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Weather and Temporal Factors Associated with Use of Emergency Medical Services

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Abstract

Background: Fluctuations in emergency medical services (EMS) responses can have a substantial impact on the ability of agencies to meet resource needs within an EMS system. We aimed to identify weather characteristics as potentially predictable factors associated with EMS responses.

Methods: We reviewed hourly counts of scene responses documented by 24 EMS agencies in Western Pennsylvania from January 1, 2014 to December 31, 2017 and compared rates of responses to weather characteristics. Responses to counties nonadjacent to the studied weather reporting station and interfacility/scheduled transports were excluded. We identified the mean temperature, meters visibility, dew point, wind speed, total millimeters of precipitation, and presence of rain or snow in 6-hour windows prior to dispatch, in addition to temporal factors of time of day and weekend vs. weekday. Analysis was performed using multivariable linear regression of a negative binomial distribution, reporting incidence rate ratios (IRR) with 95% confidence intervals (CI). Secondary analyses were performed for transports to the hospital and cases involving transports for traumatic complaints and pediatric patients (age <18 years).

Results: We included 529,058 responses (54.8% female, mean age $57.2 \pm SD 24.7$ years). In our multivariable model, responses were associated with (IRR, 95% CI) rain (1.10, 1.08–1.11) snow (1.07, 1.05–1.09), and both rain and snow (1.15, 1.11–1.19). A lower incidence of responses occurred on weekends (0.84, 0.83–0.85) and at night (0.62, 0.61–0.62). Increasing temperature in 5 °C increments was associated with an increase in responses across seasons with an effect that varied between 1.16 (1.15–1.17) in winter to 1.31 (1.28–1.33) in summer. Windy weather was associated with increased responses from light breeze (1.10, 1.09–1.11) to fresh breeze or greater (1.23, 1.16–1.30). Transports occurred in a similar pattern to responses. Trauma transports ($n =$

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64,235) occurred more during weekends (1.04, 1.02–1.06). Pediatric transports ($n = 21,880$) were not significantly associated with precipitation or season.

Conclusion: EMS responses increased with rising temperature and following rain and snow. These findings may assist in planning by EMS agencies and emergency departments to identify periods of greatest resource utilization.

Keywords

modeling; weather patterns; predictive model; climatologic; seasonal

Introduction

Emergency medical services (EMS) is an essential component of the overall health system and demands for prehospital medical care are continuously increasing. A report of the National Emergency Medical Services Information System (NEMSIS) research data set identified that EMS utilization in the United States is increasing by 17.4 million EMS responses per year (1). Other studies of EMS utilization performed in New York (2), Victoria, Australia (3), and London (4) have similarly identified increasing demand for EMS over time. Between 2002 and 2011, Medicare, the largest source of revenue to most American EMS systems (5), noted a disproportionate increase of EMS utilization among its beneficiaries, amounting to a 69% increase in ambulance transports during that period (6).

As the need for prehospital care has increased, EMS agencies have faced substantial challenges regarding reimbursement for EMS response (7–10), along with staffing and other operational needs to meet the increase in demand (11–13). To adequately address this increased burden on EMS, better data are needed to predict the timing and frequency of EMS utilization. Such data would be of value in resource optimization for EMS agencies, where having sufficient staffing and resources is paramount. Previous investigations have identified that day of the week, time of day, and location are associated with utilization of emergency services (14). Additional information on factors impacting EMS demand could inform EMS administrators in ways to better optimize staffing levels to meet the peaks and troughs of EMS demand (15).

Limited work has been done evaluating the role of weather factors affecting EMS utilization. Previous investigators have identified temporal and weather-associated factors associated with motor vehicle collisions (16) and the effects of weather on EMS response times (17). Periods of extreme heat, for example, have been associated with increased EMS responses (18). To date, no study has evaluated utilization of EMS based on overall weather patterns using detailed, hourly weather data. Such data, widely available for public use, could inform efforts to optimize staffing and resource management at the local and regional level. In this study, we aimed to identify if weather and temporal factors are associated with changes in EMS response. Additionally, we aimed to identify the role of these factors in three subgroups: patients transported to a hospital, pediatric patients, and patients with traumatic complaints.

Methods

Study Setting

We retrospectively reviewed prehospital medical records for 24 ground urban, suburban, and rural EMS agencies in Western Pennsylvania. These EMS agencies receive centralized medical oversight and have research data use agreements with the University of Pittsburgh Medical Center. We included all EMS responses by these agencies within Allegheny County and adjacent Butler, Armstrong, Westmoreland, Washington, and Beaver counties (Figure 1). These six counties encompass an area of 4,491 square miles in land area and have a population of 2,222,645 per 2010 U.S. Census data (19). On average, Allegheny County has 10 days below 0 degrees Celsius (°C) and 10 days above 32 °C, has 189 days with rain and 79 days with freezing precipitation (20). Approval for this study was obtained from the University of Pittsburgh Institutional Review Board with a waiver of informed consent.

Patient Inclusion and Data Collection

We included EMS scene responses between January 1, 2014 and December 31, 2017. Data were obtained from a NEMSIS-compliant electronic prehospital medical record system (emsCharts, Warrendale, PA) used by all participating EMS agencies. Data were obtained from emsCharts in XML format and compiled into a research dataset using Matlab (MathWorks, Natick, MA) for extraction and Stata (StataCorp, College Station, TX) for synthesis into a prehospital registry dataset. From the available records, we excluded patients with (1) no listed response time, (2) missing both age and sex, and (3) interfacility transports. Patient information extracted in the database included age, sex, race and ethnicity, date and time of response, and medical complaint. Medical categories for each response were assigned into categories by the EMS provider. We further reclassified these into 12 medical category groups: general medical, trauma, respiratory, allergic, gastrointestinal, cardiovascular, neurologic, psychiatric, toxicological, dizziness/syncope, other, and unknown.

Weather Data

We reviewed hourly weather data obtained from public records from the National Oceanic and Atmospheric Administration (NOAA) for Pittsburgh International Airport, located within Allegheny county (latitude 40.48, longitude -80.21) (21). We defined weather events for this study using Meteorological Terminal Aviation Routine Weather Report (METAR) codes (22) as rain (drizzle, rain, and thunderstorm) or frozen precipitation (snow, ice crystals, hail, ice pellets, snow shower, snow pellets, and snow grains). We defined precipitation as mix when both rain and snow occurred during the 6-hour window. We used weather variables of temperature, visibility, dew point, and wind speed. While temperature and dew point variables were encoded as °C in the NOAA dataset, other units were converted into SI units for this analysis (visibility from statute miles to meters, wind speed from miles per hour to meters per second). Visibility was converted into a dichotomous variable, taking a value under 1000 meters (the definition for fog (23)) as low visibility. Precipitation was classified as no precipitation, rain, snow, and mixed (for combinations of rain and snow). Using the Beaufort scale for wind speed (24), we re-classified this variable into categories: none to light air (0–2.4 meters/second), light to gentle breeze (2.4–6.7

meters/second) moderate breeze (6.7–9.3 meters/second) and fresh breeze or greater (9.3 meters/second). For the primary analysis we created six-hour windows prior to each data point and recorded the following: means of temperature, visibility, and wind speed, total precipitation, and presence of rain or snow (defined as categorical variables). As the six-hour time windows were arbitrarily chosen, we performed a sensitivity analysis using 3 and 12-hour windows for weather data. We also acquired meteorological season (Winter, January 1 to March 31; Spring April 1 to June 30; Summer, July 1 to September 30; Fall, October 1 to December 31). Using historical data, we classified each hourly time into 2 categories: daytime (defined as the time between sunrise and sunset for each day) and nighttime. Our intention *a priori* in this study was to identify if weather-related variables were potential predictors of EMS demand after accounting for other factors known to affect the timing of EMS responses. As such, we included weekend/weekday status in our model as this variable has been specifically known to be associated with EMS demand (25, 26).

Data Analysis

Our primary outcome was counts of EMS responses. Our secondary outcomes were all transported patients, trauma, and pediatric transports (age <18 years). We used a negative binomial distribution to estimate associations between regional weather and counts of EMS response. Compared to Poisson regression, the negative binomial distribution is an effective model to use when data are over-dispersed (as measured by the ratio of variance to the mean) and has been applied to other models of time-dispersion analyses including trauma admissions (16, 27) and motor vehicle crashes (28). After testing for linear relationship of the response with the predictor, candidate variables were assessed in a univariate model. Variables with *P* values <0.1 in univariate analysis were used to construct a multivariable model, which was further optimized by backward selection. As we suspected that the effects of weather variables might vary by season, we performed a stratified analysis by season. We observed that the incidence risk ratio (IRR) for temperature from each season differed, though results from other variables remained similar. In order to best estimate the impacts of temperature in each season separately, we created a multivariable model including an interaction between these 2 variables.

For our secondary outcomes, we performed analyses for all transported patients, trauma transports and pediatric transports. In order to understand if the results from the primary analysis differed by population density, we performed a sensitivity analysis in which we obtained population estimates for all ZIP code tabulation areas (ZCTA) from the 2011–2015 American Community Survey (29) for all responses for which such data were available. This figure was divided by the area of each ZCTA (30). These estimates were categorized into tertiles of low, medium, and high density and the analysis was repeated on each subgroup. *P* values <0.05 in the multivariable analysis was considered statistically significant. Results were reported as IRR around which 95% confidence intervals (CI) were derived, giving the rate ratio of EMS response per hour. All analyses were performed using the MASS package (31) in R version 3.5.1 (R Foundation for Statistical Computing, Vienna, Austria).

Results

Description of Responses

From a total number of 799,894 EMS cases reviewed, 640,443 were in the study geographic inclusion area. Of these, 529,058 responses were included (Figure 2); 373,493 (70.6%) responses resulted in transport to a hospital. 64,235/373,493 (17.2%) transports were in the trauma category. Of those with a listed age, 21,880/373,493 (5.6%) were pediatric. Additional descriptive patient data are provided in Table 1.

Description of Weather Data

The included time period ranged from December 31, 2013 18:51 to January 1, 2018 00:51. From this time period we reviewed 35,068 weather data points, including 35,065 reports of temperature, 35,022 reports of visibility, 35,062 reports of dew point, 35,059 reports of wind speed, and 6,151 reports of weather type including precipitation events.

Multivariable Analysis

Results from univariate analyses are presented in Table 2. After multivariable analysis (Table 3), an increased IRR of EMS responses was noted with rain, snow, mixed precipitation, and with greater wind speeds. A decreased IRR of EMS responses was noted with increasing 5 °C units of dew point, at night, and on weekends. Our stratified analysis by season demonstrated a varying effect of temperature with a re-adjustment of the intercept within each model, suggesting a difference in the baseline number of responses by season. We therefore incorporated season as an interaction effect on temperature. The resultant model demonstrated that higher temperatures were associated with higher EMS need across all seasons, but with an effect size that varied by season (Figure 3).

Stratified Analyses for all Transports, Pediatric Transports, and Trauma Transports

Demographics for secondary outcomes are provided in Supplementary Tables 1–3. Findings were similar overall to the primary outcome. We did not find precipitation or season to be associated with pediatric transports (Supplementary Tables 4–6).

Sensitivity Analysis

Sensitivity analyses performed using 3 and 12-hour windows were similar to the primary analysis with respect to temperature, dew point, visibility, wind speed, time of day, and weekday/weekend status (Supplementary Tables 7 and 8). A sensitivity analysis performed by tertiles of population density showed similar results between groups (Supplementary Table 9).

Discussion

In this study, we used a large prehospital dataset to evaluate rates of EMS response based on weather. We identified a significant association between 6-hour mean temperature and EMS responses which increased with each 5 °C temperature increase in a manner that varied by season. Additionally, we identified an increased demand for EMS services associated with periods of rain and snow. These findings may be helpful in the development of modeling to

identify periods of greatest resource utilization. The widespread availability of weather data and forecasting could be an untapped resource for real-time planning of EMS deployments.

Previous investigations of the relationship between EMS utilization and climate have been primarily limited to the impact of temperature. Warmer weather may lead to an increase in outdoor activity, leading to a higher rate of trauma. An 8% increase in BLS demand and a 14% increase in ALS demand on days with extreme heat was recently reported in King County, Washington during the spring and summer months over a 5-year period (18). Similar studies evaluating heat waves and increased EMS use have been reported in Boston (32), Atlanta (33), and Phenix (34), Australia (35, 36), Canada (37, 38), Italy (39), Japan (40), and Switzerland (41). The findings from our study support and add to these studies by identifying a greater all-cause need for EMS during periods of higher temperature using granular hourly temperature data. Other studies have suggested that poor air quality may be related to sudden cardiac death (42) and acute ischemic stroke (43). Collectively, these studies suggest that changes in climate (44) and air quality may lead to rises in EMS demand over time.

Our findings suggested that lower temperatures were associated with lower EMS utilization. Fewer studies have evaluated the effects of cold temperature on EMS utilization, and these have been inconsistent: some studies have suggested that periods of extreme cold are associated with a higher call volume (45), while others have not demonstrated such an effect (46). In comparison to these previous investigations, we separated events of frozen precipitation, wind and temperature as separate variables in the development of our multivariable model, suggesting that all three of these variables have independent associations with EMS utilization. Findings from our study suggest that cold weather may be overall associated with lower EMS utilization in this region, though the effects of cold weather remain incompletely explored.

Rain, snow, and windy weather were positively associated with EMS utilization in our multivariable analysis. The reasons for these findings are likely multifactorial. Precipitation may have indirect effects on the environment which may increase the risk of injury (47). While an increase in asthma-related transports was previously observed after stormy weather in one Australian study, comprehensive models incorporating these weather variables for the prediction of EMS utilization have not been previously reported (48). Additionally, previous investigators have noted that transport times are significantly affected by rainy weather (17, 49), which in combination with the increase in EMS transports during these periods would suggest that periods of rain may be significantly associated with EMS resource need.

Our sub-analyses suggest that weather variables play a significant effect with respect to transports, pediatric transports, and trauma transports. Our findings with respect to trauma are corroborated by a study in Taipei, Taiwan suggesting a rise in trauma-related transports with higher temperature and in association with any precipitation (16), from studies evaluating the epidemiology of fatal motor vehicle accidents in relation to rain and snow events (33) and from a study evaluating fractures with freezing conditions in the Netherlands (49). While no study has specifically identified weather patterns in pediatric transports, other

studies have identified variations in pediatric trauma emergency department visits and admissions for trauma-related visits in association with warmer weather (50–52).

The findings from this study have multiple implications. While we aimed to identify trends in EMS use using short-term fluctuations in weather, future models of EMS use may benefit from incorporation of forecasted weather variables in order to optimize staffing by agencies. As forecasts continue to improve (53), a better understanding of factors affecting EMS use can facilitate efficient staffing and resource utilization by both EMS and receiving hospitals. Prospective investigation incorporating forecasted weather patterns would best determine how this information can best be used as one of many operational considerations for staffing EMS agencies to meet continually fluctuating demands for service.

Limitations

Our study was limited by its retrospective nature and inherent limitations in existing medical records. This dataset was unable to account for clustering events such as multiple EMS calls to the same scene (such as from a mass causality or multiple-vehicle accident) which may have increased counts at some time points; however, given the large sample size we suspect that these effects were likely minimal and would not affect overall conclusions. A small number of hourly weather measurements were not available. While a broad concordance between temporal events (time of day and weekend/weekday) and transports has been observed across multiple regions (14), the generalizability of weather findings to different geographic regions cannot be fully established. Additionally, the findings from this study may not be easily extrapolated to extreme weather events, such as severe blizzards, as these occurred infrequently during the studied time period. However, despite these limitations, we suspect that the overall trends with respect to the timing and weather-related prediction of EMS utilization are broadly applicable to regions with temperate climates.

Conclusion

We identified multiple weather factors independently associated with EMS utilization. Most importantly, we identified an increase in the incidence of EMS use per hour with each increased 5 °C increase in ambient temperature which varied between 16 and 31% depending on season. Additionally, we identified an association with EMS utilization in the presence of rain or snow. The findings from this study can facilitate the development in predictive models of EMS utilization and can assist in planning and resource management by EMS agencies and emergency departments.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Figure 1.
Study inclusion region in western Pennsylvania. Figure created using data provided by Esri, Garmin, HERE, and OpenStreetMap.

Figure 2.
STROBE diagram illustrating patient inclusion.

Figure 3.
Incidence rate ratios and 95% confidence intervals of model fitted for all responses.

Table 1.

Demographics of all EMS responses

Events	All responses (<i>n</i> = 529,058)
Age, $\pm$ SD	57.2 $\pm$ 24.7
Number female (%)	288,079/528,982 (54.5)
Race/Ethnicity (%)	
White non-Hispanic	260,952 (49.3)
White Hispanic	2,588 (0.5)
Black non-Hispanic	95,630 (18.1)
Black Hispanic	960 (0.2)
Other/unknown	168,928 (31.9)
Medical category (%)	
General medical	143,233 (27.1)
Trauma	82,107 (15.5)
Respiratory/airway	40,055 (7.6)
Allergic	2,789 (0.5)
Gastrointestinal	31,051 (5.9)
Cardiovascular	25,223 (4.8)
Cardiac arrest	3,323 (0.6)
Neurologic	29,676 (5.6)
Psychiatric/behavioral	11,535 (2.2)
Toxicologic	20,153 (3.8)
Dizziness/syncope	19,946 (3.8)
Other	26,965 (5.1)
Unknown	93,002 (17.6)
Weekend (%)	129,907 (24.6)
Day period (%)	
Day time (sunrise to sunset)	336,641 (63.6)
Night time (sunset to sunrise)	192,417 (36.4)

SD = standard deviation.

Table 2.

Incidence rate ratios (IRR) and 95% confidence intervals (CI) from univariate linear logistic regression for EMS responses

	IRR	<i>p</i>
5 °C temperature change	1.03 (1.03–1.03)	<0.001
Precipitation		
No precipitation	Ref	–
Rain	1.02 (1.00–1.03)	0.024
Snow	1.00 (0.98–1.01)	0.633
Mixed	1.05 (1.00–1.10)	0.040
Season		
Winter	Ref	–
Spring	1.00 (0.99–1.02)	0.831
Summer	0.99 (0.97–1.00)	0.066
Fall	0.98 (0.96–0.99)	0.009
Poor visibility	0.83 (0.73–0.94)	0.003
5 °C dew point change	1.00 (1.00–1.01)	<0.001
Wind speed		
Calm to light air	Ref	–
Light to gentle breeze	1.22 (1.21–1.24)	<0.001
Moderate breeze	1.35 (1.33–1.36)	<0.001
Fresh breeze or greater	1.46 (1.37–1.57)	<0.001
Day period		
Day time (sunrise to sunset)	Ref	–
Night time (sunset to sunrise)	0.60 (0.59–0.61)	<0.001
Time of week		
Weekday	Ref	–
Weekend	0.81 (0.80–0.82)	<0.001

Table 3.

Incidence rate ratios (IRR) and 95% confidence intervals (CI) from multivariable linear logistic regression for EMS responses.

	IRR	<i>p</i>
5 °C temperature change (interaction effect by season)		
Winter	1.16 (1.15–1.17)	<0.001
Spring	1.23 (1.21–1.25)	<0.001
Summer	1.31 (1.28–1.33)	<0.001
Fall	1.18 (1.16–1.19)	<0.001
Season		
Winter	Ref	–
Spring	0.72 (0.70–0.74)	<0.001
Summer	0.55 (0.53–0.58)	<0.001
Fall	0.99 (0.97–1.00)	0.127
Precipitation		
No precipitation	Ref	–
Rain	1.10 (1.08–1.11)	<0.001
Snow	1.07 (1.05–1.09)	<0.001
Mixed	1.15 (1.11–1.19)	<0.001
Poor visibility		
5 °C dew point change	0.87 (0.87–0.88)	<0.001
Wind speed		
Calm to light air	Ref	–
Light to gentle breeze	1.10 (1.09–1.11)	<0.001
Moderate breeze	1.15 (1.13–1.16)	<0.001
Fresh breeze or greater	1.23 (1.16–1.30)	<0.001
Day period		
Day time (sunrise to sunset)	Ref	–
Night time (sunset to sunrise)	0.62 (0.61–0.62)	<0.001
Time of week		
Weekday	Ref	–
Weekend	0.84 (0.83–0.85)	<0.001