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Emergency department asthma diagnosis risk associated with the 2012 heat wave and drought in Douglas County NE, USA

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ABSTRACT

Background: Global climate change concerns are forcing local public health agencies to assess potential disease risk.
Objective: Determine if risk of an emergency department asthma diagnosis in Douglas County, NE, was higher during the 2012 heatwave compared to 2011.
Methods: Retrospective, observational, case-control design selecting subjects from 2011 and 2012 emergency department (ED) admissions. Risk was estimated by conditional logistic regression.
Results: The asthma ED risk estimate was 1.23 (95%CI = 0.96–1.57) times higher in 2012 than 2011, for the same calendar period. Asthma ED diagnosis risk was 3.37 (95%CI = 2.27–4.17) times higher among subjects <19 years old compared to older subjects, and 3.25 (95%CI = 2.63–4.02) times higher among African-Americans than non-African–Americans, adjusted for heatwave exposure. Absolute humidity appears inversely related to asthma diagnosis risk ($\chi 2 = 16.6$; $p < 0.001$).
Conclusion: Asthma ED diagnosis risk was not significantly higher in 2012 compared to 2011. Risk was elevated among subjects less than 19 years old, and among African Americans; adjusted for heatwave exposure.

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Introduction

Approximately twenty-five million people in the United States (US) have asthma.[1] It is the most common chronic respiratory disease among US children.[2] A growing public concern about global climate change, ambient temperature anomalies (heatwaves), and heat-related illnesses,[3] is compelling local health practitioners to adopt methods to study relationships between heatwaves and respiratory health.

Reports of associations between heatwaves and asthma are disparate. In 2014 Zhang et al observed that asthma hospitalization risk was 1.20 (95% CI; 1.01–1.41) times higher during increasingly colder temperatures among Shanghai, China, adults, but observed no association between asthma hospitalization risk and increasingly warmer temperatures.[4] Similarly, Son and co-investigators observed statistically significant increased asthma hospitalizations associated with low temperature (i.e., 2 °C compared to 15 °C) among residents in eight major Korean cities from 2003 to 2008, but no statistically significant increase in hospitalization risk when comparing heatwave and non-heatwave periods.[5] In contrast, other reports described increased asthma diagnosis risk among hospital emergency department (ED) populations during heatwaves.[6–10]

Fortunately, only two extreme heatwaves occurred in the US in the past one hundred years: the summers of 1936 and 2012.[11] Douglas County, NE USA residents endured twenty-six total and fifteen consecutive July days in 2012 with temperatures greater than or equal to (≥) 90 °F (32.2 °C).[12–14] This anomaly was accompanied by extreme drought.[15] In Douglas County the three-year mean asthma prevalence among adults (≥19 years old) who were told they had asthma from 2011 to 2013 was 7.4%.[16] Among Douglas County children less than (<) 19 years old and who were told they had asthma from 2011 to 2013, the three-year mean asthma prevalence was 6.0%. In 2012, this represented approximately 29,708 adults and 8507 children who currently had asthma among an estimated 543,253 Douglas County residents.[16]

The aim of this study was to determine if the odds of asthma hospital emergency department (ED) diagnosis was relatively higher during the rare 2012 heatwave and drought compared to the same 2011 calendar period in Douglas County, NE.

Abbreviations: AQI, air quality index (unitless); DCHD, Douglas County Health Department, Omaha, NE; DCHD AQL, Douglas County Health Department Air Quality Lab; COPD, chronic obstructive lung disease; DMAT, daily mean ambient temperature (average temperature per 24 h); DMATm, median of the daily mean ambient temperature; ED, emergency department; ESSENCE, Electronic Surveillance System for Early Notification of Community-based Epidemics; °F, degrees Fahrenheit; HMAT, hourly mean ambient temperature per month; ICD9, International Classification of Disease, 9th Revision; NCEI, National Center for Environmental Information; NE, Nebraska, USA; PM10, particulate matter 10 μm; PM2.5, particulate matter 2.5 μm

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Methods

Study design

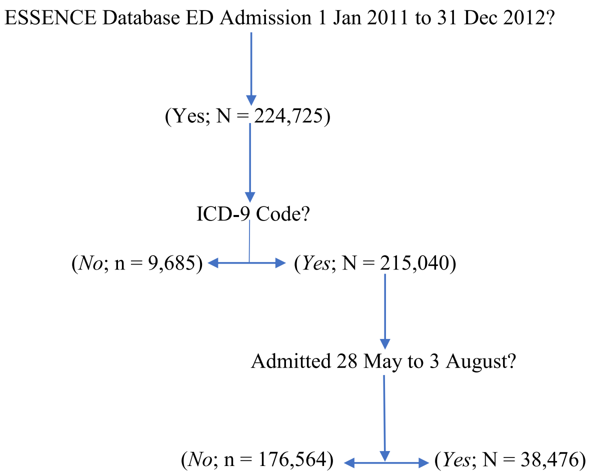
This was an observational, retrospective, case-control study.

Risk period

The risk period was 28 May through 3 August in 2011 and 2012, respectively.

Target and study population

Eligible subjects included all admissions to Douglas County EDs from 1 January 2011 to 31 December 2012. The target population (N = 224,725) was a dynamic cohort of all admissions to three Douglas County, NE, EDs (ED_A, ED_B, and ED_C) from 1 January 2011 to 31 December 2012 in the Electronic Surveillance System for Early Notification of Community-based Epidemics (ESSENCE)[17] database. An additional 9685 subjects were excluded because International Classification of Disease, Ninth Revision, Clinical Modification (ICD-9-CM) diagnosis codes are missing. A further 176,564 subjects were excluded because they were not admitted during the risk period 28 May – 3 August. The final study population (i.e., final analysis sample) contained 38,476 admissions. Exclusions were summarized in the following flow diagram.



Case ascertainment

Records containing codes 493.00–493.99 in ESSENCE data field “DiagnosisICD9Code1” were cases (i.e., morbid asthma outcomes).[18] All other records were controls. Cumulative density sampling was applied throughout except where noted.[19] The term “ED admission” was restricted to diagnosed cases.[20]

Heatwave exposure assessment

Heatwave exposure was defined by two methods: ED admission year (regardless of temperature) or daily mean ambient temperature (DMAT) on admission day relative to the median DMAT ($DMAT_m$), regardless of year. When comparing ED asthma risk by admission year (Model A) for this study, subjects admitted in 2012 were “exposed” and subjects admitted in 2011 were “unexposed” to the heatwave. When comparing ED asthma risk by temperature (Model B), subjects were classified as “exposed” [to higher temperatures] if admitted when the DMAT was > $DMAT_m$ and “unexposed” if admitted when the DMAT was ≤ the $DMAT_m$, regardless of the admission year. Temperature data were obtained from federal and Douglas County Health Department sources.[12,21] Data variability was typically associated with time units (i.e., per minute, per hour, per day, etc.) and methodology.[22] The $DMAT_m$ was derived by ranking all DMAT values (n = 38,476) in ascending order and using the following formula to find the middle value:

$$DMAT_m = \frac{n+1}{2};$$

where n is the number of values in the sample.

Ambient temperature and relative humidity were monitored using residentially-located Met One Model # 083E-1-35 sensors (Met One Instruments, Inc. 1600 Northwest Washington Blvd. Grants Pass, OR 97526).

The hourly mean ambient temperature (HMAT) was derived from raw NOAA data during July 2012 in Omaha, NE. Mean hourly temperature estimates were calculated for 0:55 A.M., 1:55 A.M., 2:55 A.M., ..., 21:55 P.M., 22:55 P.M., and 23:55 P.M. for July 2012.

In an analysis of only 2012 admissions, subjects admitted from 19 June through 3 August 2012 (exposed) were compared with subjects admitted 28 May to 18 June 2012 (unexposed). The 19 May to 3 August risk period included the longest period of consecutive extreme-heat days and incorporated duration, an important criterium of contemporary heatwave definitions.[12,23]

In an analysis using incidence density sampling, controls were frequency matched by admission date and time with cases. Only subjects admitted on the same day and within one hour of a specific asthma case were randomly selected as controls for that case at a ratio of five controls per case. Unfortunately, ED_A and ED_C admission-time data were not recorded in the ESSENCE database for the period of interest.

Secondary predictor variables

Meteorologic (i.e., relative humidity, dew point, wind rose, ambient temperature, etc.), air pollution (SO_2, NO_x, lead, PM_{10}, $PM_{2.5}$, CO, etc.) and ozone air quality index (O_3 AQI) parameters were obtained from the National Center for Environmental Information (NCEI), the US EPA, and the Douglas County Health Department Air Quality Laboratory (DCHD AQL).[11,24] The DCHD AQL is an NCore air pollution monitoring site and provides daily air pollution data in National Ambient Air Quality Standard (NAAQS) units to the US EPA for core-based statistical area #36,540 which includes Omaha, NE, Council Bluffs, IA, and the surrounding area.[25] A mean was calculated for pollutants with multiple monitoring sites (i.e., DCHD-AQL monitors ozone at three separate County locations). Missing data were substituted with the nearest known 24-h mean value, or the mean of the two known values before and after the missing value. For example, a missing raw data sequence of ... 90 80 __ __ __ 60 70 ... would appear as ... 90 80 80 70 60 60 70 ... in the analysis file. Less than one percent of meteorologic and air quality data were missing.

Data analysis

Data were analyzed using contemporary statistical software (*STATA*®, Stata/SE 12, Release 12; StataCorp LP, 4905 Lakeway Drive, College Station, TX 77845; and *R*, Vienna, Austria) and methods. All estimates were presented with ± 95% confidence intervals (95% CI). The relative odds were estimated by conditional logistic regression and represented either a relative odds (odds ratio; OR) or an incidence density ratio (IDR).[19] The dependent variable was an ED asthma diagnosis. Independent predictor variables included dichotomous demographic (age, gender, race), air quality index (O_3 AQI), air pollution (nitrous oxide, sulfur dioxide, PM_{10}, $PM_{2.5}$), and meteorologic (temperature, relative humidity, absolute humidity) parameters.

Air pollution and meteorologic exposure categories were derived from the median of the admission-weighted sample. However, ozone exposure categories were derived from an ozone AQI < 50 on the admission date. An AQI < 50 indicated "Good" air quality.[26]

Ambient pollen air quality data were missing or incomplete for the risk period and were omitted from logistic regression models. Indoor tobacco smoke exposure data were also missing. However, the impact of these unknown confounders on risk estimates was assessed in sensitivity analyses (See "Bias" section).

Bias

Systematic bias was mitigated to some extent by using (1) only uniform, widely-accessible, federally-audited (i.e., EPA, NOAA) meteorologic and air quality data; and (2) monitoring instruments that are federally approved and routinely calibrated and audited within narrowly prescribed federal standards. Information bias was mitigated by (1) selecting subjects from a uniform, regularly-managed, and widely-used database of anonymous ED populations, and (2) using predictor variables that were complete or near complete (>95%) in their data sources in conditional logistic regression models.

Risk estimate uncertainty arising from differential selection, exposure, and unknown confounder bias was assessed by sensitivity analyses.[27] Differential exposure misclassification sensitivity analysis was based on 20,000 simulation replicates that assumed exposure sensitivities and specificities of (0.75, 0.85, 0.95, and 1.0) among cases and exposure sensitivities and specificities of (0.70, 0.80, 0.90, and 0.95) among controls. Selection misclassification sensitivity analysis was based on 20,000 replicates in a log-Normal distribution with a mean equal to zero, and a standard deviation of 0.21. Unmeasured confounding from grass pollen exposure was based on 20,000 simulation replicates with respective pollen exposure prevalence between 0.4 and 0.7 among the heatwave exposed and unexposed, a relative risk of 1.42,[28] and a standard deviation of 0.28. Similarly, probabilistic sensitivity analyses for unmeasured confounding from tobacco smoke exposure was based on 20,000 simulation replicates with a respective smoking prevalence of 9.5% in one scenario and 23.0% in another scenario among heat-wave-exposed and unexposed subjects, a relative risk of 1.20, and a standard deviation of 0.102.[29]

Dichotomous variable factor analyses with rotated factor loading $\geq \pm$ 0.4 and three to five retained factors were used to explore latent constructs.

Results

In 2012 the County's general population median age was 33.7 years and the male to female ratio was 0.97. Racially, residents were 79.4% White, 11.2% African–American, 3.3% Asian/Pacific Islander, 0.5% Native American/Alaskan Native, and 5.6% identified as "Other." Hispanics were 12.0% of all residents. In contrast, the ED study population median age was 28 years and the male to female ratio was 0.79. Racially, subjects were 74.0% White, 16.4% African–American, 0.8% Asian/Pacific Islander, 0.8% Native American/Alaskan Native, and 8.0% other "racial" categories. The ED population's ethnicity was 5.4% Hispanic/Latino, "Hispanic" or "Latino" were grouped together. There were 18,539 ED admissions and 19,937 ED admissions during the 2011 and 2012 risk periods, respectively. Daily mean admissions and daily mean asthma admissions were higher during the 2012 risk period than the 2011 risk period (not shown). The mean ED admission age was 31.2 (30.84–31.54) years during the 2011 risk period and 31.5 (31.14–31.84) years during the 2012 risk period. Overall, subjects 0 to 9 years old represented twenty-four percent and subjects 65 years and older represented almost eleven percent of admissions, indicating a right skew ($p < 0.0001$).

ED admission and DMAT were negatively correlated ($r = -0.0384$; -0.204 to -0.027) during the 2011 risk period, but positively correlated ($r = 0.279$; 0.042–0.487) during the 2012 risk period (Fig. 1). *P*-values suggested no correlation (i.e., H_o: $\rho = 0$) between ED admission and DMAT in 2011 ($\alpha = 0.05$; $p < 0.81$), but a significant correlation in 2012 ($\alpha = 0.05$; $p < 0.03$). Estimated least square plots clearly showed that DMAT was a positive predictor of ED admissions during the 2012 risk period and a negative predictor during the 2011 risk period. Mean temperature, mean maximum temperature, maximum temperature $\geq$90 °F, and the frequency of five-day episodes in which the maximum temperature $\geq$90 °F, were higher for both 2011 and 2012 risk periods compared to the same months of the previous three decades (not shown). The admission-weighted DMAT mean for the 2012 risk period (84.2 °F; 84.13–84.33) was significantly different from 2011 risk period (81.7 °F; 81.54–81.76) (*t*-test = 34.8; $p < 0.0001$; $\alpha = 0.05$).[30]

ED admissions peaked for nearly all age groups as DMAT neared 75°, 81°, and 89 °F, regardless of admission year (Fig. 2). The peak asthma admission rate in 2012 coincided with the longest period of consecutive and intense temperatures in 2012 (not shown). ED admissions in July 2012 rose and fell with the HMAT, peaked during the hottest time of the day (3 P.M.–5 P.M.), and declined afterward (not shown). Most 2012 admissions occurred between 10 A.M. and 10 P.M., when the HMAT was approximately 85 °F or above. The higher correlations ($r \geq 0.76$) between ED admission age and DMAT occurred among persons $\leq$10 years old, 60–64, and 85–89 years old (not shown). Fig. 3 illustrates how DMAT accelerated approximately 1.35 times (i.e., a ratio of regression coefficients) faster through the 2012 risk period than the 2011 risk period, and predicted an 89.6 °F DMAT by 3 August 2012 compared to an 85.1 °F DMAT by 3 August 2011. Persons diagnosed with asthma were disproportionately younger than 19 years old, were male, were African-American, and were admitted during the 2012 risk period compared to the 2011 risk period (not shown). Chi-square (χ^2) test of equal distribution of cases and controls among dichotomous age ($\chi^2 = 167.8$; $\alpha = 0.05$; $p < 0.0001$), gender ($\chi^2 = 9.7$; $\alpha = 0.05$; $p < 0.003$), race ($\chi^2 = 161.6$; $\alpha = 0.05$; $p < 0.001$), admission-year ($\chi^2 = 4.6$; $\alpha = 0.05$; $p < 0.04$), and admission temperature ($\chi^2 = 9.7$; $\alpha = 0.05$; $p < 0.03$) groups indicated that their distributions could not be explained by chance alone.

Asthma ED diagnosis relative odds based on admission year (Model A; OR = 1.23 (0.96–1.57)) or temperature on admission day (Model B; 1.19 (0.96–1.47)) analyses were similar. The Wald chi-square was 317.8 ($p < 0.0001$) for Model A and 312.2 ($p < 0.0001$) for Model B. The odds of being diagnosed with asthma was 3.4 (2.72–4.17) times higher among subjects less than 19 years old compared to subjects 19 years and older (Table 1). The odds of being diagnosed with asthma were 3.3 (2.63–4.02) times higher among African–American subjects compared non-African–Americans (Table 1). ED-specific relative odds estimates based on admission year (Model A) ranged from 1.54 (1.07–2.22) at ED_A, 1.19 (0.79–1.79) at ED_B, to 0.65(0.34–1.26) at ED_C. ED-specific relative odds based on the admission temperature ranged from 1.26 (0.93–1.72) at ED_A, 1.14(0.80–1.61) at ED_B, to 1.03(0.58–1.83) at ED_C. Absolute humidity concentrations above 12.7 g/m^3 suggested a lowering of ED asthma relative odds.

Analyses limited to a specific stratum (i.e., only subject < 19 years old, only males, or only subjects who identified as African–American, or only subjects admitted when the absolute humidity was less than the median) modified asthma ED diagnosis relative odds in both models (not shown).

The overall asthma diagnosis odds were 1.37 (0.98–1.91) times higher among subjects admitted from 19 June to 3 August 2012 admissions compared to subjects admitted from 28 May to 18 June (Table 2). ED stratified asthma diagnosis odds were 1.38 (0.86–2.15), 1.41 (0.79–2.50), and 1.04 (0.38–2.49) times higher at ED_A, ED_B, and ED_C respectively, among admissions from 19 June to 3 August compared to admissions from 28 May to 18 June 2012. A factor-analysis-derived model that excludes gender, SO_2, and $PM_{2.5}$ produces an overall relative odd of 1.41(1.0–1.93).

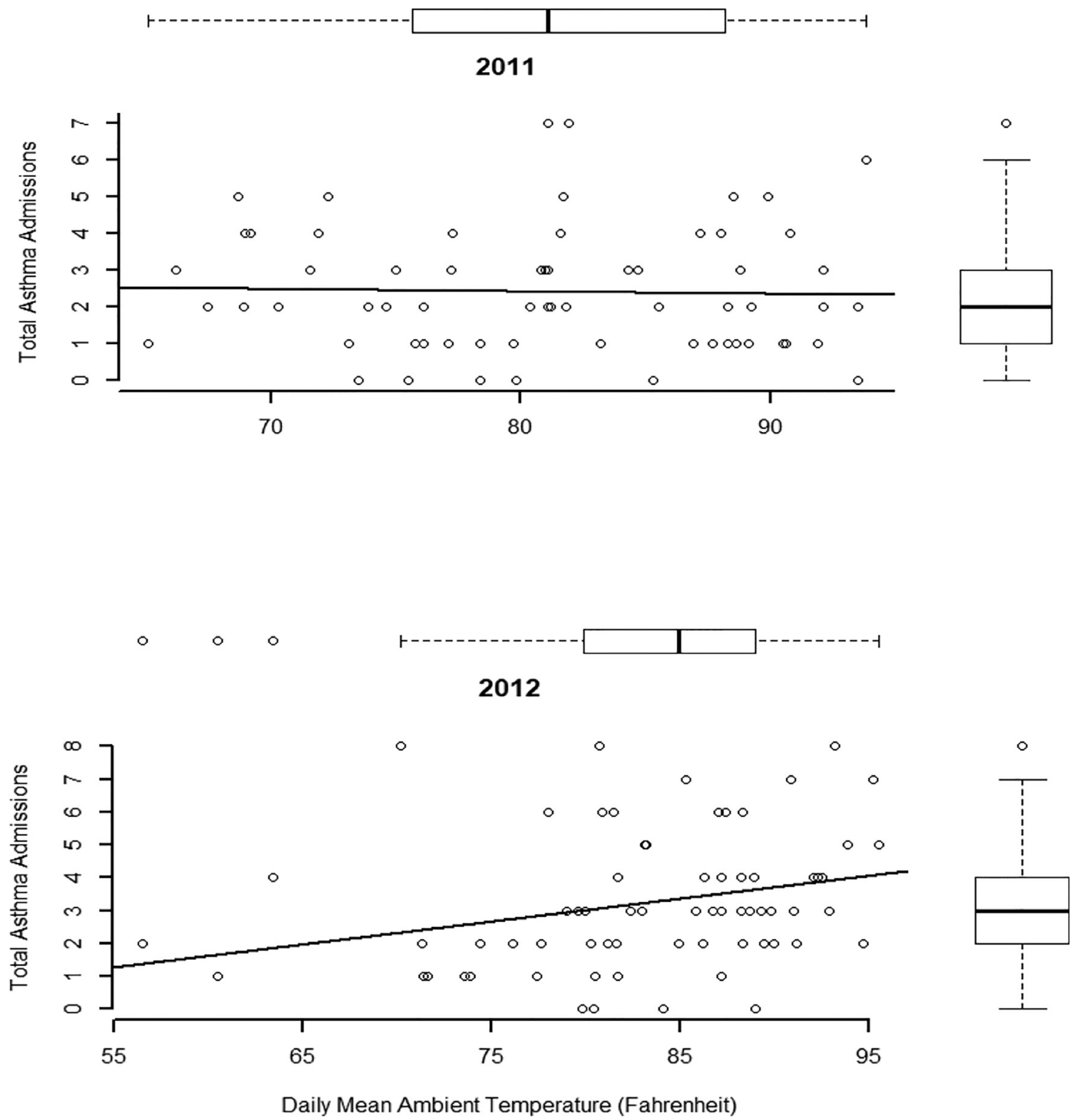


Fig. 1. All 2011 (Top) and 2012 (Bottom) Asthma ED Admissions by Mean Temperature with Regression Line (▯) and Box and Whisker Plots ().

Relative odds (odds ratio) derived from cumulative density sampling and incidence density ratios (IDR) derived from incidence density sampling produced identical asthma ED diagnosis relative odds in Model A. However, as expected, the IDR risk estimate was attenuated in Model B (OR $_{\text{cumulative density sampling}}$ = 1.41 (0.80–1.61) vs. IDR $_{\text{incidence density sampling}}$ = 0.96 (0.65–1.42)) due to indirect temperature matching that occurred during incidence density sampling and frequency matching of cases and controls on the date and time-of-day of the admission.

The relative odds of an asthma ED diagnosis appeared to be inversely related to ambient absolute humidity (Table 1, Fig. 4).

Probabilistic sensitivity analyses produced an adjusted relative odds of 1.32 (0.90–1.95) for exposure misclassification, 1.25 (0.79–1.97) for selection misclassification, 1.25 (0.89–1.77) for unknown grass pollen exposure assuming 0.4–0.7 exposure prevalence among subjects and a relative risk of 1.42, and 1.25 (0.95–1.64) for unknown tobacco smoke exposure assuming 9.2–23.0 exposure prevalence among subjects and a relative risk of 1.20. The unadjusted (i.e., crude) relative odds estimate was 1.25 (1.02–1.53) in each scenario above.

Factor analysis variables grouped into categories that could be called “air quality” (PM_{10}, $PM_{2.5}$, SO_2 and O_3 AQI), “meteorologic” (absolute humidity, heatwave), and “demographic/biologic” (age) constructs. These constructs (i.e., air quality, meteorologic, and demographic/biologic) are known to impact asthma onset and severity. Scree plots suggested that three factors accounted for 84% of all the variation, with factor #1 (“air quality;” eigenvalue = 1.216) explaining 42% of all the variation in the estimate. No new constructs clearly emerged.

Discussion

Overall ED asthma diagnosis risk was elevated approximately 1.23 times higher from 28 May through 3 August 2012 compared to the same risk period in 2011; regardless of the model. Although the 95% confidence intervals of both relative odds included 1.0 and the *p*-values indicated that the estimate may have been a chance occurrence, the overall probability that asthma ED risk was equal to zero was less than 0.0001. Since both 2011 and 2012 were warmer years than the prior three decades for the same calendar period (see Results section), the temperature differences between the exposed and

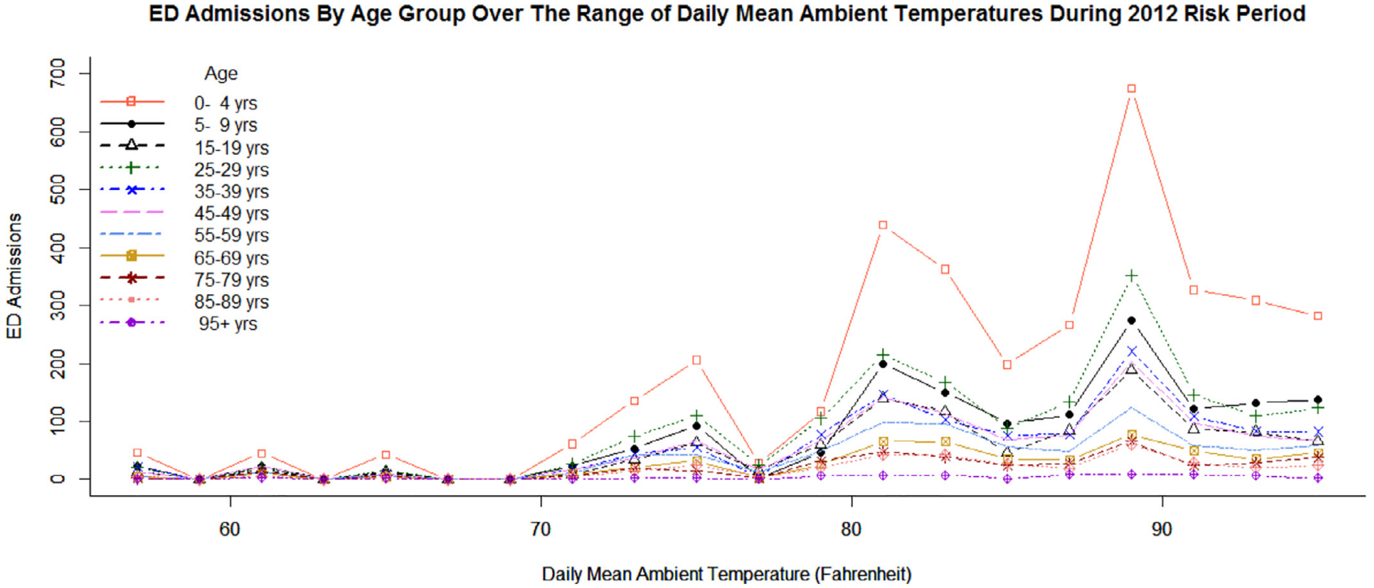


Fig. 2. Douglas County ED admissions frequency over the range of daily mean ambient temperature (°F) during the 2012 risk period (i.e., 28 May – 3 August 2012).
Daily Mean Ambient Temperature from 28 May–03 August 2011 and 2012.
In Douglas County, NE.

unexposed based on only 2011 and 2012 data were not sufficient to demonstrate a statistically significant difference. Similarly, an analysis of only those subjects admitted during the 2012 risk period indicated that asthma diagnosis risk was approximately 1.4 times higher for subjects admitted from 19 June to 3 August compared to subjects admitted from 28 May to 18 June. Again, the estimated relative odds although elevated, was not statistically significant and the 95% confidence interval included 1.0. Observing risk estimates in Douglas County's ED population that were similar to estimates reported elsewhere, highlighted the consistency and continuity of an association between heatwaves and asthma and suggested that people living in this region of the United States responded similarly to people living elsewhere.[31] It is remarkable that asthma diagnosis risk is elevated across three different comparisons: between years (Model A), between $DMAT_m$ (Model B), or between admissions that occurred prior to or following an extended period of consecutive days with DMAT $\geq$ 90 °F (Table 1).

The study's strengths included a well-defined population, concurrent case and control selection, and complete high-quality air pollution and meteorologic data. Three-fold relative odds among subjects less than 19 years old and among African-American subjects suggested that the age and race associations were strong in specific subgroups and concurred with a majority of previous reports. Furthermore, this was an inexpensive approach because nearly all

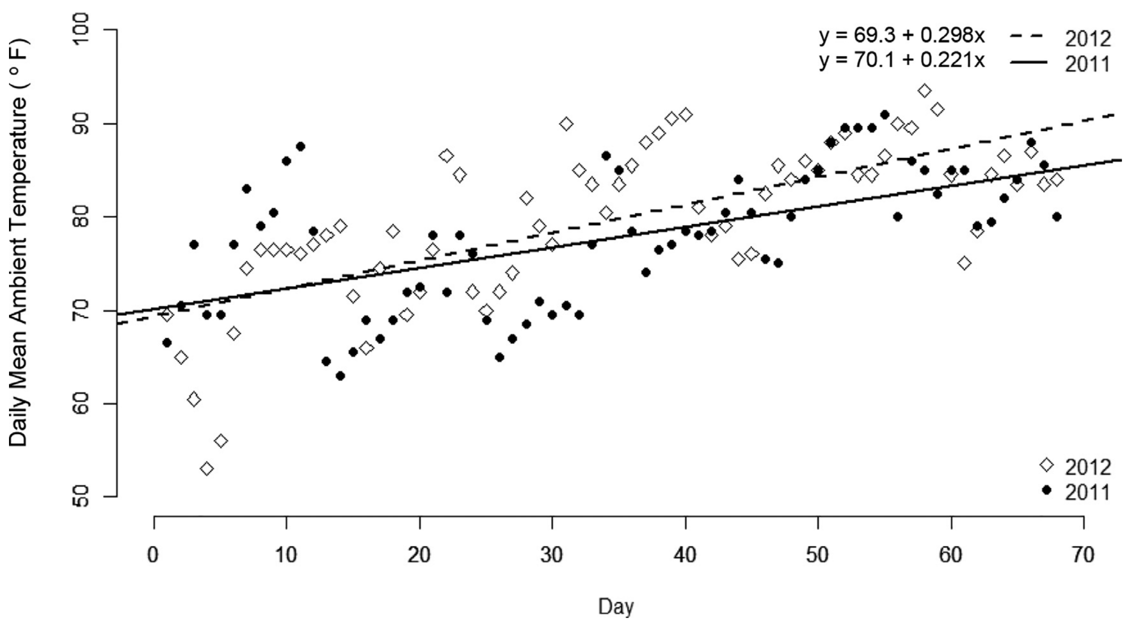


Fig. 3. Daily mean ambient temperature (*y* axis; °F) scatter and predicted regression line plots over the 2011 and 2012 risk period (*x* axis; day) in Douglas County, NE.
Asthma ED Admission Frequency Scatter and Predicted Regression Line Plots
Over the Range of Ambient Absolute Humidity Concentration.
28 May–3 August in 2012 in Douglas County, NE.

Table 1
Comparison of regression models by exposure of interest and confounding factors ($N = 38{,}474$)

Primary Exposure/Predictor of Interest	Model A*	Model B*
ED Admission in 2012	Crude 1.25(1.02–1.53) Adjust 1.23(0.96–1.57)	–
> Daily Mean Ambient Temperature ($DMAT_m$)	–	Crude 1.21(0.99–1.48) Adjust 1.19(0.96–1.47)
Secondary Predictor/Modifier of Interest		
Demographic Factors		
• Age < 19 years old	3.37(2.72–4.17)	3.35(2.71–4.15)
• Male Gender	1.19(0.96–1.45)	1.19(0.97–1.45)
• African-American	3.25(2.63–4.02)	3.26(2.64–4.02)
• Ethnicity (Hispanic)**	0.59(0.33–1.05)	0.59(0.33–1.06)
Air Quality Factors		
• PM_{10} > Median	0.99(0.76–1.18)	0.99(0.78–1.25)
• $PM_{2.5}$ > Median	1.07(0.84–1.35)	1.03(0.82–1.30)
• SO_2 > Median	0.95(0.76–1.19)	0.90(0.74–1.12)
• Ozone AQI > Median	0.95(0.78–1.18)	0.92(0.74–1.16)
ED Strata		
• A (Mean age 4.9, s.d. 5.0, range 0–61)	1.54(1.07–2.22)	1.26(0.93–1.72)
• B (Mean age 34.5, s.d. 24.4, range 0–111)	1.19(0.79–1.79)	1.14(0.80–1.61)
• C (Mean age 42.5, s.d. 23.7, range 0–110)	0.65(0.34–1.26)	1.03(0.58–1.83)
Meteorologic Factors		
• Absolute Humidity > median (g/m^3)	0.90(0.72–1.13)	0.86(0.71–1.07)
• Absolute Humidity Concentration Strata		
°(>15.6)	Reference	Reference***
°(>12.7 and ≤15.6)	1.22(0.86–1.74)	0.91(0.67–1.24)
°(>9.4 and ≤12.7)	1.22(0.87–1.71)	1.05(0.77–1.46)
°(≤9.4)	1.35(0.97–1.87)	1.14(0.82–1.56)

s.d. = standard deviation, range = [age] range in years.
* Odds Ratio (±95% Confidence Interval) adjusted for demographics (age, gender, African-American race, and ethnicity), air pollutants (greater than the median PM_{10}, $PM_{2.5}$, SO_2, O_3 AQI > 50), and greater than the median absolute humidity.
** Hispanic includes subject labeled as Hispanic or Latino in the database.
*** Chi Squared for trend: χ^2 ($p < |z|$) < 0.001.

Table 2
ED stratified asthma diagnosis risk among subjects admitted 28 May–18 June 2012 (unexposed) vs. subjects admitted June 19–3 August 2012 (exposed)

Emergency department	N	Mean age in years (s.d.; range)	OR_{adj} (95% CI)[a]
Overall	19,936[b]	31.4 (24.4; 0–101)	1.37(0.98–1.91)
A	4262	4.9 (4.3; 0–45)	1.38(0.86–2.15)
B	7537	30.5 (20.6; 0–101)	1.41(0.79–2.50)
C	8137	42.1 (23.6; 0–100)	1.04(0.38–2.87)

[a] OR_{adj} = adjusted for demographic, O_3 AQI > 50, and > median ambient air $PM_{2.5}$, PM_{10}, SO_2, and absolute humidity.
[b] Gender unknow for one observation.

the needed resources were in the public domain. Finally, and most important, the risk was assessed during a rare meteorologic event and represented an opportunity to study these phenomena in the context of related health outcomes.

Despite these strengths, there were limitations and threats to study validity arising primarily from systematic, selection and information bias. One of the primary sources of systematic bias associated with this approach was poorly and/or improperly calibrated air quality and meteorologic monitoring instruments that consistently overestimated or underestimated air pollutants.[24] If exposure assignment error (misclassification) is differential among cases and controls the risk estimate will overestimate or underestimate the risk. Bias sampling, selecting only those study subjects who sought care in an ED, may also lead to biased risk estimates because ED subjects may have different exposure histories than people seeking care in non-ED settings. If exposure assignment or subject participation is nondifferential, the overall estimate is attenuated. Information bias arises from misclassification of exposure, case, and predictor subgroups. Any could attenuate or exaggerate asthma ED risk estimates based on the sensitivity or specificity of the exposure and/or case assignment.[32,33] Case ascertainment bias might have occurred as a result of diagnostic code errors (or omissions) and differential case ascertainment among study subjects, either underestimating or overestimating risk. Ecologically-assigned exposures may either overestimate or underestimate individual-level exposure to temperature and/or air quality. Either could have affected the time of symptom onset, severity, and/or duration of the asthma episode.

Sensitivity analyses suggested that selection bias (i.e., cases vs. controls) had the greatest impact on risk estimate uncertainty. However, these bias-adjusted risk estimates merely represented the best available evidence and current scientific knowledge about the distribution and role of bias in this specific exposure-disease association. Clearly, one cannot ignore that the 2012 heatwave was rare in intensity, duration, precipitation, and frequency compared to previous heatwaves in this community. Consequently, the unique meteorologic conditions might explain the higher Douglas County asthma ED risk estimates, compared to results elsewhere reported.[6–10]

Yet to be resolved is how comorbid disease, medications, gene-environment interaction (biology), pollen concentrations, indoor air quality (especially tobacco smoke exposure), and how ecologic exposure assignment affected relative odds estimates.[28,34–40] Clearly, the risk estimates presented in this study were generalized to the ED population and were directed at whether ED diagnosis risk is elevated during the 2012 risk period relative to the 2011 risk period. It was also unclear how Hispanic/Latino ethnicity might lower ED diagnosis risk relative to non-Hispanic ethnicity.

Despite these validity threats, prior reports support the meteorologic[4,5,9,41,42] and sociodemographic[9,10,43] observations. Obviously, ambient absolute humidity (Tables 1) associated risk was an interesting observation and requires further study.[44]

What else should health practitioners take away from this study? First, public health practitioners should note that (1) weather forecasts that include five or more consecutive days of DMATs ≥ 90 °F (32.2 °C) and absolute humidity ≤ 10 g/m^3 may be criteria for activating local heatwave emergency response plans that emphasize children less than ten years old and adults 65 years and older,[2,41,45,46] and (2) all of the meteorologic and air quality raw data and R statistical software are in the public domain.[11,15,47–49] Although access to human subject records

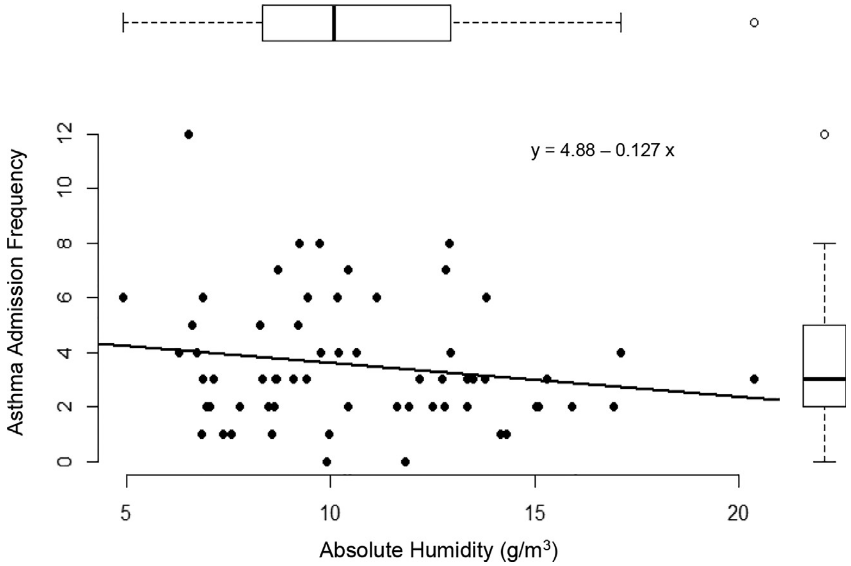


Fig. 4. Asthma admission frequency scatter and predicted regression line plots over the range of ambient air absolute humidity concentrations from 28 May–3 August 2012 in Douglas County, NE.

can be more challenging, this study suggested that case data are potentially available for many locations.[50] Furthermore, public health practitioners must recognize that asthma suffers are at an increased risk of other heat-related illnesses because breathing is a thermoregulatory process that impacts other organ systems.[51] Practitioners must understand how heat stress impacts overall lung function; particularly among asthma sufferers. Pulmonary disease practitioners must integrate gene-environment pathway models that include heat stressors.[36,39] Acute care practitioners must understand how the chief complaint in an array of symptoms is modified by extreme, prolonged ambient temperatures, and how that array of signs and symptoms fits into asthma's diagnostic spectrum during heatwaves. Pulmonary disease and acute care practitioners must simultaneously assess additional comorbid conditions and associated medication that compromise thermoregulation and exacerbate comorbidity in other organ systems. Finally, acute care practitioners must conduct an indoor environmental assessment that can be as simple as asking patients (or guardians) if their dwellings are currently air-conditioned. If air conditioning is unavailable, arrangements can be made with social networks to ensure that indoor air-conditioned environments await patients prior to discharge.

The overall climate implications are obvious. If heatwaves become more prevalent and severe, so will heat-related illnesses.[52] Absolute humidity and the DMAT rate increase suggest further study (Figs. 3 and 4).[53] The next steps involve developing and adopting epidemiologic methods that aid in estimating general population risk.[54] Follow-ups to this investigation should include better study designs that mitigate systematic bias such as nested case-control designs that collect information not available for this study (i.e., tobacco smoke exposure, sibling information, diet, and other hypersensitivity-related health outcomes, etc.).

Conclusion

Asthma ED diagnosis risk was not significantly elevated among subjects admitted in 2012 compared to ED subjects admitted for the same calendar period in 2011. The probability that modeled independent variables had no effect on asthma ED diagnosis risk estimates was very low. Subjects who were less than 19 years old or African-American experienced a three-fold increase in asthma diagnosis risk, adjusted for heatwave exposure. The risk associated with ambient absolute humidity requires further study.

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Disclosure

Dr. Figgs has nothing to disclose.

Supplementary materials

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.hrtlng.2018.12.005.

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