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Large-scale agricultural burning and cardiorespiratory emergency department visits in the U.S. state of Kansas

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Abstract

Background: Prescribed agricultural burning is a common land management practice, but little is known about the health effects from the resulting smoke exposure.

Objective: To examine the association between smoke from prescribed burning and cardiorespiratory outcomes in the U.S. state of Kansas.

Methods: We analyzed a zip code-level, daily time series of primary cardiorespiratory emergency department (ED) visits for February–May (months when prescribed burning is common in Kansas) in the years 2009–2011 (n=109,220). Given limited monitoring data, we formulated a measure of smoke exposure using non-traditional datasets, including fire radiative

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Author Contribution Statement

FY, FA, and KS conceived of the work. AP, AV, AM, MM, KS, and WDF contributed to study design. FA obtained the health data. AV and AM developed the exposure estimate. AP and WDF completed the analysis. AP and AV drafted the manuscript. All authors contributed to the interpretation of results and to the revision of the manuscript.

Ethical Approval

This activity was reviewed by the Centers for Disease Control and Prevention (CDC) and was conducted consistent with applicable federal law and CDC (See e.g., 45 C.F.R. part 46, 21 C.F.R. part 56; 42 U.S.C. §241(d); 5 U.S.C. §552a; 44 U.S.C. §3501 et seq.)

Competing Interests

The authors declare they have no competing financial interests. Dr. Flanders discloses that he owns a consulting company, Epidemiologic Research & Methods, LLC that does consulting work for clients. He knows of no conflicts with this work.

power and locational attributes from remote sensing data sources. We then assigned a population-weighted potential smoke impact factor (PSIF) to each zip code, based on fire intensity, smoke transport, and fire proximity. We used Poisson generalized linear models to estimate the association between PSIF on the same day and in the past 3 days and asthma, respiratory including asthma, and cardiovascular ED visits.

Results: During the study period, prescribed burning took place on approximately 8 million acres in Kansas. Same-day PSIF was associated with a 7% increase in the rate of asthma ED visits when adjusting for month, year, zip code, meteorology, day of week, holidays, and correlation within zip codes (rate ratio [RR]: 1.07; 95% confidence interval [CI]: 1.01, 1.13). Same-day PSIF was not associated with a combined outcome of respiratory ED visits (RR [95% CI]: 0.99 [0.97, 1.02]), or cardiovascular ED visits (RR [95% CI]: 1.01 [0.98, 1.04]). There was no consistent association between PSIF during the past 3 days and any of the outcomes.

Significance: These results suggest an association between smoke exposure and asthma ED visits on the same day. Elucidating these associations will help guide public health programs that address population-level exposure to smoke from prescribed burning.

Impact Statement: In this time series study, we examined the health effects of smoke exposure from prescribed agricultural burning in Kansas. Our findings suggest an association between smoke from prescribed burning and emergency department visits for asthma, but not for cardiovascular outcomes.

Keywords

prescribed burning; smoke; asthma; respiratory; cardiovascular; epidemiology

Introduction

Wildland fire smoke is associated with irritation of the respiratory system, exacerbations of chronic diseases such as asthma and chronic obstructive pulmonary disease, and premature mortality [1, 2]. Exposure to smoke is particularly hazardous for individuals with preexisting respiratory and cardiovascular disease [3].

Large-scale prescribed agricultural burning, a contributor to wildland fire smoke emissions, is a common land management practice. Prescribed burning of invasive vegetation and old growth returns nutrients back to the soil and can be beneficial to the surviving plants and landscapes [4]. It is used to reduce fuel loading in forested and agricultural areas and hence potentially prevent wildfires, and also used to enhance native vegetation, and maintain ecosystems [4, 5]. The smoke from prescribed burning contains numerous air pollutants including particulate matter, carbon monoxide, nitrogen oxides, and volatile organic compounds [5]. The known health effects of inhalation of air pollution include detrimental effects on the cardiovascular and respiratory systems [6].

Although the impact of prescribed burning on air quality is well described [7–11], research on its impact on health is limited [7, 12]. Results from the few studies on the health effects of prescribed burning suggest adverse health impacts from this practice. One study conducted in the southeastern United States estimated a modest increase in emergency department (ED) visits for asthma due to exposure to smoke from prescribed burning [13]. A second study conducted in this region used information from burn permits and concentration-response functions to estimate that prescribed burning is associated with asthma ED visits, hospital admission for respiratory reasons, and premature death [14]. In a different region of the United States, a study in the Pacific Northwest used a health impact assessment tool and observed associations between prescribed burning and an increase in respiratory symptoms, bronchitis, lost days of work, and death [15].

The Flint Hills region of Kansas and northern Oklahoma is a tallgrass prairie where approximately 2 million acres are cleared by prescribed agricultural burning each spring [16]. Burning in this region promotes the growth of desired grass species and controls woody species growth ultimately resulting in increased cattle weight gain [17, 18]. These burns are a substantial contributor to air pollution [19, 20]. Levels of air pollution that exceed the National Ambient Air Quality Standards have been recorded in Kansas and nearby states following prescribed burning activities [18]. In 2017, it was estimated that prescribed burning was responsible for 44% of primary fine particulate matter ($PM_{2.5}$) emissions in Kansas, compared with only 14% nationally [21]. Despite elevated air pollution levels, the health effects of smoke exposure resulting from prescribed burning in Kansas is currently unknown. This study sought to determine the impact of prescribed agricultural burning on cardiorespiratory ED visits in Kansas.

Materials/Subjects and Methods

We conducted a time series study in the state of Kansas using a measure of smoke exposure formulated from non-traditional datasets and daily zip-code level cardiorespiratory ED visits from 2009 to 2011.

Limited air quality monitoring data were available for the region and time period of interest. Additionally, we found no accessible information on the dates and locations of prescribed burns. In the absence of this information, we used remote-sensing data and model-based predictions to calculate a “potential smoke impact factor” (PSIF; described below) and used the PSIF to characterize population-level exposure to smoke from agricultural burning. We downloaded burn-related information from the National Aeronautics and Space Administration’s (NASA) Fire Information for Resource Management System [22]. Specifically, we obtained information from NASA’s Moderate Resolution Imaging Spectroradiometer aboard the Terra and Aqua satellites, which identify fire pixels that have had one or more fires. From these 1×1 kilometer (km) pixels, we extracted information on maximum fire radiative power (FRP) for each day in our spatial and temporal domains. Typically, FRP is used to ascertain emission rates and factors [23–26], but for this assessment we used it to approximate fire intensity.

Initially, we considered using a distance-weighted measure of FRP for each block group without considering other meteorologic factors. However, as highlighted by Waller and colleagues [27], distance-weighting alone will not capture the true “exposure potential” as air pollutant impacts may depend not just on distance to emission sources but also on other factors such as wind characteristics. Hence, population-exposure resulting from fires with differing fire intensities was estimated factoring in both smoke dispersion and proximity to each fire location. Smoke dispersion from the location of each individual fire was assumed to be heavily influenced by wind speed and direction as agricultural burning happens over grasslands with no significant elevation differences.

We combined information on fire intensity with estimates of surface meteorological parameters generated from the North American Land Data Assimilation System Phase 2 (NLDAS) model [28]. First, we created eight wind sector designations of 45° each based on a continuous measure of wind direction (i.e., 22.5°– 67.4°, 67.5°– 112.4°, 112.5°– 157.4°, 157.5°– 202.4°, 202.5°– 247.4°, 247.5°– 292.4°, 292.5°– 337.4°, 337.5°– 22.4°). Using hourly wind characteristics, we calculated daily wind probability and speed for each of the eight wind-sector designations, for each fire pixel and separately for each U.S. Census block group. We also created a distance matrix, providing the distance between each fire pixel and block group in Kansas. We limited the radius of influence for each fire to block groups within 100 km. After using wind direction and location to identify block groups that potentially could receive smoke from a fire due to congruent wind direction, we used the inverse of the squared distances between centroids of each block group and fire pixel as weights to calculate a daily smoke exposure metric for each block group. Of note, using a distance-weighted approach is common in environmental health, especially to assign pollution impacts from a specific source [27, 29, 30]. We then generated population-weighted estimates of this potential smoke impact factor (PSIF) at the zip code level from block group level estimates to align with the geographic resolution of the available health data.

We evaluated the PSIF metric using the limited available air quality monitoring data. During the period of this analysis, air quality data were available on $PM_{2.5}$ and ozone from 4 air quality monitors, coarse particulate matter (PM_{10}) from 2 air quality monitors, and carbon monoxide from 1 air quality monitor. $PM_{2.5}$ was sampled every 3 to 6 days; all other pollutants were sampled daily. The monitors were located in the cities of Wichita, Peck, Topeka, and Olathe; all in Eastern Kansas. We matched PSIF data with air monitoring data by zip code and estimated Pearson’s correlation coefficient (r).

We analyzed a zip code-level, daily time series of primary cardiorespiratory ED visits for the years 2009–2011. We examined three outcomes: 1) asthma ED visits 2) respiratory ED visits including asthma, wheeze, chronic obstructive pulmonary disease, pneumonia, and upper respiratory tract infections, and 3) cardiovascular ED visits including ischemic heart disease, dysrhythmia, congestive heart failure, and ischemic stroke (International Classification of Diseases, Ninth Revision, Clinical Modification [ICD-9-CM] codes listed in Table 1). Daily counts of ED visits for each outcome were calculated for each zip code in Kansas from individual-level data. We used zip code of patient residence for aggregating ED visits; ED visits were excluded if the patient resided outside the state of Kansas. ED data were obtained from the Kansas Hospital Association (KHA) and the Veterans Health Administration. On average, ED data were available from 100 KHA hospitals each year, representing approximately 73% of KHA member hospitals in Kansas during this period. Data were obtained from all Veterans Affairs hospitals in Kansas.

We used Poisson generalized linear models that accounted for overdispersion to estimate the association between PSIF (same-day [lag 0] and 3-day moving average [lag 0–2], i.e., same day and two previous days]) and asthma, respiratory, and cardiovascular ED visits. Analyses were restricted to the months when prescribed burning is common in Kansas (February–May) and to zip codes with at least one primary asthma ED visit and one primary cardiovascular ED visit during the analysis months. The distribution of PSIF was highly skewed towards 0 and was modeled in two ways: 1) a binary variable (presence vs. absence of smoke exposure) and 2) a 4-level variable (zero vs. tertiles of non-zero exposure). All models were implemented using generalized estimating equations with a first-order autoregressive correlation structure to allow for correlation within zip code. Covariate control for temporal and meteorologic factors was based on a previously developed model for estimating the association between air pollution and cardiorespiratory outcomes [31]. Adjusted models controlled for parametric cubic splines with monthly knots, year, zip code, day of week, holidays, cubic polynomials for lag 0 maximum temperature, cubic polynomials for lag 0 mean dew point, and cubic polynomials for lag 1–2 moving average minimum temperature (for models assessing 3-day moving average PSIF exposure).

For models with results indicating a health effect of prescribed burning, we also considered a negative control exposure (NCE) to evaluate residual confounding, model miss-specification and measurement error. In these analyses, we added PSIF 2 days in the future to the model and assessed its association with the outcome of interest. This negative control approach uses the fact that a future exposure cannot cause past health outcomes to assess potential biases [32–34]. We used PSIF 2 days in the future (rather than the typical 1 day used in this approach) because there is a morning satellite pass that may identify fires that started late on the previous day and were hence not captured in the previous day's exposure estimate.

All analyses were conducted in SAS 9.4 (SAS Institute, Cary, NC, USA) and R 4.02 [35]. This activity was reviewed by the Centers for Disease Control and Prevention (CDC) and was conducted consistent with applicable federal law and CDC policy[1].

Results

During the study years (2009–2011), prescribed burning took place on approximately 8 million acres in Kansas [36]. PSIF levels were highest in April, the month when prescribed burning was most frequent (Table 2, Figure 1). Levels were highest in the Eastern part of the state where the Flint Hills region is located (Figure 1). Comparing the PSIF to the limited available air quality monitoring data, there was moderate overall correlation between PSIF and $PM_{2.5}$ (r=0.33) with correlation at individual air monitors ranging from a minimum of r=0.16 to a maximum of r=0.49. Poor correlation was observed between PSIF and other air pollutants, such as, ozone, PM_{10}, and carbon monoxide.

Between February–May, 2009–2011, 9,824 primary asthma ED visits, 69,620 primary respiratory ED visits, and 39,600 primary cardiovascular ED visits were identified in the health dataset (Table 1). Of these ED visits, 98% were to KHA hospitals with the remaining

[1]See e.g., 45 C.F.R. part 46, 21 C.F.R. part 56; 42 U.S.C. §241(d); 5 U.S.C. §552a; 44 U.S.C. §3501 et seq.

2% to Veterans Affairs hospitals. The average patient age was 41 years old; 34.7% of ED visits were to individuals under the age of 18 (Table 3). Approximately half of visits were to patients of female sex (49.2%). The majority of visits were to patients of White or Black race (72.3% and 10.7% respectively) and non-Hispanic or Latino ethnicity (81.0%). Counts of asthma ED visits peaked in the spring and fall months (Figure 2).

Having a non-zero PSIF level was associated with a 7% increase in the rate of asthma ED visits on the same day in both unadjusted and adjusted models (rate ratio [95% confidence interval (CI)]: 1.07 [1.02, 1.13], 1.07 [1.01, 1.13] respectively) (Table 4). When comparing tertiles of exposure to a reference group of non-exposure, adjusted rates of asthma ED visits on the same day were 3% higher in the first tertile, 10% higher in the second tertile, and 7% higher in the third tertile (rate ratio [95% CI]: 1.03 [0.93, 1.15], 1.10 [1.01, 1.19], 1.07 [0.99, 1.15] respectively) than rates in the reference group of no exposure (PSIF=0). Having a non-zero three-day moving average PSIF level was associated with a 2% increase in the rate of asthma ED visits when adjusting for covariates (rate ratio [95% CI]: 1.02 [0.97, 1.08]) (Table 4). When comparing tertiles of 3-day moving average exposure to a reference group of non-exposure, the pattern was not monotonic; adjusted rates of asthma ED visits were 4% higher in the first tertile, 2% lower in the second tertile, and 6% higher in the third tertile (rate ratio [95% CI]: 1.04 [0.96, 1.12], 0.98 [0.92, 1.05], 1.06 [0.99, 1.04], respectively) than rates in the reference group of no exposure.

For the analysis between PSIF modeled as a binary variable and asthma, we evaluated the association of a NCE with the outcome, adding PSIF 2 days in the future to the model. We found no meaningful association between the future variable and asthma (results not shown) and inclusion of the future variable did not change the association between same-day PSIF and asthma. For this model to converge, we omitted zip code control for which had little impact in the main analyses.

When examining respiratory ED visits including asthma (Table 1), we found no evidence of an association with PSIF level. The adjusted rate ratios for both same-day PSIF level and 3-day moving average PSIF level were close to the null value of 1 (rate ratio [95% CI]: 0.99 [0.97, 1.02], 0.99 [0.97, 1.01], respectively) as were most of the rate ratios when comparing tertiles of exposure to a reference group of no exposure (Table 4).

For cardiovascular ED visits, we found no consistent evidence of an association with PSIF level. Having a non-zero PSIF level was associated with a 1% increase in the adjusted rate of ED visits on the same day (rate ratio [95% CI]: 1.01 [0.98, 1.04]), and having a non-zero 3-day moving average PSIF level was associated with a 3% decrease in the adjusted rate of ED visits (rate ratio [95% CI]: 0.97 [0.94, 0.99]). When comparing tertiles of exposure to a reference group of no exposure, results were mixed, with some results suggesting an increased rate of ED visits with increasing level of PSIF and other results suggesting a decreased rate of ED visits with increasing level of PSIF (Table 4).

Discussion

Our results suggest an association between smoke exposure during the months when prescribed burning is common (i.e., February–May) and asthma ED visits on the same day. Although negative controls are less than 100% sensitive for detection of bias due to confounding or model misspecification, the results of our NCE analyses showed no indication of major modeling or confounding issues impacting this result. We found no consistent evidence of an association between smoke exposure and all respiratory ED visits or cardiovascular ED visits. This study adds to the limited previous research suggesting adverse health impacts of smoke exposure resulting from prescribed burning.

Public health officials and land managers can take steps to limit exposure to smoke from prescribed burning. During seasons of prescribed burning activities, health departments can educate residents about protecting themselves from smoke exposure using some of the same actions recommended during episodes of wildfire smoke, including monitoring local air quality and keeping indoor air clean [3]. These precautions are particularly important for individuals at the highest risk for health impacts from smoke such as those with preexisting respiratory and cardiovascular disease. For land managers, the Kansas Flint Hills Smoke Management Plan details fire management practices that can be used to help limit smoke from prescribed burns [18]. These practices include using environmental and air quality conditions to inform when to burn and reducing fuel loads prior to burning. In the Flint Hills Region of Kansas, expanding the timing of prescribed burning to help diminish resulting smoke concentrations may also be an option [37, 38].

This study expands the scope of literature on the health effects of prescribed burning by being conducted in the state of Kansas and by using a different approach to estimating exposure to smoke from prescribed burning. Combining multiple environmental datasets to create the PSIF metric allowed us to estimate zip-code level exposure to smoke from prescribed burning in the absence of robust monitoring data. The combination of remote sensing data with surface wind characteristics allowed us to identify communities that are impacted by smoke from these fires. Because burning in Kansas occurs on a large-scale and in grasslands with a flat terrain, remote sensing data is expected to perform well at capturing prescribed burns in Kansas. However, our PSIF metric will not capture smoke exposure resulting from secondary formation and may misclassify exposure resulting from long-range transport of smoke and air pollution from sources that are outside of Kansas. Improving record keeping on the location and timing of prescribed burns along with increasing air quality monitoring in areas with prescribed burning could help reduce any potential exposure misclassification in future studies addressing the health impact of burning activities.

We should consider several potential limitations in addition to creating exposure measures from non-traditional data sources. Although exposure to and the impacts of smoke from prescribed burning may be larger in certain demographic groups, we did not examine potential differential effects by race, ethnicity, or socioeconomic factors. By examining combined outcomes of respiratory and cardiovascular illnesses, we may have masked true associations with individual respiratory or cardiovascular conditions. Using zip code as the spatial unit of analysis has limitations because zip codes do not align directly with the spatial unit of data collection for health or environmental factors. We observed low correlations between the PSIF metric and air quality monitoring data; the limited availability of monitoring data prevented us from determining how representative these results may be for the full study region. We estimated ambient smoke exposure which may differ from personal smoke exposure due to behavior modifications such as avoiding going outside on days with poor air quality or using indoor air filtration systems. Although we adjusted for a wide range of potential confounders, given the large number of factors that can impact cardiorespiratory exacerbations it is possible that uncontrolled confounding may have impacted findings. Examples of potential confounders that were not accounted for include additional meteorological factors, area-level socioeconomic status, and land use factors. A previous study in the state of Georgia observed higher levels of social vulnerability in areas impacted by prescribed burning [14]. If the same association exists in Kansas, social vulnerability could potentially confound the results of this study given the known disparities in cardiorespiratory outcomes by components of social vulnerability such as socioeconomic status and race [39, 40].

The data for this study are for the years 2009 to 2011. Nevertheless, prescribed burning is still a common practice in Kansas. During the years of this study, an average of approximately 2.7 million acres were burned in prescribed fires each year in the Flint Hills region of Kansas. Comparatively, between 2019 and 2021, in the same region, an average of approximately 2.4 million acres were burned annually [36]. Given the similarities in acreage burned, we anticipate that our results are relevant to the health impacts of prescribed burning in Kansas today.

Prescribed burning is a common agricultural practice in Kansas and in many other geographic locations. In this study using ED data from across Kansas and a novel metric of smoke exposure, we observed an association between smoke during the months in which prescribed burning is common in Kansas and asthma ED visits. Continuing to elucidate the impact of smoke from prescribed burning on health will help guide public health programs that address population-level smoke exposure. Educating the public on protecting themselves from the smoke of prescribed burning and ensuring that land managers take steps to limit smoke production from these burns may be important steps to help limit health impacts.

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Data Availability Statement

The computing code can be obtained by contacting the corresponding author. The data are not available because they include medical information that cannot be released.

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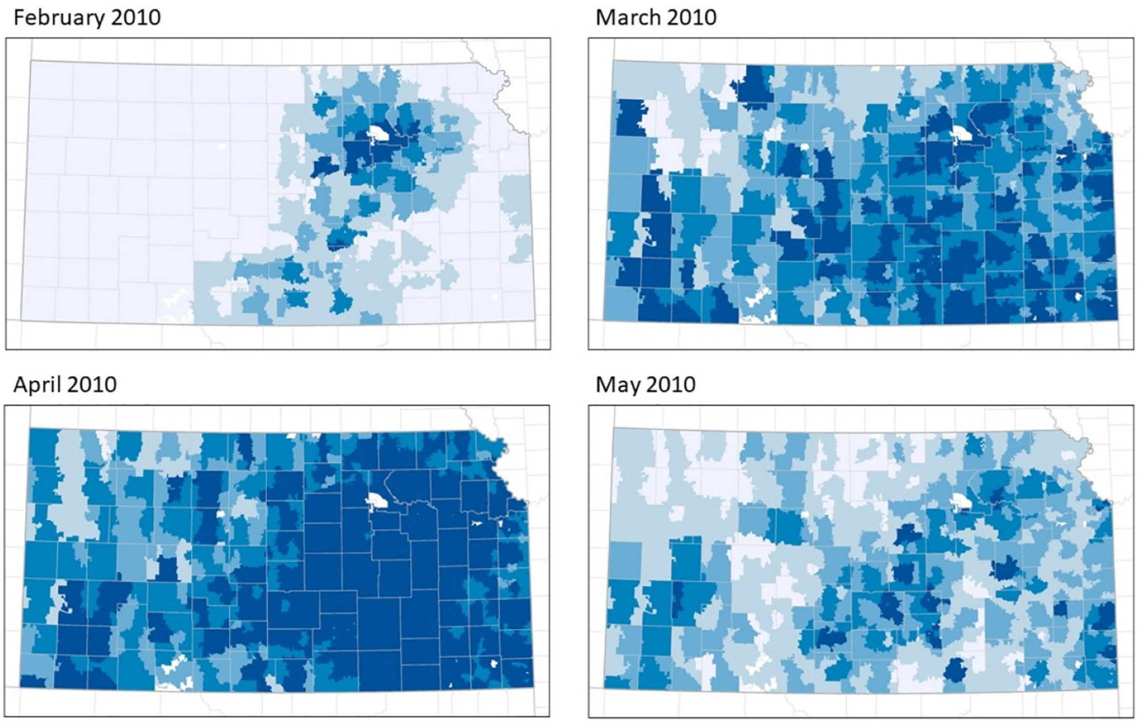

Figure 1.

Quintiles of Potential Smoke Impact Factor (PSIF) levels, Kansas, February – May 2010. The darkest color indicates the highest PSIF quintile; white indicates no data.

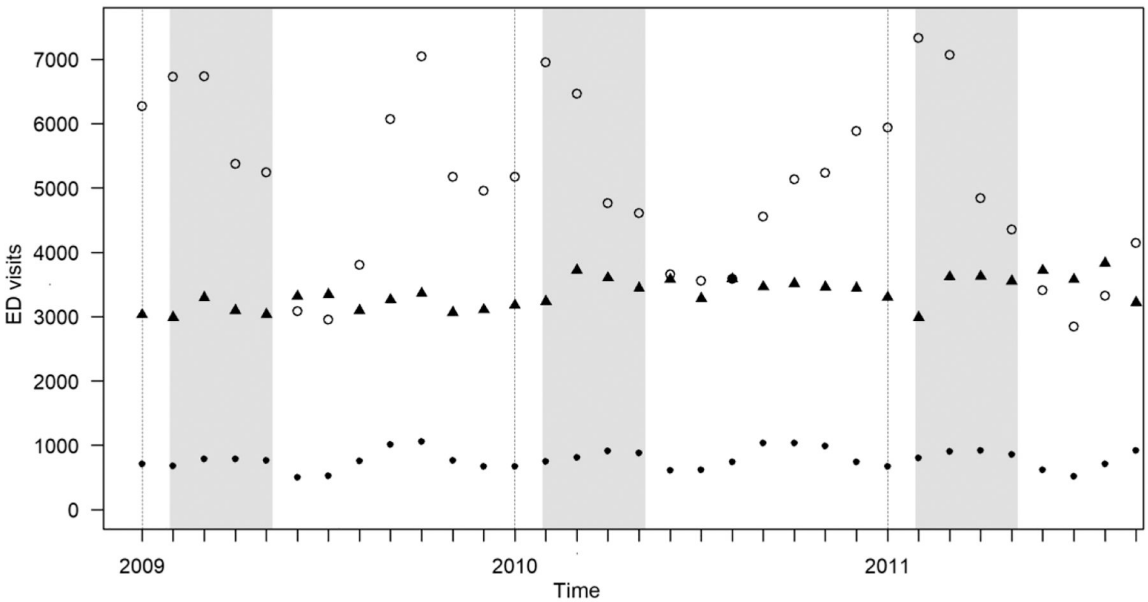

Figure 2.
Primary respiratory, cardiovascular, and asthma ED visits by month, Kansas 2009 – 2011. Shading identifies visits in February – May that were used in the analysis. Open circles indicate respiratory ED visits, shaded triangles indicate cardiovascular ED visits, and shaded circles indicate asthma ED visits.

Table 1.

Distribution and primary ICD-9-CM codes for asthma, respiratory, and cardiovascular emergency department visits, February–May, 2009–2011

Outcome	ICD-9-CM codes[1]	Total	Visits per day		
			Mean (SD)	Minimum	Maximum
Asthma	493	9,824	27.3 (7.3)	7	55
Respiratory	460–466, 477, 480–486, 491–492, 493, 496, 786.07	69,620	193.4 (49.8)	109	350
Cardiovascular	410–414, 427, 428, 433–437, 440, 443–445, 447	39,600	110.0 (48.5)	25	286

[1] Including extensions

Table 2.

Distribution of potential smoke impact factor levels in zip codes used in the analysis, by month

Month	Mean	Percentiles		
		50th	75th	90th
February	407.9	0	0	15.2
March	1,729.1	0	96.7	1,448.5
April	4,509.2	0	393.9	4,776.3
May	280.2	0	0	17.0

Table 3.

Characteristics of asthma, respiratory, and cardiovascular emergency department visits, February–May, 2009–2011

Characteristic	Frequency (%)
Age, in years	
<18	37,882 (34.7)
18–39	13,968 (12.8)
40–54	11,358 (10.4)
55–64	12,149 (11.1)
65–74	13,248 (12.1)
75+	20,614 (18.9)
Unknown	1 (0.0)
Sex	
Female	53,748 (49.2)
Male	55,471 (50.8)
Unknown	1 (0.0)
Race	
American Indian/Alaska Native	335 (0.3)
Native Hawaiian/Pacific Islander	20 (0.0)
Asian	1,445 (1.3)
Black	11,656 (10.7)
White	78,926 (72.3)
More than one race	892 (0.8)
Other	10,455 (9.6)
Unknown	5,491 (5.0)
Ethnicity	
Hispanic/Latino	7,583 (6.9)
Non-Hispanic/Latino	88,499 (81.0)
Unknown	13,138 (12.0)

Table 4.

Association between estimated smoke exposure and cardiorespiratory ED visits, Kansas 2009–2011

	Asthma ED visits		Respiratory ED visits		Cardiovascular ED visits	
	Unadjusted RR (95% CI)	Adjusted RR (95% CI)	Unadjusted RR (95% CI)	Adjusted RR (95% CI)	Unadjusted RR (95% CI)	Adjusted RR (95% CI)
Lag 0						
Binary exposure[a]	1.07 (1.02, 1.13)	1.07 (1.01, 1.13)	0.97 (0.95, 1.00)	0.99 (0.97, 1.02)	1.04 (1.01, 1.07)	1.01 (0.98, 1.04)
4-level exposure[b]						
No exposure	Reference	Reference	Reference	Reference	Reference	Reference
Tertile 1	0.92 (0.82, 1.03)	1.03 (0.93, 1.15)	0.92 (0.88, 0.96)	0.96 (0.92, 1.00)	1.03 (0.97, 1.09)	1.03 (0.98, 1.08)
Tertile 2	1.10 (1.01, 1.20)	1.10 (1.01, 1.19)	1.00 (0.97, 1.03)	1.01 (0.98, 1.05)	1.08 (1.03, 1.13)	1.05 (1.00, 1.09)
Tertile 3	1.13 (1.05, 1.22)	1.07 (0.99, 1.15)	0.98 (0.95, 1.01)	1.00 (0.97, 1.03)	1.00 (0.96, 1.05)	0.97 (0.93, 1.01)
3-day moving average						
Binary exposure[a]	1.04 (0.98, 1.09)	1.02 (0.97, 1.08)	0.96 (0.94, 0.99)	0.99 (0.97, 1.01)	0.95 (0.92, 0.98)	0.97 (0.94, 0.99)
4-level exposure[c]						
No exposure	Reference	Reference	Reference	Reference	Reference	Reference
Tertile 1	0.94 (0.86, 1.03)	1.04 (0.96, 1.12)	0.95 (0.91, 0.99)	1.00 (0.97, 1.03)	0.93 (0.88, 0.98)	0.99 (0.95, 1.03)
Tertile 2	0.97 (0.90, 1.04)	0.98 (0.92, 1.05)	0.95 (0.92, 0.98)	0.99 (0.96, 1.02)	0.99 (0.95, 1.04)	0.97 (0.94, 1.00)
Tertile 3	1.14 (1.07, 1.22)	1.06 (0.99, 1.14)	0.99 (0.95, 1.02)	0.99 (0.96, 1.02)	0.93 (0.89, 0.97)	0.94 (0.91, 0.98)

All models adjust for correlation within zip code. Adjusted models also control for time splines with monthly knots, year, zip code, day of week, holidays, cubic polynomials for lag 0 maximum temperature, cubic polynomials for lag 0 mean dew point, and cubic polynomials for lag 1–2 moving average minimum temperature (for models assessing 3-day moving average PSIF exposure).

[a]Binary exposure is calculated as zero (reference) vs. non-zero exposure.

[b]Lag 0 4-level exposure is calculated as no exposure (PSIF = 0) vs. tertiles of non-zero exposure (tertile 1 [0 < PSIF ≤ 84.3], tertile 2 [84.3 < PSIF ≤ 1135.5], tertile 3 [1135.5 < PSIF]).

[c]3-day moving average 4-level exposure is calculated as no exposure (PSIF = 0) vs. tertiles of non-zero exposure (tertile 1 [0 < PSIF ≤ 41.3], tertile 2 [41.3 < PSIF ≤ 630.43], tertile 3 [630.43 < PSIF]).