County-Level Influenza-Attributable Emergency Department Visits and their Spatial Correlates in the United States

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Abstract

Background: Burden of seasonal influenza on emergency department (ED) visits is poorly quantified due to case ascertainment and data availability challenges. This study estimates county-level respiratory ED visits attributable to influenza using time-series models and examines spatial heterogeneity in county-level burden in three states.

Objective: To estimate county-level seasonal influenza–attributable emergency department (ED) visit rates and examine their associations with socioeconomic, environmental, and chronic health covariates in three US states (California, Georgia, and New York).

Methods: We used daily hospital discharge records to measure community-level influenza activity in California (2005–2018), Georgia (2010–2018), and New York (2005–2018). County-level influenza-attributable respiratory ED visit rates were estimated using quasi-Poisson time-series models that adjusted for temporal trends and environmental factors. Under a meta-regression framework, Bayesian spatial hierarchical models were then applied to evaluate associations between ED visit rates and county-level socioeconomic status (SES), environmental exposures, and chronic health conditions.

Results: Influenza-attributable respiratory ED visit rates per 100,000 population were 226 (95% CI: 206, 246) in New York, 232 (95% CI: 206, 259) in California, and 547 (95% CI: 506, 589) in Georgia. A 10% increase in county-level poverty and uninsured rates were associated with higher influenza burden, increasing influenza-attributable respiratory ED visit rates by 160 (95% CrI: 127, 196) and 217 (95% CrI: 168, 265), respectively. Long-term PM2.5, humidity, and temperature also exhibited positive associations. Chronic conditions also increased ED visit rates by 1,476/100,000 (95% CrI: 1,167, 1,778), 588/100,000 (95% CrI: 400, 747), and 488/100,000 (95% CrI: 402, 574) per 10% increase in stroke, chronic obstructive pulmonary disease, and diabetes prevalence, respectively. These associations weakened after adjusting for SES.

Conclusions: Influenza-attributable respiratory ED visit rates exhibit significant spatial heterogeneity that is associated with county-level socioeconomic factors, environmental exposures, and chronic disease prevalences.

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Abstract

Background

Burden of seasonal influenza on emergency department (ED) visits is poorly quantified due to case ascertainment and data availability challenges. This study estimates county-level respiratory ED visits attributable to influenza using time-series models and examines spatial heterogeneity in county-level burden in three states.

Methods

We used daily hospital discharge records to measure community-level influenza activity in California (2005-2018), Georgia (2010-2018), and New York (2005-2018). County-level respiratory ED visit rates attributable to influenza were estimated by quasi-Poisson time-series models, adjusting for temporal trends and environmental factors. Bayesian spatial models were used to assess associations with county-level socioeconomic status (SES), environmental exposures, and chronic health condition prevalences.

Results

Influenza-attributable respiratory ED visit rates per 100,000 population were 226 (95% CI: 206, 246) in New York, 232 (95% CI: 206, 259) in California, and 547 (95% CI: 506, 589) in Georgia. A 10% increase in county-level poverty and uninsured rates were associated with higher influenza burden, increasing influenza-attributable respiratory ED visit rates by 160 (95% CrI: 127, 196) and 217 (95% CrI: 168, 265), respectively. Long-term $PM_{2.5}$, humidity, and temperature also exhibited positive associations. Chronic conditions also increased ED visit rates by 1,476/100,000 (95% CrI: 1,167, 1,778), 588/100,000 (95% CrI: 400, 747), and 488/100,000 (95% CrI: 402, 574) per 10% increase in stroke, chronic obstructive pulmonary disease, and diabetes prevalence, respectively. These associations weakened after adjusting for SES.

Conclusion

Influenza-attributable respiratory ED visit rates exhibit significant spatial heterogeneity that is associated with county-level socioeconomic factors, environmental exposures, and chronic disease prevalences.

Keywords: Infectious diseases, air pollution, environmental epidemiology, environmental disparities, spatial statistics

INTRODUCTION

Seasonal influenza is a significant public health concern in the (United States) US, contributing to substantial morbidity, mortality, and healthcare economic burden. In 2023-24, influenza resulted in an estimated 40 million illnesses, 470,000 hospitalizations, and 28,000 deaths [1]. While influenza-associated hospitalizations and mortality are well documented [2,3], emergency department (ED) visits as a morbidity measure remain underexamined. Quantifying influenza-associated ED burden is important because it can capture both severe cases that lead to hospitalization and mild cases that do not. Also, the percentage of annual ED visits with an influenza test ordered or provided increased from 2.5% in 2013 to 10.9% in 2022, with children aged 0-5 years accounting for the highest testing rates [4]. These rising numbers highlight the growing role of EDs in influenza surveillance and the need for accurate burden estimates to guide program planning.

Despite advances in influenza surveillance, current burden estimates face several limitations. First, many rely on multipliers or prevalence-based models [5], which require extrapolating key parameters from smaller studies. While some incorporate statistical regression models [6], these often overlook key analytical complexities, including temporal autocorrelation, spatial heterogeneity, and environmental confounders. Hence, these studies can lead to underestimation and poorer uncertainty quantification.

A further gap in the influenza burden literature is the lack of localized estimates. Most studies utilize aggregate data at the state [7] and the national level [8], or restrict to specific subpopulations, such as children [9] or veterans [10]. However, growing evidence suggests that other health and environmental factors – such as stroke [11], high body mass index (BMI) [12], air pollution [13], and lower socioeconomic status (SES) [14] can increase vulnerability to respiratory health outcomes. Hence, quantifying influenza disease burden at a finer spatial scale and examining its association with spatial covariates can better identify populations or communities for the development of more effective, targeted interventions.

Motivated by the above research gaps, we aim to estimate county-level seasonal influenza-attributable ED visit rates and associated spatial covariates in three US states (California, Georgia and New York), selected for their geographic diversity and availability of comprehensive hospital data. We first employed a time-series model to estimate excess annual seasonal influenza-attributable respiratory ED visits [15]. Next, under a meta-regression framework, we employed a spatial Bayesian hierarchical model to examine associations between respiratory ED visit rates and various county-level covariates, including SES, chronic health conditions, and environmental exposures. This study offers a local perspective on the public health impact of seasonal influenza.

METHODS

Hospital Discharge Records

We obtained patient-level hospital discharge data for 2005-2018 in California and New York, and 2010-2018 in Georgia, from hospital associations and state health departments. ED visits included both outpatient visits with discharges directly from the ED and inpatient visits with admissions via the ED, excluding scheduled admissions. Records included information on admission date, age in years, patient's residential ZIP code, and International Classification of Diseases (ICD) diagnosis codes. ICD-9 codes were utilized before October 1, 2015, after which ICD-10 codes were adopted. Both primary and secondary ICD diagnosis codes were used to identify cause-specific ED visits for overall respiratory diseases (RESP, ICD-9 460-519; ICD-10 J00-J99) and influenza (FLU, ICD-9 487-488; ICD-10: J09-J11).

For RESP, FLU, and non-FLU RESP, we created time-series of daily ED visit counts for each county by aggregating ED visits based on the patient's residential ZIP code that overlapped with these counties. For ZIP codes that overlapped with multiple counties, we assigned ED visits to the county with which the ZIP code had the largest population overlap. There were a total of 279 counties (California: 58, Georgia: 159, New York: 62). As a proxy of influenza activity, we further calculated the daily FLU ED visit rates per

100,000 population for each county using population data obtained from the US Census Bureau. CDC defined an influenza season typically runs from MMWR-week 40 to 18 of the following year [1]. Our analysis thus included 11 influenza seasons from 2005-2018. Data from the 2009-2010 influenza A(H1N1) pandemic were excluded.

Air Pollution and Meteorology Data

Daily ambient air pollution data for 24-hour average fine particulate matter ($PM_{2.5}$), 1-hour maximum nitrogen dioxide (NO_2), and 8-hour maximum ozone concentrations from 2005 to 2018 were based on a data product with complete spatial-temporal coverage across the US at a 12 km x 12 km spatial resolution [16]. These estimates used monitoring data to bias-correct Community Multi-scale Air Quality (CMAQ) model simulations that integrate emissions, meteorological conditions, and atmospheric chemistry to improve air quality assessments.

Daily maximum and minimum temperature in degrees Celsius, and water vapor pressure (as a proxy for humidity) in pascals at a 1 km × 1 km spatial resolution were obtained from Daymet [17]. Daily average temperature was calculated as the mean of daily maximum and minimum.

Air pollution and meteorology data were first aggregated to the ZIP code level, and then up-scaled to the county-level to match the health outcome with population-weighted averaging ZIP code-level exposures. Population size data were obtained from the US Census at ZIP code tabulation area (ZCTA) level for 2010 to 2020, and we estimated annual populations via linear interpolation of decadal Census data. A three-day moving average was computed based on previous work[13] in the acute health effects of both air pollution and meteorology on respiratory ED visits.

County-Level Covariates

We considered three categories of county-level covariates - socioeconomic status (SES), environmental exposures, chronic health condition prevalence. SES indicators such as the percent of population living under the poverty line and percent uninsured individuals were obtained from the American Community Survey. Long-term county-level environmental exposures were obtained by averaging levels of $PM_{2.5}$, NO_2, O_3, humidity, and temperature across all influenza seasons. Chronic health conditions were obtained from the Behavioral Risk Factor Surveillance System (BRFSS), including the prevalence rates of individuals with disability, and other major chronic diseases such as stroke, diabetes, and high blood pressure. *Supplementary Table 1* summarizes all the covariates considered.

Statistical Analysis

Stage 1: Estimating County-level Disease Burden

We conducted excess morbidity modeling to estimate the total respiratory ED visits attributed to influenza (without ICD-coded influenza counts) based on a previously developed model [15]. First, an over-dispersed Poisson log-linear model was used to estimate county-level associations between the daily influenza activity proxy and daily respiratory ED visits, for which visits with influenza listed as a primary or secondary cause were removed. For each county $j=1,2,..m_i$ in state $i=1,2,3$, let Y_t denote the number of total RESP ED visit count on day t. We assume Y_t follows a quasi-Poisson distribution with mean λ_t such that

$$y_t \quad Quasi-Poisson(\lambda_t),$$

$$\ln(\lambda_t)=\beta_0+\beta_1 x_t+f(t)+g_1(temp_t)+g_2(hum_t)+h_1(PM_{2.5,t})+h_2(Ozone_t)+h_3(NO_{2,t})+I_{H_t}+I_{Dw_t} \quad (1)$$

where (1) x_t is influenza ED visit rate per 100,000 on day *t* (i.e., the influenza activity proxy), (2) *f(t)* is a temporal smoother for seasonal and long-term trends modeled using natural cubic splines with 4 degrees of freedom per influenza season, (3) $g_1(temp_t)$ and $g_2(hum_t)$ are non-linear effects of 3-day moving average temperature and humidity using natural cubic splines with 6 degrees of freedom, (4) $h_1(PM_{2.5,t})$,

$h_2(Ozone_t)$ and $h_3(NO_{2,t})$ represent linear effects of 3-day moving average air pollution levels; and (5) I_{H_t} *and* I_{Dw_t} are indicators for national holidays and day of week. For meteorological variables, 6 degrees of freedom were applied to capture U-shaped associations [18]. To address residual autocorrelation, we utilized the Newey-West estimator [19] with a maximum lag of 2 to calculate the standard errors of each model coefficient.

For each county ij, we calculated average annual ED visits attributable to influenza by first summing, over the entire flu season S_i, the difference between (1) predicted counts with the observed flu proxy rate and (2) counterfactual expected counts assuming there is no influenza activity (i.e., setting covariates x_t to zero), and divided by the number of flu season S.

The delta method was applied to obtain standard errors and construct 95% confidence intervals for the influenza-attributable respiratory ED visit rates. We then calculated the annual total respiratory ED visits rates attributable to influenza per 100,000 population, $\hat{\theta}_{ij}$, using the formula below:

$$\hat{\theta}_{ij} = \left[\hat{A}_{ij} + C_{Flu_{ij}}\right] \cdot \frac{100{,}000}{Population_{ij}} \quad (2)$$

where $\widehat{A}_{ij}$ is the expected annual excess ED visits that were not ICD-coded, $C_{Flu_{ij}}$ is the annual ICD-coded influenza ED counts, calculated by averaging the seasonal total flu-coded counts across the entire flu season S_i, and $Population_{ij}$ denotes the catchment population for county j in state i.

Stage 2: Bayesian Spatial Hierarchical Modeling

We used spatial meta-regression [20] to examine associations between county-level rates of respiratory ED visits attributable to influenza and spatial covariates while accounting for spatial autocorrelation. The true county-level burden rate θ_{ij} is modeled as:

$$\theta_{ij} = x_{ij}^T \beta + \phi_{ij} + \epsilon_{ij}, \epsilon_{ij} \sim N\left(0, \sigma_\epsilon^2\right) \quad (3)$$

where x_{ij}^T is a vector of county-level covariates with corresponding regression coefficient β. ϕ_{ij} is a random spatial effect that captures residual spatially dependent heterogeneity among counties in each state. We modeled ϕ_{ij} with a proper conditional autoregressive model specification [21], independent across states, where spatial adjacency defined as two counties that share a border. Finally, ϵ_{ij} is an independent random error term with state-specific variance parameter that accounts for additional between-county variation. The full specification of the hierarchical spatial model is provided in the *Supplementary Material.*

We first assessed univariate associations for each spatial covariate. To account for potential non-linear population effects, in a secondary analysis, we included the logarithm of the population as a cubic spline with three degrees of freedom. Additionally, we examined the associations between environmental exposures or chronic health outcomes after adjusting for SES (poverty and uninsured rates) in multivariable models.

We conducted a sensitivity analysis restricted to a high severity influenza season (2017-18) to evaluate the robustness of results. Data compilations were conducted in SAS Statistical Software Version 9.4, and statistical analyses were conducted in R software Version 4.0.3.

RESULTS

The study included 61.81 million RESP ED visits (inpatient and outpatient), of which 1.52 million (2.5%) were coded as influenza during the influenza season. *Table 1* summarizes the ED visit counts by state. California accounted for approximately 33.17 million RESP ED visits (of which 0.78 million, 2.4%, coded as influenza), Georgia had 7.48 million RESP ED visits (0.31 million, 4.1%, influenza-coded), and

New York for 21.16 million RESP ED visits (0.43 million, 2.0%, influenza-coded).

Table 1. Summary of emergency department (ED) visit counts for ICD-coded influenza (Flu) and respiratory disease (RESP) across California (2005-2018), Georgia (2010-2018), and New York (2005–2018).

	RESP ED Visits	Flu ED Visits (%)	Non-Flu RESP (%)	Years Covered	Number of Counties
California	33,172,708	781,310 (2.4%)	32,391,398 (97.6%)	2005-2018	58
Georgia	7,481,121	306,234 (4.1%)	7,174,887 (95.9%)	2010-2018	159
New York	21,160,209	432,495 (2.0%)	20,727,714 (98.0%)	2005-2018	62
Total	61,814,038	1,520,039 (2.5%)	60,293,999 (97.5%)	-	279

Table 2 provides summary statistics for the spatial covariates across 279 counties. Poverty and uninsured rates varied widely spatially (median: 13.5% and 14.1%; IQRs: 8.65% and 8.00%, respectively). Environmental exposures also displayed notable spatial variability during influenza seasons: temperature (-10.80 ℃ to 17.18 ℃, IQR: 6.54 ℃), humidity (2.86 g/kg to 10.66 g/kg, IQR: 3.05 g/kg), $PM_{2.5}$ (3.89 μg/m³ to 12.68 μg/m³, IQR: 0.86 μg/m³), and NO_2 (1.07 ppb to 43.15 ppb, IQR: 7.50 ppb). Among chronic conditions, high blood pressure rates (IQR 10.20%) and obesity prevalence (IQR 8.10%) showed the greatest variation, while asthma had the least (IQR 0.90%).

Table 2. Summary statistics of spatial covariates at the county level across California, Georgia, and New York.

	Minimum	**Q1**	**Median**	**Q3**	**Maximum**	**IQR**	**Mean**	**SD**
Socioeconomic Status (SES)[1]								
% Poverty	2.70	9.65	13.5	18.3	38.4	8.65	14.26	6.14
% Uninsured	4.40	8.95	14.1	16.95	32.8	8.00	13.63	5.09
% Renter	14.85	26.92	32.15	38.93	80.93	12.01	33.56	9.98
% Crowding	0.16	1.52	2.20	3.61	12.82	2.09	3.05	2.37
Environmental Exposures[2]								
$PM_{2.5}$ ($\mu g/m^3$)	3.89	7.31	7.75	8.17	12.68	0.86	7.84	1.17
NO_2 (ppb)	1.07	5.77	8.19	13.27	43.15	7.50	10.52	7.09
Ozone (ppb)	23.37	35.25	36.66	37.20	43.70	1.91	36.22	2.33
Humidity (g/kg)	2.86	5.01	7.09	8.06	10.66	3.05	6.72	1.74
Temperature (℃)	-10.80	7.78	12.63	14.32	17.18	6.54	10.67	5.06
Chronic Health Outcome[3]								
% Disability	7.00	12.7	15.1	17.7	27.00	5.00	15.2	3.77
% Stroke	2.10	3.00	3.40	4.10	6.30	1.10	3.56	0.77
% Depression	14.8	21.3	22.7	23.8	26.9	2.5	22.42	2.05
% Diabetes	7.10	9.4	11.10	13.05	18.10	3.65	11.33	2.25
% Obesity	17.70	33.59	37.10	41.60	48.60	8.10	37.70	5.71
% Asthma	8.50	10.4	10.90	11.30	13.10	0.90	10.80	0.73
% COPD	3.20	6.10	7.30	8.55	12.10	2.45	7.32	1.72
% BPHigh	21.60	28.85	33.70	39.05	47.8	10.20	34.03	5.82

Figure 1 presents pairwise correlations among county-level spatial covariates. Strong positive correlations were observed within SES indicators, (e.g., poverty and uninsured rates r = 0.68) and among chronic health outcomes, with high blood pressure strongly correlated with obesity, stroke, diabetes, and COPD (r = 0.82 to 0.88). Environmental exposures exhibited moderate correlations with SES and health outcomes (r = -0.63 to 0.75). Within environmental exposures, strong positive correlations were observed between $PM_{2.5}$ and NO_2 (r = 0.69) and between humidity and temperature (r = 0.86).

Figure 1. Pairwise Pearson's correlations heatmap of spatial covariates across social economic status (SES), chronic health outcomes, and environmental exposures (Counties, n = 279).

State-level estimates of influenza-attributable respiratory ED visit rates per 100,000 population and a pooled estimate across the three states are presented in *Supplementary Table 2.* Georgia had the highest burden (547/100,000; 95% CI: 506, 589), followed by California (232/100,000; 95% CI: 206, 259) and New York (226/100,000; 95% CI: 206, 245). ICD-coded influenza ED visits represented 54% (California), 75% (Georgia), 62% (New York) of the total estimated influenza-attributable ED visits. Using a random-effects meta-analysis, the pooled burden estimate across the three states was 410/100,000 (95% CI: 379, 440).

Figure 2 shows the estimated county-level influenza-attributable respiratory ED visit rates from the stage 1 model. These were calculated by summing seasonal ED visits (*Supplementary Figure 1*) and then dividing by the number of influenza seasons for each county. Georgia showed the highest spatial variability, with several counties in the southern and central regions having annual influenza-attributable respiratory ED visit rates exceeding 1,500 per 100,000. In contrast, California and New York had lower rates. Most counties in California had ED visit rates below 1,000 per 100,000 in California, except for a few hotspots in the southern region. New York displayed a more consistent pattern, with most counties having moderate rates between 500 and 1,000 per 100,000. The Moran's I statistics (*Supplementary Table 3*) confirms the spatial heterogeneity across the study regions. Maps of influenza-attributable respiratory ED visit rates per 100,000 for each season are given in *Supplementary Figure 1.* Numerical values of all estimated rates with 95% CI by state and influenza season are in *Supplementary File 1.*

Figure 2. Heatmap of annual estimated influenza-attributable respiratory emergency department (ED) visit rates per 100,000 at the county level in California (CA), Georgia (GA), and New York (NY) from 2005-2006 to 2017-2018. Rates are averaged across all influenza seasons during the study period.

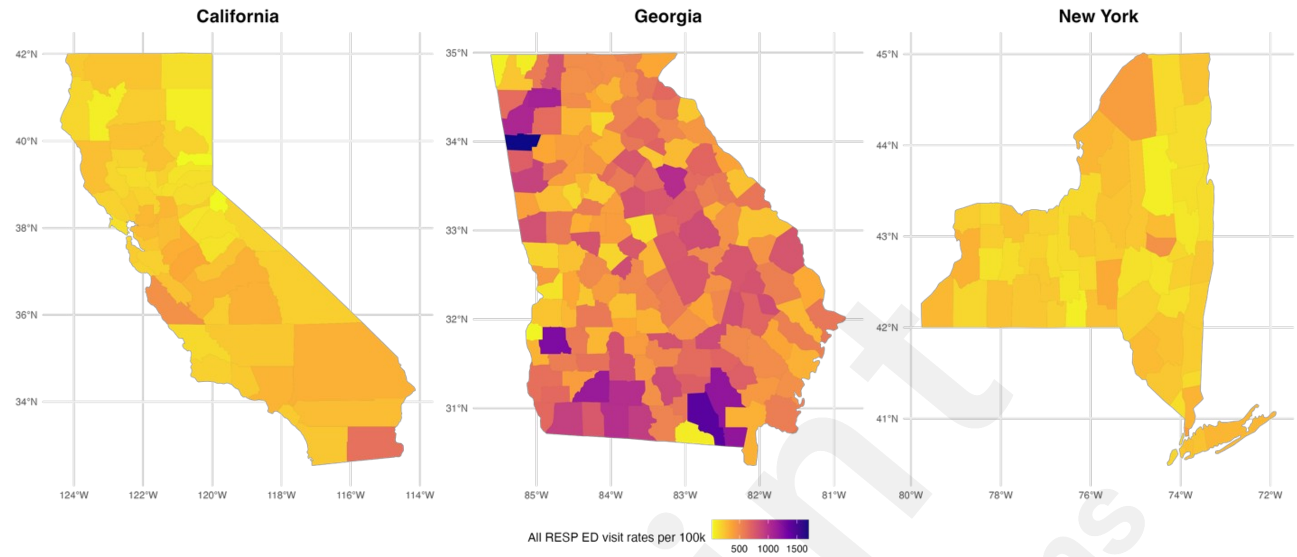

Table 3 summarizes the spatial meta-regression results. Univariate analyses identified positive associations between socioeconomic status (SES), environmental exposures, and chronic health factors with influenza-attributable respiratory ED visit rates. A 10% increase in higher percentages of poverty and uninsured populations were strongly associated with increased ED visit rates, with estimated increases of 160/100,000 (95% credible interval [CrI]: 127, 196) and 217/100,000 (95% CrI: 168, 265), respectively. For environmental exposures, notable positive associations were observed for higher humidity, with an increase of 222/100,000 (95% CrI: 183, 260) ED visit rates per IQR increase, and temperature, with an increase of 71/100,000 (95% CrI: 42, 108) per IQR increase. In contrast, $PM_{2.5}$ showed a smaller association, with an increase of 14/100,000 (95% CrI: 6, 22) per IQR increase. NO_2 exhibited a comparable effect size of 14 per 100,000 (95% CrI: –0.1, 27), and although the lower bound slightly crosses zero, the association remains noteworthy. Ozone had negligible associations with influenza-attributable respiratory ED visit rates.

Table 3. Results from spatial meta-regression models examining associations between county-level covariates and annual influenza-attributable respiratory emergency department (ED) visit rates per 100,000 population. Model 1 includes univariate associations; Model 2 adjusts for poverty rates; Model 3 adjusts for uninsured rates; Model 4 adjusts for both poverty and uninsured rates (coefficients of two SES are in supplementary table 4). Posterior mean point estimates and 95% quantile-based credible intervals are presented.

Covariates	Model 1	Model 2	Model 3	Model 4
Socioeconomic Status (SES)				
% Poverty (×10%)	160 (127, 196)	-	121 (84, 159)	-
% Uninsured (× 10%)	217 (168, 265)	115 (66, 167)	-	

Environmental Exposures				
$PM_{2.5}$ ($\times IQR\ \mu g/m^3$)	14 (6, 22)	2 (-7, 10)	9 (-1, 18)	2 (-8, 11)
NO_2 ($\times IQR\ ppb$)	14 (-0.1, 27)	2 (-11, 15)	3 (-13, 18)	0 (-14, 14)
Ozone ($\times IQR\ ppb$)	6 (-2, 13)	4 (-3, 12)	-4 (-12, 4)	-1 (-9, 7)
Humidity ($\times IQR\ g/kg$)	222 (183, 260)	148 (109, 187)	151 (104, 197)	130 (87, 174)
Temperature ($\times IQR$ ℃)	71 (42, 108)	35 (14, 58)	29 (2, 58)	20 (-3, 44)
Chronic Health Outcome				
% Having a Disability (×10%)	26 (-23, 79)	-45 (-86, -1)	13 (-38, 64)	-35 (-81, 12)
% Stroke (×10%)	1476 (1167, 1778)	699 (243, 1164)	994 (653, 1336)	467 (6, 933)
% Depression (×10%)	-19 (-72, 35)	-57 (-106, -1)	-238 (-80, 33)	-48 (-101, 5)
% Diabetes (×10%)	488 (402, 574)	383 (244, 521)	410 (301, 517)	297 (138, 46)
% Obesity (×10%)	124 (89, 163)	48 (16, 82)	88 (58, 119)	56 (25, 89)
% Asthma (×10%)	196 (57, 340)	-45 (-185, 95)	149 (6, 294)	-1 (-147, 145)
% COPD (×10%)	588 (400, 747)	157 (1, 313)	308 (174, 445)	145 (8, 289)
% BPHigh (×10%)	217 (183, 250)	152 (108, 194)	169 (131, 209)	139 (95, 184)

Chronic health outcomes also showed strong positive associations with influenza-attributable RESP ED visit rates. The percentage of stroke had the largest association, with an increase of 1476/100,000 (95% CrI: 1167, 1778) per 10% increase in county-level prevalence, followed by diabetes (488/100,000, 95% CrI: 402, 574) and COPD (588/100,000, 95% CrI: 400, 747). Other chronic health factors such as obesity, asthma, high blood pressure were also positively associated with increases in influenza-attributable respiratory ED visit rates.

These results are robust to adjustment for the prevalence of poverty, uninsured, or both, but with attenuated associations. The poverty and uninsured rates remained positively associated with ED visit rates across all models, or when they were both included in the model (*Supplementary Table 4*). Environmental exposures, including humidity and temperature, continued to exhibit positive associations, while associations with air pollution became null after SES adjustment. Chronic health outcomes, including stroke, diabetes, and COPD, continued to show strong positive associations, with stroke remaining the strongest associations with influenza-attributable respiratory ED visit rates, following by asthma and COPD.

After adjusting for non-linear population effects, most associations remained consistent, with slightly stronger increasing trends observed (*Supplemental Table 5*). The prevalence of having a disability, which showed no significant association in previous univariate model, became positively associated with ED visit rates (86/100,000, 95% CI: 32, 143). Ozone exposure also was positively associated with ED visit rates after adjustment for population, while associations for $PM_{2.5}$ and NO_2 became negatively associated after SES and population adjustment. We also fitted models with population as the only covariate (*Supplementary Figure 2*). There is a non-linear association between log population and influenza-attributable respiratory ED visit rates, with sharper increases at lower population levels and a flattening association as population size increases.

The results of sensitivity analysis (*Supplementary Table 6*) showed that associations between spatial covariates and influenza-attributable respiratory ED visit rates remained in the same directions as the primary analyses, though with larger effect estimates. For instance, a 10% increase in stroke prevalence during 2017-18 influenza season was associated with a 2614/100,000 (95% CI: 2143, 3075) increase in influenza-attributable respiratory ED visit rates.

DISCUSSIONS

We analyzed influenza-attributable respiratory ED visits from 2005-06 to 2017-18 in three US states. Utilizing a meta-regression modeling framework, we estimated county-level influenza-attributable respiratory ED visit burdens and their associations with socioeconomic (SES), environmental, and chronic health factors.

Substantial regional heterogeneity in ED burden was observed, with Georgia exhibiting rates over twice those of California and New York. This may reflect differences in SES, healthcare access, population health, and health-seeking behaviors. Georgia also had the highest proportion of all RESP ED visits coded as influenza (4.1%) and higher baseline rates of poverty and chronic health conditions.

Meta-regression analysis revealed that county-level higher poverty rates and lower insurance rates were associated with higher rates of respiratory ED visits attributable to influenza. This aligns with previous research indicating that social determinants of health play a crucial role in chronic respiratory disease disparities [22], with lower SES being associated with severe respiratory conditions and more emergency department visits.

For environmental exposures, higher levels of $PM_{2.5}$, humidity, and temperature were associated with increased influenza-attributable respiratory ED visit rates in univariate models. Among these factors, humidity exhibited the strongest association, followed by temperature. However, these findings contrast with previous research [23,24], suggesting peak influenza transmission occurs during colder, drier conditions. One explanation is that ED visits capture both new infections and exacerbations of existing conditions. Elevated humidity — especially during winter — may worsen respiratory illness through indoor dampness and mold [25]. And even modest increases in wintertime temperature may lead to more outdoor activity or allergen exposure, triggering respiratory events [26]. Our analysis suggests that modest rises in humidity and temperature during influenza season may be different than other periods during the year.

A small but positive association between $PM_{2.5}$ levels and influenza-attributable respiratory ED visit rates was observed in the univariate models. This finding is consistent with prior research [27] showing a positive link between ambient $PM_{2.5}$ and respiratory diseases and respiratory-related ED visits. After adjusting for nonlinear population effects, we observed statistically significant positive association between ozone and influenza-attributable respiratory ED visit rates, suggesting that ozone may contribute to respiratory burden when factors associated with population size are accounted for. This finding is supported by previous epidemiological studies that link ambient ozone exposures to airway inflammation and increased hospital admissions for asthma and other respiratory conditions [28].

Our findings demonstrated strong associations between the prevalence of county-level chronic health conditions and influenza-attributable respiratory ED visit rates. Among these conditions, stroke exhibited the strongest estimated association across all models. This may be attributed to the long-term effects of cerebrovascular disease, including compromised immune function [29], increased susceptibility to infection, and difficulties in clearing respiratory pathogens due to weakened muscular function [30]. Prior studies have shown that stroke survivors are at an elevated risk of pneumonia and other respiratory infections [31].

Diabetes and COPD rates also showed strongest associations. These findings align with existing evidence that diabetes and COPD significantly contribute to respiratory health complications. Diabetes impairs immune response, increasing susceptibility to infections, including influenza and pneumonia [32], while COPD is characterized by chronic lung inflammation and reduced pulmonary function [33], making individuals more prone to severe respiratory infections and exacerbations requiring emergency care.

Adjusting for poverty and uninsured rates attenuated most associations, suggesting that part of the association between county-level chronic disease and influenza-attributable respiratory ED visits may reflect underlying socioeconomic disadvantage. The effects of poverty and uninsured prevalence remained similar and increased in some two-SES adjusted models. If chronic conditions is a mediating factor between SES and influenza-attributable respiratory ED visits, we would expect SES effects to decrease when controlling for health status. The observed stronger association points to an independent and possibly more direct role of SES in shaping emergency care use.

Our study has several key strengths in estimating the burden of influenza-attributable respiratory ED visits at the county level. First, we leverage a large hospital discharge dataset spanning over a decade across three states with diverse populations. Our use of state-wide hospital discharge data includes all ages and all payors, enabling a more comprehensive analysis compared to use of insurance claim databases. Second, our study focuses on ED visits, which is an under-studied morbidity outcome compared to hospitalization and mortality. By including ED visits, this study captures less severe influenza cases, providing a more complete estimate of healthcare burden.

This study has several limitations. First, our reliance on ICD-coded influenza ED visit data as a proxy for influenza burden may still be subject to misclassification bias, given coding practices vary across hospitals and over time. However, we conducted a validation analysis by comparing ICD-coded influenza hospitalizations from our datasets to laboratory-confirmed influenza cases reported by the US FluSurv-NET surveillance system [34]. In counties with overlapping data, we aligned weekly counts from both sources using the MMWR-week framework. Pearson correlation analysis (*Supplementary Figure 3*) demonstrated good agreement between ICD-coded hospitalizations and FluSurv-NET data.

Second, our analyses areas may not fully generalize to other regions with different healthcare access, demographic, or environmental exposures. Third, although we considered key environmental and socioeconomic variables, important factors such as vaccination status, healthcare-seeking behavior, and medical history were unavailable at the county level.

CONCLUSION

This study provides a county-level assessment of influenza-attributable respiratory ED visits across California, Georgia, and New York. Our findings highlight the importance of socioeconomic status, environmental exposures, and chronic health conditions as key spatial predictors of local influenza-related respiratory ED visit rates. Counties with higher poverty and uninsured rates, greater humidity and temperature, and elevated prevalence of chronic conditions such as stroke, COPD, and others, were strongly linked to higher influenza-attributable respiratory ED visits. These findings highlight the need for targeted interventions, such as improving healthcare access, mitigating environmental risks, and managing chronic diseases, to reduce influenza severity and demonstrate the value of incorporating spatial data into public health planning.

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Conflict of Interest Disclosure

None noted.

Ethics Approval Statement

This work is approved by the Emory Institutional Review Board (STUDY00006348)

Patient consent statement

Not applicable.

Data Availability

Please contact corresponding author Howard Chang (howard.chang@emory.edu) to request the data we use.

Authors' Contributions

Contributions made by each author of the manuscript are: conceptualization (Chang), data acquisition (Chang), methodology (Chang), data analysis (Huang, Lin), manuscript preparation (Huang), manuscript review and editing (Warren, Ebelt, Chang), and research support (Warren, Ebelt, Chang).

Abbreviations

- RESP: respiratory disease
- BRFSS: Behavioral Risk Factor Surveillance System
- ICD: International Classification of Diseases
- CDC: Centers for Disease Control and Prevention
- CMAQ: Community Multiscale Air Quality
- ZCTA: ZIP Code Tabulation Area

- ED: emergency department
- CI: confidence interval
- CrI: credible interval (Bayesian posterior distribution)
- IQR: interquartile range
- NO_2: nitrogen dioxide
- O_3: ozone
- $PM_{2.5}$: fine particulate matter ≤2.5 μm
- SES: socioeconomic status
  - Pct_pov (%) – % living below poverty line
  - Pct_uninsured (%) – % without health insurance
  - Pct_renter (%) – % renter households (lower homeownership)
  - Pct_crowd (%) – % crowded households (multiple occupants per room)
- Disability: with at least one disability among hearing, vision, cognitive, ambulatory, self-care, or independent living difficulty
- BPHIGH: high blood pressure (hypertension)

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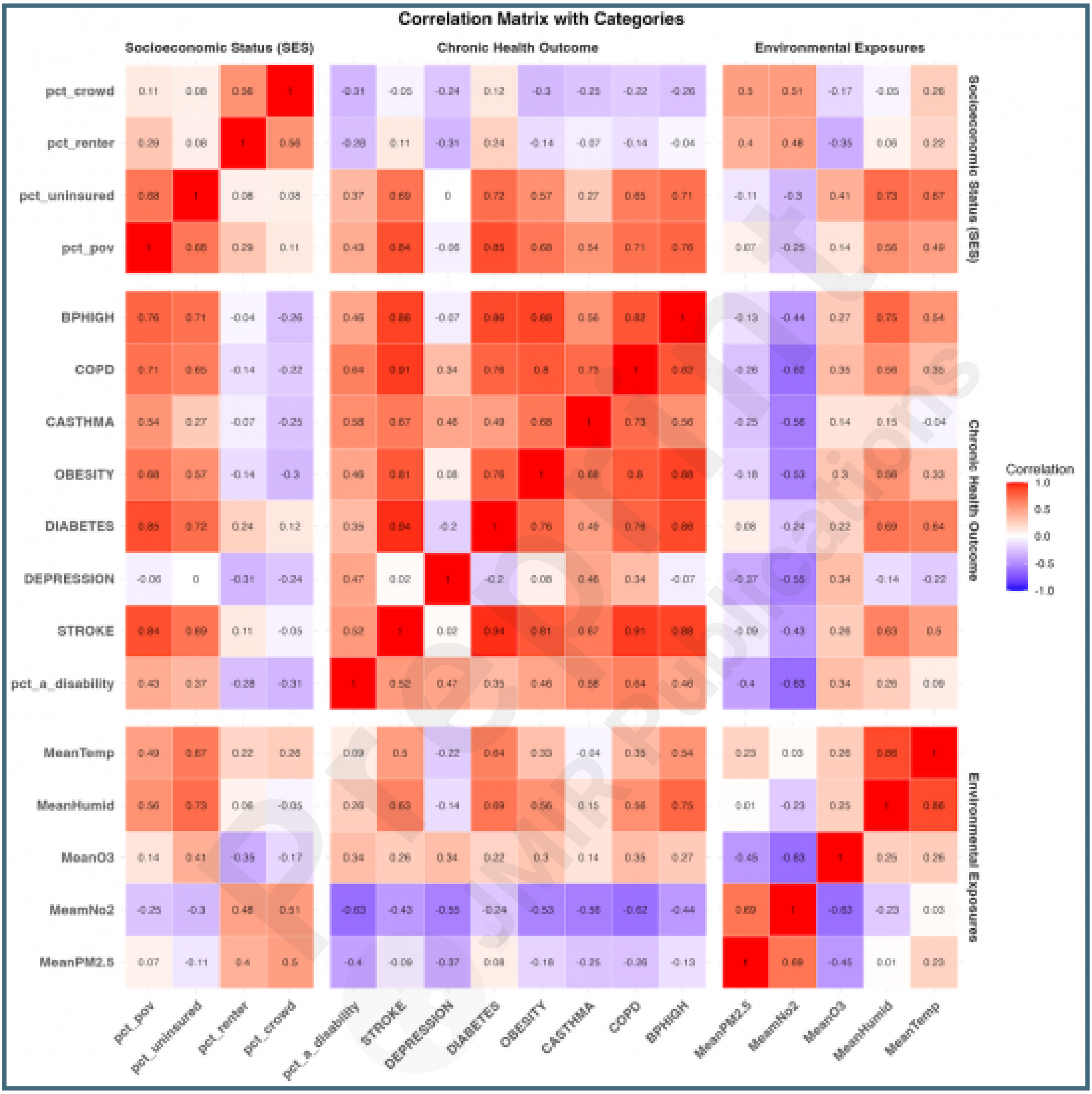
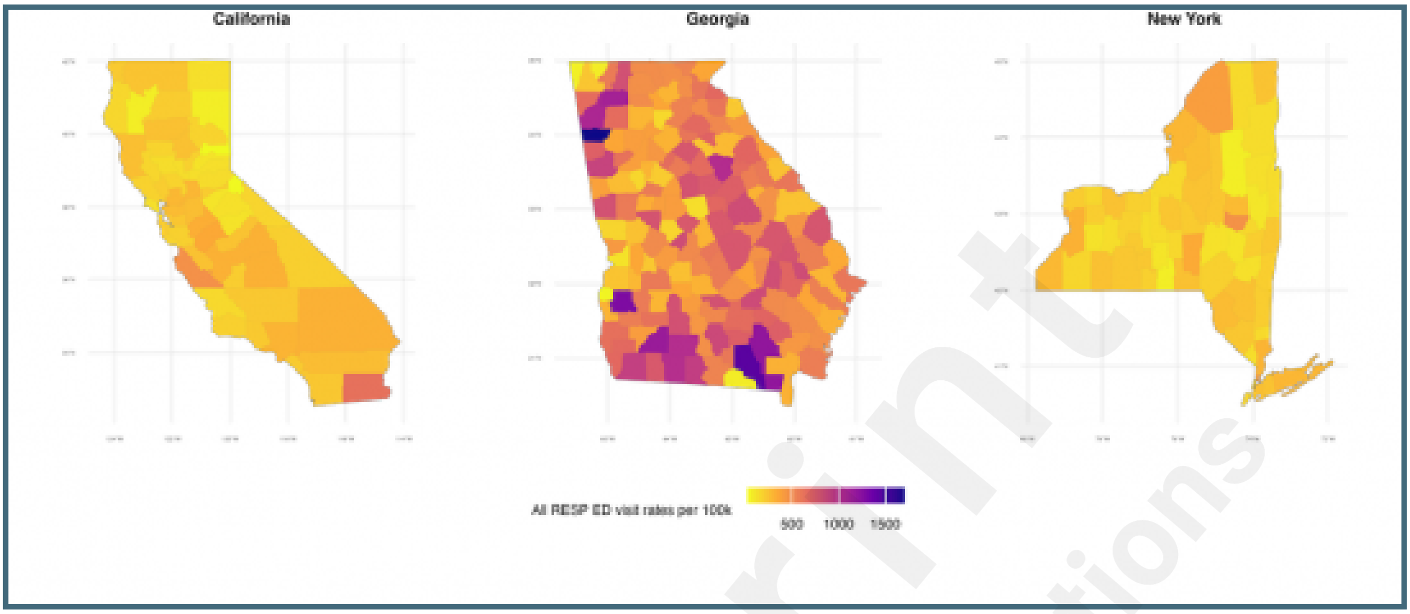
Supplementary Files

Figures

This figure presents Pairwise Pearson correlation heatmap of county-level socioeconomic, chronic health, and environmental covariates (n = 279 counties).



Heatmap of annual estimated influenza-attributable respiratory emergency department (ED) visit rates per 100,000 at the county level in California (CA), Georgia (GA), and New York (NY) from 2005-2006 to 2017-2018. Rates are averaged across all influenza seasons during the study period.



Multimedia Appendixes

This file contains the supplementary figures and tables, each of which is referenced in the main manuscript.
URL: http://asset.jmir.pub/assets/5f942041a574d2c36f6c09f8c62afb8d.docx

This file contains the detailed modeling process of the Bayesian hierarchical modeling described in the Methods, Stage 2 statistical modeling section.
URL: http://asset.jmir.pub/assets/082c88ccfa27df7fb0ac0896a6dbf9e3.docx

This excel sheet includes the numeric values for cottony-level influenza-attributable RESP ED visit rates for each season.
URL: http://asset.jmir.pub/assets/39c80d086197b2dc7f800e3dcaab9a14.xls