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Research Paper

The impact of cold weather on respiratory morbidity at Emory Healthcare in Atlanta

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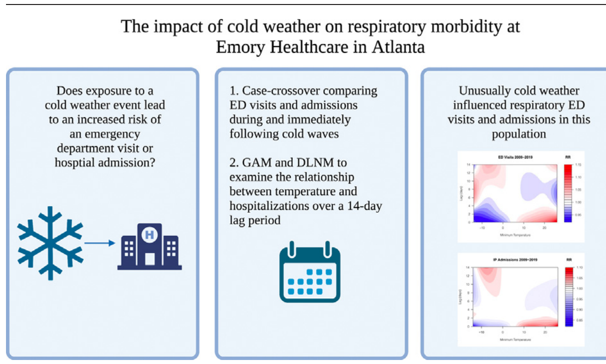
HIGHLIGHTS

- Case-crossover compared respiratory hospitalizations during and after cold waves
- GAM and DLNM models analyzed impact of cold wave over 14-day lag
- Cold waves influence respiratory hospitalizations even where they are uncommon
- Emergency department visits increase around one week following a cold event
- Inpatient admissions follow a similar, but muted, pattern

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Research on temperature and respiratory hospitalizations is lacking in the southeastern U.S. where cold weather is relatively rare. This retrospective study examined the association between cold waves and pneumonia and influenza (P&I) emergency department (ED) visits and hospitalizations in three metro-Atlanta hospitals.
Methods: We used a case-crossover design, restricting data to the cooler seasons of 2009–2019, to determine whether cold waves influenced ED visits and hospitalizations. This analysis considered effects by race/ethnicity, age, sex, and severity of comorbidities. We used generalized additive models and distributed lag non-linear models to examine these relationships over a 21-day lag period.
Results: The odds of a P&I ED visit approximately one week after a cold wave were increased by as much as 11%, and odds of an ED visit resulting in hospitalization increased by 8%. For ED visits on days with minimum temperatures >20 °C, there was an increase of 10–15% in relative risk (RR) for short lags (0–2 days), and a slight decrease in RR (0–5%) one week later. For minimum temperatures <0 °C, RR decreased at short lags (5–10%) before increasing (1–5%) one week later. Hospital admissions exhibited a similar, but muted, pattern.
Conclusion: Unusually cold weather influenced P&I ED visits and admissions in this population.

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1. Background

With human-induced climate change influencing global weather patterns,(IPCC, 2021) it is important to understand how changes in the environment may affect human health and to develop methods for adaptation to these changes. Weather has been shown to affect human health in a variety of ways, including through changes to the spread of infectious pathogens that impact the transmission of diseases.(Butler, 2012; Daily and Ehrlich, 1996; Flahault et al., 2016; Myers and Patz, 2009) Respiratory diseases, especially influenza and pneumonia, are a significant source of global mortality and morbidity,(Global Health Estimates, 2019; GBD 2017 Influenza Collaborators, 2019) and their incidence and transmission appear to be affected by environmental conditions.(Mirsaeidi et al., 2016; Morin et al., 2018; Pica and Bouvier, 2012) A variety of meteorological factors have been shown to correlate with influenza and pneumonia incidence, hospitalization, and mortality, with cold, dry air tending to precede increases in influenza-related incidence.(Chen et al., 2019; Davis and Enfield, 2018; Davis et al., 2016; Jaakkola et al., 2014; Caini et al., 2018; Liu et al., 2019; Murtas and Russo, 2019; Spiga et al., 2016; Zheng et al., 2021) Research conducted in the laboratory setting has found that influenza viruses survive better in environments with low temperatures and humidity.(Lowen et al., 2007; Davidson et al., 2010) It is also hypothesized that the human immune system may be impacted by weather conditions, increasing susceptibility in cold, dry conditions.(Ference et al., 2020) As climate change influences weather variability, it is necessary to understand how these fluctuations may impact the spread of respiratory diseases.

Research over the past decade that has elucidated linkages between weather and influenza has emphasized influenza mortality in midlatitude cities, where influenza severity is thought to drive the seasonality mortality curve and its cold-season peaks.(Gasparrini et al., 2015; Reichert et al., 2004; Davis et al., 2004) In an effort to provide a more complete understanding, other studies have examined these linkages in tropical and subtropical locations, where cold, dry air is virtually nonexistent.(Davis et al., 2016; Chan et al., 2009; Chong et al., 2015; Chong et al., 2020; Guo et al., 2019; Monamele et al., 2017; Soebiyanto et al., 2015; Tamerius et al., 2013) Comparatively little research has examined weather and emergency department visits and hospitalizations from influenza and other respiratory diseases, particularly in the humid and temperate climate of the southeastern United States. This region is interesting because cold, dry air incursions are uncommon but not unprecedented, and respiratory disease burden is nonetheless seasonal. To examine whether temperature plays a role in the transmission of respiratory illnesses in an area of the U.S. with less seasonally variable weather, this retrospective study modelled the association between cold waves and emergency department visits and inpatient admissions for pneumonia and influenza illnesses in a healthcare system in metropolitan Atlanta.

2. Methods

Data on emergency department (ED) visits and inpatient (IP) admissions for pneumonia and influenza (P&I) from 2009 to 2019 were collected from the data warehouse at Emory Healthcare. Since the data were aggregated and deidentified, the Emory University Institutional Review Board did not require approval for this project. Three hospitals in the Emory Healthcare system had IP data available for this period, and two had ED data. The data collected included demographics, date of admission, International Classification of Disease, Ninth Revision (ICD-9) and Tenth Revision (ICD-10) codes for admission, and Charlson Comorbidity Index scores.(Charlson et al., 1987) Patients with ED visits and IP admissions with primary cases of pneumonia and influenza upon admission (ICD-9 codes 483–488; ICD-10 codes B25.0, B44.0, and J09-J18) were included together in this analysis. Pneumonia and influenza are often combined in analyses because their symptomology and treatment are similar, influenza diagnostic testing is not always done, and mortality from influenza is coded as pneumonia.(Noymer, 2008) Only those patients who lived in the 11 counties that the Atlanta Regional Commission outline as metro-Atlanta (Atlanta Regional Commission, n.d.) were included in analysis, based on the zip code listed in their admission record.

The demographic data included the age, sex, race, and ethnicity of the patients (Table 1). This analysis only included patients 18 years and older. The patients in these hospitals were approximately 30% white and 70% non-white. Though most of the non-white patients identified as “African American or Black,” there were a relatively small number of patients in each of the non-white race and ethnicity categories. Therefore, the race variable in this study was dichotomous: non-white and white. These two categories were determined from self-reported hospital-collected race and ethnicity information. The former included patients who selected “African American or Black,” “American Indian or Alaskan Native,” “Asian,” “Hispanic or Latino,” “Multiple,” or “Native Hawaiian or Other Pacific Islander.” The latter included those who selected “Caucasian or White.” Those patients coded in the data as “Not Recorded,” “Patient Declines,” or “Unknown, Unavailable or Unreported” accounted for less than 6% of total encounters and were not included in the subgroup analysis of race and ethnicity.

The Charlson Comorbidity Index (CCI) is used to predict a patient's risk of death within one year of hospitalization for patients with specific comorbid conditions.(Charlson et al., 1987) This classification was chosen because it is the method the Emory Healthcare system uses to assess the risk of mortality in patients. The Index is categorized into three grades: mild, moderate, or severe. An individual with a score of 3 (or severe) was in the high-risk group for this study. Details on the calculation of the CCI are given in the supplementary material.

Atlanta is in the southeastern United States and has a humid subtropical climate according to the Köppen climate classification, with warm, humid summers and mild winters. Meteorological data from 2009 to 2019 were collected from the weather station at the Atlanta Hartsfield Jackson International Airport. The data included a variety of meteorological variables with surface air temperature and humidity sampled four times per day (0100, 0700, 1300, and 1900 Local Standard Time) for our analysis and all other variables measured daily.

Air pollution data, which included daily average particulate matter ($PM_{2.5}$) and ozone, were collected from Environmental Protection Agency Air Data website (https://www.epa.gov/outdoor-air-quality-data). All the sites located within the Atlanta-Sandy Springs-Roswell (GA Metropolitan Statistical Area, CBSA 12060) were mapped using R leaflet package (R 4.0.3), as shown in Fig. 1 below. Based on the map, the sites within Interstate Highway Circle 285 (I-285) were selected and a daily average was created across sites for each day. On the days when data were missing from all the sites within I-285, the area of the sites was broadened outside I-285 until data were found. The total ED visits and IP admissions for each day were merged with the weather and air pollution variables.

2.1. Statistical analysis

2.1.1. Case-crossover

We first conducted a case-crossover analysis to determine whether ED visits and IP admissions were elevated during, and immediately following,

Table 1
Patient frequencies for emergency department visits and inpatient admissions by age, race, and sex.

	Emergency Department	Inpatient
Age		
<65	16,258 (62.5%)	10,971 (54.3%)
>65	9759 (37.5%)	9244 (45.7%)
Race		
White	6802 (26.1%)	7002 (34.6%)
Non-White	18,368 (70.6%)	13,134 (65.0%)
Sex		
Female	13,484 (51.8%)	10,168 (50.3%)
Male	11,706 (45.0%)	10,021 (49.6%)
Severe Charlson Comorbidity Index	10,435 (40%)	12,372 (61.2%)

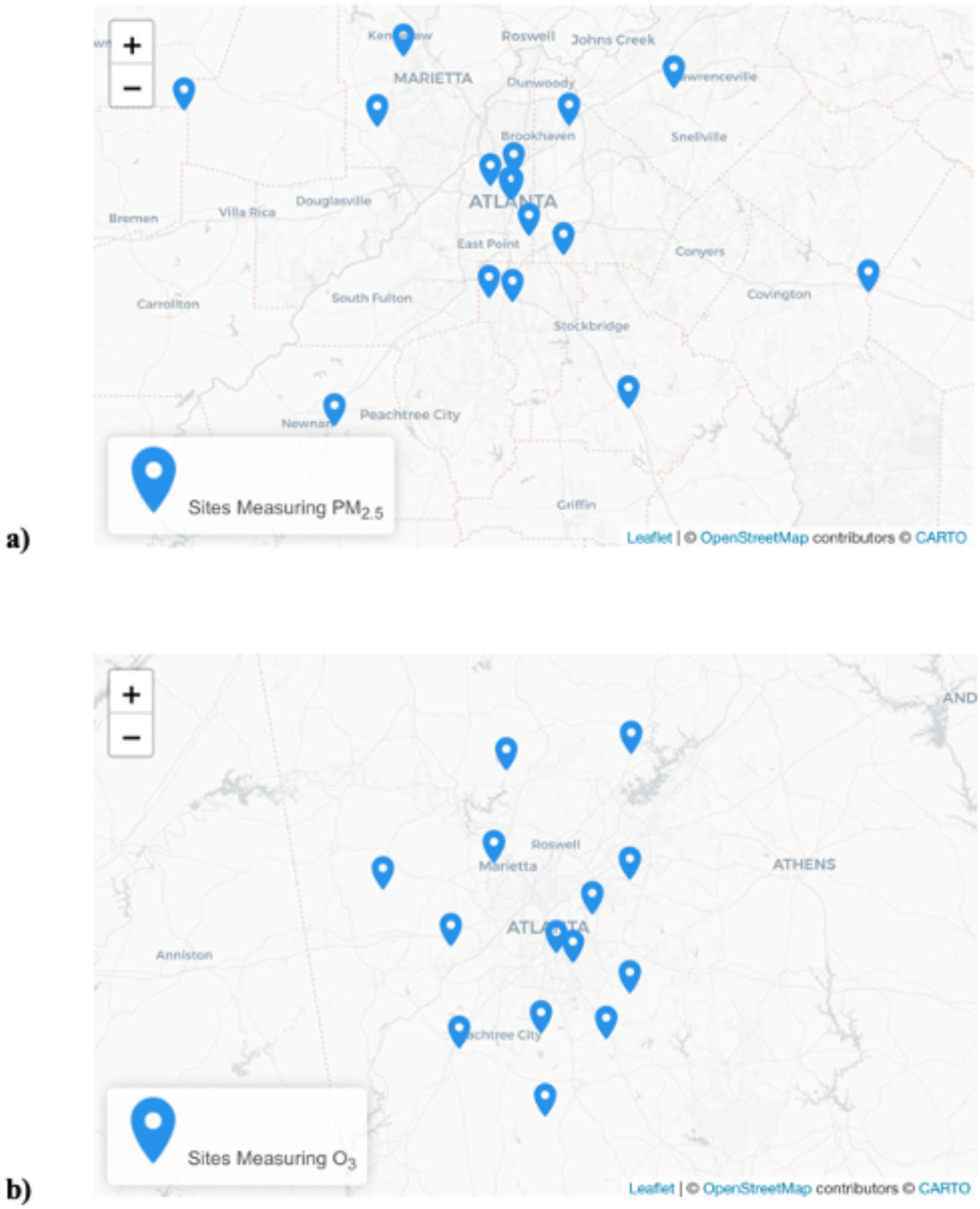

Fig. 1. Sites Measuring a) $PM_{2.5}$ and b) O_3 within Atlanta-Sandy Springs-Roswell.

cold waves (prolonged cold periods) as compared to control periods when no cold waves occurred. Cold days were defined as those days in which temperature was at least one standard deviation below the 30-year mean (1981–2010) for that day. Cold waves were defined as a minimum of three cold days, and a cold wave was terminated by two consecutive days that did not exceed the cold threshold.(Davis and Novicoff, 2018) These analyses were completed for the cool portion of the year only (October–April). After exploring different weather parameters and definitions of cold waves in this analysis, we chose minimum temperature to define cold waves, but the results were similar when defined using mean temperature (as shown in the Supplementary Material).

We examined the impact of cold waves on ED visits and IP admissions using a time-stratified case-crossover analysis, in which time periods immediately prior to the onset of the cold wave serve as controls. This approach alleviates the need to control for time-varying factors, such as trends and seasonality, by assuming that any temporal factors unrelated to weather would only vary at longer time scales.(Fuhrmann et al., 2016; Semenza and Ebi, 2019; Basu et al., 2012) Thus, each cold wave is associated with a control period within the same 28-day range, and that control period cannot also include a different cold wave. We also matched the data on day of the week. The sensitivity analysis for these factors is shown in the Supplementary Material. Odds ratios were calculated using conditional logistic regression via the “casecross” function in the “season” package in R 4.0.5 (R Core Team, 2021). Because there is often a substantial time lag in the cold season between a putative impactful weather event and any subsequent morbidity, these analyses were extended out through a lag of 21 days. We also conducted this analysis for different groups organized by race, sex, age (<65 years, ≥65 years), and co-morbidity index by re-running the model on each subset across the 21-day lag. After obtaining the odds ratios for each subgroup, we compared them using a test of interaction at each lag to determine whether there was a significant difference between subgroups.(Altman and Bland, 2003)

2.1.2. GAM and DLNM analyses

We further explored the relationship between temperature and ED visits and IP admissions using generalized additive models (GAMs) and distributed lag non-linear models (DLNMs). We developed GAMs to estimate the relative risk of ED visits and IP admissions related to weather. In the GAM framework, smoothing cubic splines are fit to potential predictor variables to model the temporal behavior in these variables. Other factors are included as categorical variables in a fashion similar to dummy variables in multiple least-squares regression.(Gasparrini, 2011; Guo et al., 2016; Lee et al., 2018) Our GAMs examined the total effect over a 21-day lag (day of observation and subsequent three weeks). Specifically, our GAMs were structured as follows:

$$Y_t = a + bT_{t,l} + S(trend, 11*4) + cDOW_t + dHoliday_t + eTPM_{t,l} + fOZ_{t,l} \quad (1)$$

where "Y" is the daily predicted count (ED or IP), "t" is time (daily time step), "l" is the lag day, "T" is minimum temperature, "S" is a natural cubic spline with 4 degrees of freedom, "DOW" is a nominal variable for day of week, "Holiday" is a binary variable to account for morbidity changes impacted by the Thanksgiving and Christmas holidays, "TPM" is log-transformed $PM_{2.5}$, and "OZ" is ozone, "a" is the y-intercept, and "b"–"f" are fitted coefficient vectors. A quasi-Poisson link function accounts for potential over-dispersion in the morbidity variables. The final model shown in Eq. 1 was selected through systematic testing of a suite of different predictors and varying degrees of freedom, comparing the adjusted r-squared values, the generalized coefficient of variation, and the lag one autocorrelation (see Supplementary Materials). We used four equally spaced knots to fit a natural cubic spline to the temperature and trend terms.

To determine the likelihood of elevated or reduced morbidity at specific lags, a distributed lag non-linear model (DLNM) was employed. The DLNM provides estimates of the relative risk as a function of predictor (minimum temperature) and lag.(Gasparrini, 2011; Guo et al., 2016; Lee et al., 2018) Since in most cases there is some time lag between a weather event and the potential health outcome, our models were run from day zero (no lag) through day 21 to account for possible delayed effects in IP admissions and ED visits. The results shown below are the non-cumulative effects, or the relative risk on each lag day.

Output of both the GAM and DLNM is the relative risk (RR) of morbidity. The RR was centered on the value corresponding to the minimum risk. These models were run on the entire dataset, January–December, to assess the impacts of temperature throughout the annual cycle. The cold season, October–April, was compared to the warm season, May–September, in a separate analysis to assess whether there were differences between the two seasons, but the warm season results are not included herein as there was not a clear influence of cold weather on warm season respiratory hospitalizations.

3. Results

Over the 11-year analysis period, there were a total of 26,017 ED visits and 20,215 IP admissions for influenza and pneumonia. ED visits were highest in the months of December through February, with a daily average of 8.6 visits (Supplementary Materials Fig. S1). ED visits were lowest in the months of June through September, with a daily average of 4.7 visits. The highest number of daily ED visits throughout the analysis period was 42 in December of 2019. Average IP admissions followed a similar pattern, with a daily average of 6.1 admissions in December through February, and a daily average of 4.1 admissions in June through September. The maximum number of admissions throughout the analysis period was 25 on December 22, 2010. The patient characteristics are outlined in Table 1.

We identified 43 cold waves, an average of 3.9 per year, based on a − 4.9 °C departure (1 standard deviation) from the 30-year average minimum temperature for each day. 192 days out of a total of 2333 cold season days in the data set (8%) occurred within a cold wave. The longest cold wave was 13 days and occurred in January 2010. The minimum temperature throughout the analysis period was −14.4 °C on January 7, 2014. In 2010, there were ten cold waves, the highest annual frequency throughout the 11-year period. In both 2012 and 2016, there was only one cold wave.

The odds of an ED visit during a cold wave were decreased by 7–8% as compared to the odds during the control periods (Table 2). However, the odds of an ED visit approximately one week after the cold wave were increased by as much as 11% compared to the odds during the control periods. The odds of IP admission did not differ at the start of a cold wave but were increased by 8% about a week after the cold wave and as much as 12% two weeks after cold-wave onset.

Cold waves appeared to differentially impact ED visits across demographic groups and comorbidity status (Figure 2). At the start of a cold wave, ED visits decreased for the non-white, female, and male groups, as well as for those with a high comorbidity index (an index of 3 for this analysis). One week after a cold wave, the odds of an ED visit increased for the non-white and male groups, and for those with a high comorbidity index score. While we found significant effects for certain demographic groups at specific lags, using a test of interaction, we found that there were not statistically significant differences between the groups (Supplemental Material).

IP admissions were also differentially impacted across groups (Figure 3). At the beginning of a cold wave, IP admissions were decreased for the non-white, female, and high comorbidity index groups. At a one-week lag from a cold wave, the odds of an IP admission increased for the male, white, and high comorbidity index groups. IP admissions were also more likely to increase around 12 days after the start of cold wave for the non-white group. Similar to the pattern with ED visits, we found that there were not statistically significant differences between the demographic groups (Supplemental Material).

Next, we examine the results of the GAM and DLNM analyses. Given that cold waves appear to have influenced ED visits and IP admissions, we ran GAMs to examine the relationship between minimum temperature and hospital data. We also included the daily-average $PM_{2.5}$ and ozone concentrations in the model to account for potential effects of these variables on ED visits and hospital admissions for respiratory illness (Eq. 1). The GAM models showed that minimum temperature appeared to influence RR for ED visits and IP admission. We therefore ran DLNMs controlling for air pollution, day of week, and holiday effects, over a lag period of

Table 2
Odds ratios and 95% confidence intervals for the case crossover analysis over a lag of 21 days controlling for day of the week. The odds ratio indicates the odds of an ED visit or IP admission during a cold wave (lag day 0), or at a lag from the first day of the cold wave (lag days 1–21), as compared to the odds of a visit or admission during the control period.

Lag Day	OR ED Visits [Confidence Interval]	OR IP Admissions [Confidence Interval]
0	0.92 [0.86,0.98]$_a$	0.91 [0.85, 0.98]
1	**0.93 [0.87,0.99]**	0.95 [0.89, 1.03]
2	**0.92 [0.87, 0.98]**	0.99 [0.92, 1.06]
3	0.97 [0.91, 1.03]	1.03 [0.96, 1.11]
4	1.01 [0.95, 1.08]	1.00 [0.94, 1.08]
5	1.05 [0.99, 1.12]	1.03 [0.96, 1.04]
6	**1.08 [1.02, 1.15]**	1.03 [0.96, 1.10]
7	**1.11 [1.04, 1.18]**	**1.08 [1.00, 1.15]**
8	**1.10 [1.04, 1.17]**	**1.07 [1.00, 1.15]**
9	**1.06 [1.00, 1.13]**	1.04 [0.97, 1.11]
10	**1.08 [1.01, 1.14]**	**1.07 [1.00, 1.15]**
11	1.04 [0.98, 1.10]	1.05 [0.98, 1.13]
12	1.05 [0.99, 1.12]	**1.07 [1.00, 1.15]**
13	**1.08 [1.01, 1.14]**	**1.12 [1.04, 1.20]**
14	**1.06 [1.00, 1.13]**	**1.08 [1.01, 1.16]**
15	0.99 [0.93, 1.05]	1.01 [0.94, 1.09]
16	1.01 [0.95, 1.08]	1.04 [0.97, 1.12]
17	1.00 [0.94, 1.06]	1.02 [0.95, 1.10]
18	1.00 [0.94, 1.07]	1.04 [0.97, 1.12]
19	0.96 [0.90, 1.02]	1.01 [0.94, 1.09]
20	0.94 [0.88, 1.00]	1.00 [0.93, 1.08]
21	**0.91 [0.85, 0.97]**	1.00 [0.93, 1.07]

(a) Bolded ORs indicate significance at the 95% confidence level.

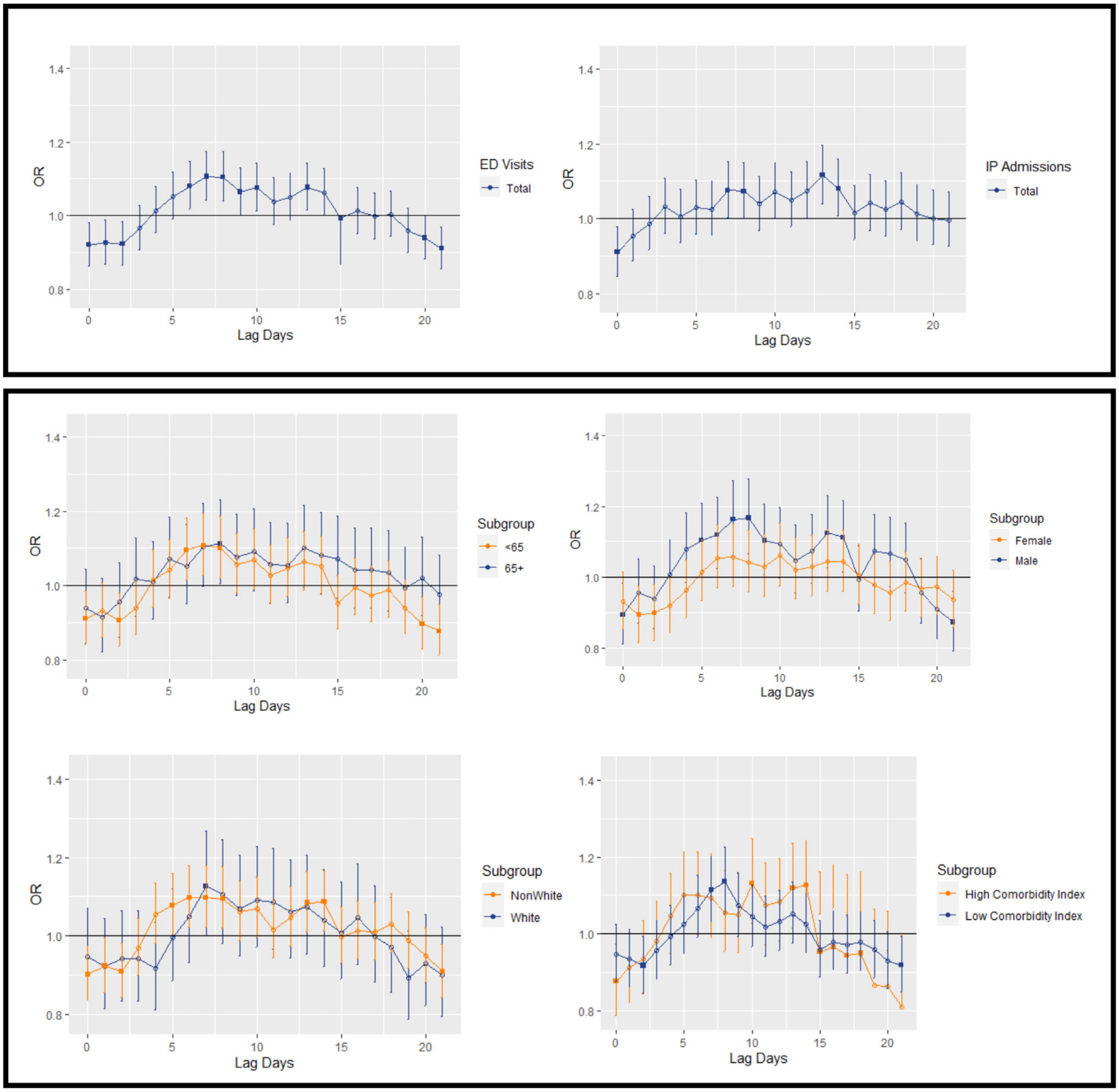

Fig. 2. Odds ratios (OR) and 95% confidence intervals for emergency department visits for ED visits and IP admissions, and by various subgroups across a 21-day lag period. Statistically significant OR are represented by shaded squares and ORs that are not statistically significant are represented by open circles.

21 days to assess the overall effect of minimum temperature on RR and to examine the effect throughout the lag. The RR for ED visits increases on days with higher minimum temperatures, peaking around 21 °C, a temperature at which the risk is about 30% higher than when the minimum temperature is −10 °C (Figure 4). For IP admissions, the effect of weather exhibits a peak around −5 °C, when the risk is elevated by about 30% relative to the minimum temperature.

For ED visits, at high minimum temperatures (around 15–25 °C), there was an increase of approximately 10–15% in relative risk (RR) for short lags and a slight decrease in RR (0–5%) around one week later (Figure 5). For low minimum temperatures (less than −10 °C), there was a decrease in RR of ED visits at short lags by approximately 5–10%. However, the RR increased 1–5% starting about one week after the cold period onset and continuing through about 14 days at which point, the RR decreases again through 21 days. IP admissions exhibited a similar, though slightly muted, pattern, with admissions increasing at a shorter lag period and decreasing again around 8 days after the cold event.

To better understand these effects by season, we repeated this analysis using a similar model for the warm and cold seasons separately and found that the overall relationship shown in Figure 4 is similar to that of the cold season only (not shown). The warm season pattern was dominated by high RR associated with a few unusually cold days in May that were responsible for the increase in ED visits and hospitalizations at short lags. This analysis suggests that the environmental effects on ED visits and IP admissions is being driven largely by the cold season effects.

4. Discussion

Cold weather appears to have influenced ED visits and IP admissions for P&I illness from 2009 to 2019 within the Emory Healthcare hospitals included in this analysis. Generally, at the beginning of cold waves, ED visits and IP admissions decrease. However, around one week after a cold wave, visits and admissions increase. This could be an effect of individuals deciding not to come to the hospital during the coldest days, resulting in an increase following the cold wave. This trend aligns with other research showing the lagged effect of cold weather on respiratory diseases, which is more likely related to the latency and incubation periods of respiratory viruses.(Spiga et al., 2016; Zheng et al., 2021; Dai et al., 2018; Zhen

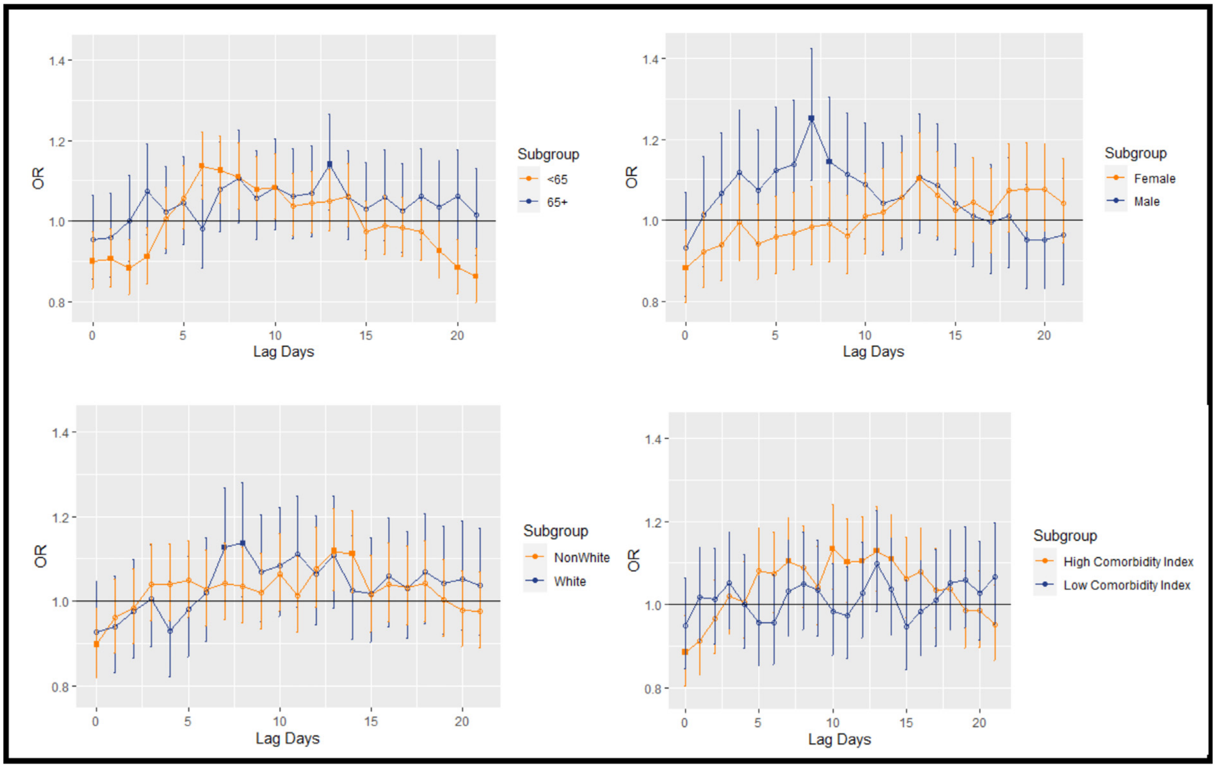

Fig. 3. Odds ratios (OR) and 95% confidence intervals for in-patient admissions by various subgroups across a 21-day lag period. Statistically significant OR are represented by open circles and ORs that are not statistically significant are represented by shaded circles.

et al., 2013) If the likelihood of viral transmission is higher during cold waves, we would expect to see an increase in incidence at a lag aligning with the typical incubation period of respiratory viruses of 1–6 days, (Lessler et al., 2009; CDC, 2018) with possible additional lag days for severe symptoms to appear requiring an ED visit or hospital admission. Given that the increase in ED visits and IP admissions occurred around a week following a cold wave, the results of this analysis align with the transmission timeline for respiratory viruses.

Winters in Atlanta are generally warm, and cold waves are relatively uncommon. What is considered a cold wave in Atlanta may be a warm winter day in another location. This begs the question of whether the temperature itself, or the rapid change in temperature, is driving the increase in ED visits and IP admissions. Studies in other subtropical climates have found that unusually cold, dry periods tend to precede increased influenza incidence, hospitalizations, and mortality.(Davis et al., 2016; Liu et al., 2019; Chan et al., 2009; Guo et al., 2019; Davis and Novicoff, 2018) In a study

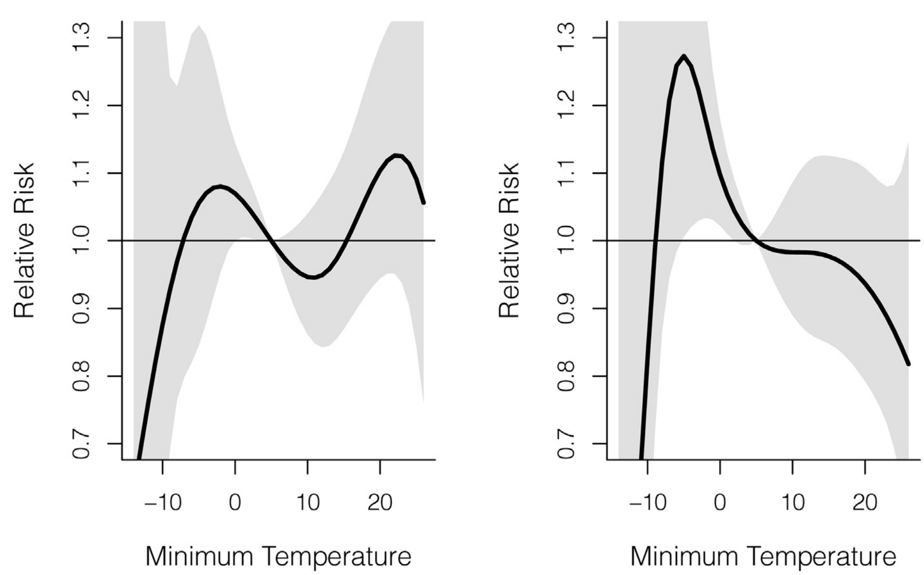

Fig. 4. The overall effect of minimum temperature on the relative risk of ED visits (left) and IP admissions (right) at Emory hospital averaged over a 21-day lag. Plots are centered on the temperature corresponding to the minimum risk, and 95% confidence intervals are shown by gray shading. Tick marks along the x-axis indicate the distribution of observations.

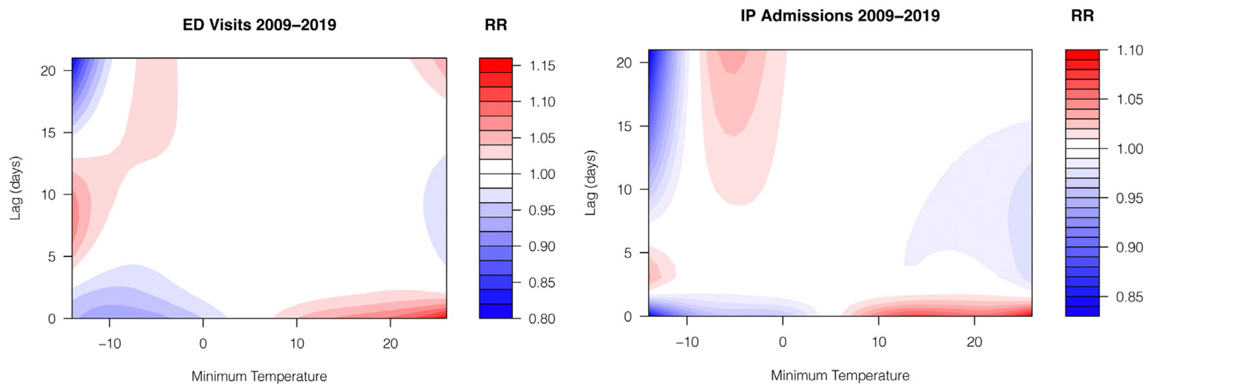

Fig. 5. Heat maps showing the relative risk of a) ED visits and b) IP admissions at various minimum temperatures as a function of lag. Note that the color scale key differs between plots.

conducted in a similar climate in Texas, the risk of respiratory emergency hospitalizations increased below a certain temperature threshold.(Chen et al., 2019) Research in temperate climates has similarly found that low temperature and humidity is associated with increased influenza incidence, often at a lag of around a week.(Caini et al., 2018; Spiga et al., 2016; Park et al., 2020) Although the impact of humidity on respiratory illness may differ between climate zones, low temperatures appear to increase respiratory transmission across climate zones.(Chong et al., 2020) Some research has found a U-shaped relationship between temperature and respiratory illness in subtropical and tropical climates, with peaks at the lowest and highest temperatures.(Chan et al., 2009; Guo et al., 2019; Dai et al., 2018; Wang et al., 2017) Similar to the present analysis, peaks at the lowest temperatures appear at a lag, while peaks at the highest temperatures appear at day 0.(Dai et al., 2018) The impact of temperature on respiratory illness has even been found in subarctic regions, with the decrease in temperature driving the increase in illness rather than the low temperature and humidity.(Jaakkola et al., 2014) These studies point to the possibility that rapid decreases in temperature, regardless of what those temperatures are, may be more impactful than low temperature alone.

The impact of cold weather on ED visits and IP admissions appears to vary between different populations based on race and sex, though the differences between the groups were not significant. Males experienced an increased risk of an ED visit or IP admission approximately one week following a cold wave. One study conducted on the impact of meteorological changes on respiratory illness in people over the age of 65 similarly found a differential effect by gender, with illness increasing for males and not females.(Zhen et al., 2013) A study conducted on the association between low temperature and humidity on influenza in children found equivalent effects on males and females, perhaps indicating a differential effect by age.(Guo et al., 2019) There does not seem to be a clear hypothesis for why these effects may differ based on sex. The impact of a cold wave on white and non-white individuals differed between the ED and IP admissions, with the non-white group having a higher likelihood of an ED visit one week after a cold wave, and the white group having a higher likelihood of an IP admission one week after a cold wave. The odds of IP admission for the non-white group did also increase between 12 and 14 days after a cold wave. Perhaps this trend is related to differences in utilization of the healthcare system. This analysis did not find an increased risk of ED visits or IP admissions for individuals over age 65, differing from some other research in this area.(Chen et al., 2019; Li et al., 2018) Though, research on other environmental factors, such as diurnal temperature range, have similarly found no difference in hospitalizations between young and elderly individuals.(Phosri et al., 2020)

A strength of this analysis is the varied statistical modelling methods used to examine the data, which allows us to better conceptualize the impact of cold waves on respiratory admissions. The analysis also included 11 years of data, which helped to reduce biases that might result from sampling a population during an unrepresentative time period. Although 11 years of data were included, only three hospitals had data for the entire time period, decreasing our ability to generalize our results to other geographic contexts and demographic groups. We did compare the demographic data for the included hospitals and for metro Atlanta over this period and found that the hospitals are representative of the larger population in terms of sex, race, and ethnicity, though they may be under representative of the Hispanic population in the metro area. There are also many other factors that play a role in whether an individual requires an ED visit or hospital admission for a respiratory illness, including vaccination status, school schedules, and the indoor environment. These other factors were outside the scope of the current analysis, and therefore could not be accounted for in our models.

This analysis provides further evidence that cold weather, specifically cold waves, impact pneumonia and influenza hospitalizations and ED visits in a temperate climate that does not typically experience large fluctuations in temperature. This knowledge will allow our healthcare system to better prepare for the impact that cold waves may have on staffing needs, by increasing staffing during the cold season when cold waves are predicted. The ability to flexibly adjust staffing capacity to predictable seasonal and environmental factors should allow hospitals to better treat patients with respiratory issues, a consideration that is especially important when those affected individuals may experience comorbidities that make immediate care even more important. Because cold waves appear to impact respiratory illnesses in this population, future research will focus on the impact of fluctuations in temperature on a small timescale, i.e., daily fluctuations, to determine whether there is an impact of large fluctuations in temperature on respiratory admissions. Future studies may also expand beyond the three hospitals included in this analysis to gain a better understanding of the environmental impacts on respiratory visits and admissions in other populations in Atlanta.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.152612.

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