determining the temporality between cause and outcome. However, the cross-sectional study design provided a valuable baseline knowledge to generate a hypothesis to be tested in future studies with a more robust epidemiological study design. More importantly, given that AERMOD modeling factored in temporality into the study design, it would draw more robust conclusions.

In conclusion, this study found that people living within 10 km of a biorefinery facility had an increased risk of visiting ED for lower respiratory diseases compared to those living in areas where no biorefineries were located. These statistically significant increases in health risks were found to be consistently associated with all three biorefinery subtypes (higher in corn and soybean biorefineries), in all seasons (higher in spring and winter), by all three pollutants (highest for NO_2), and all subtypes of the respiratory ED visits (highest for emphysema). Our findings warrant future investigation in a longitudinal study.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.1c00698.

Data sources and parameters for running AERMOD air dispersion modeling; tables including statistical distributions of AERMOD-modeled air pollutants for 15 biorefinery facilities in New York State (NYS), 2011−2015; demographic and neighborhood characteristics of the study sites; and mean smoking prevalence in the study counties in NYS (PDF)

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Notes

The authors declare no competing financial interest.

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