EcoHealth 9, 427–439, 2012
DOI: 10.1007/s10393-012-0803-5

ECOHEALTH

Original Contribution

Relating Weather Types to Asthma-Related Hospital Admissions in New York State

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Abstract: Many previous studies have looked into the relationship between asthma and individual weather variables, but comparatively few have looked at this relationship using holistic weather types (WTs). Utilizing the Spatial Synoptic Classification, this research considers up to 6 days of lag time while investigating the asthma-to-WT relationship in two age groups (under 18 and 18 and over) throughout New York State. Results indicate that a cold and dry WT in autumn corresponds to increased asthma admissions and spike days in admissions in New York City (NYC) for the school-aged population, while hot and dry WTs in summer correspond to spike days in asthma admissions in both age groups. However, results vary considerably for other regions, seasons and WTs, and spike day analysis yields clearer results than the analysis of total anomalous admissions. When stratified by multiple regions and age groups, the sample size of daily asthma admissions is a limiting factor outside of NYC.

Keywords: synoptic climatology, weather types, SSC, spatial synoptic classification, asthma, New York

Introduction and Background

Asthma affects nearly 300 million people globally and some 11% of the United States (US) population (Skrepnek and Skrepnek 2004), and is the most widespread chronic disease among children (Bryant-Stephens 2009). Undoubtedly, asthma exacerbations substantially affect the quality of life of the patient (Andersson et al. 2003). However, they are also estimated to cost over $37 billion annually in the US (Kamble and Bharmal 2009), and spikes in asthma-related hospital admissions (ARHAs) are also accompanied by additional stress to healthcare systems (Peters et al. 2006). In New York State (NYS) alone from 1995 to 2006, there were over half a million ARHAs—with the vast majority (over 82%) of those being in the New York City (NYC) area. In 2007, the cost of ARHAs was over $535 million statewide—a 70% increase from just 10 years before (New York State Asthma Surveillance Summary Report 2009).

While asthma exacerbations are dependent on a number of factors, due to a strong seasonal trend in ARHAs, the relationship of weather to asthma has received considerable attention. From a physiological standpoint, air temperature and humidity affect lung function. Koskela (2007) notes that cold air can trigger symptoms of asthma by, in effect, helping to evaporate surface fluid in the airway. This cooling and drying of the airway contributes to bronchial constriction (Bougault et al. 2009). Supporting these conclusions, in a laboratory setting, Mathur et al. (1993) found that any combination of cold and/or dry air

Published online: December 6, 2012

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significantly reduced peak expiratory flow rate in asthmatics, while warm and humid air significantly raised it.

These results have spurred several research projects aimed specifically at finding relationships between individual weather variables and asthma admissions. The majority of research looking into the relationship between asthma and weather are in agreement in finding that low temperatures are related to increases in a variety of asthma-related complications (May et al. 2011; Yuksel et al. 1996; Piccolo et al. 1988; Whittemore and Korn 1980; Beer et al. 1991; Greenburg et al. 1966). In addition to low temperatures, other meteorological conditions have been found to be associated with increased levels of asthma, including humidity (Ehara et al. 2000; Mireku et al. 2009; Santic et al. 2002; May et al. 2011; Priftis et al. 2006), thunderstorms (Girgis et al. 2000; Marks et al. 2001), and pressure (Priftis et al. 2006; Ehara et al. 2000; Garty et al. 1998; Goldstein 1980) among others. Though these studies have all found significant relationships between asthma and meteorological parameters, results have varied in the direction of some of the correlations, in different study areas, in different seasons, and by different demographics. Further, seasonal trends in asthma have been linked to a number of factors that are not related to weather at all (such as healthcare administrative decisions, socio-economic status, and the timing of the beginning of the school year), in addition to factors indirectly (e.g., pollen and pollution levels) and directly linked to weather (Chen et al. 2006; Lin et al. 1999, 2011; Johnston and Sears 2006)

While most of the climatological studies above took an interest in the association of asthma with individual weather variables, the daily weather presents itself not just as one single variable, but rather as a *weather situation* comprised of multiple weather variables—and it is this weather situation to which an individual is ultimately subjected. So, while some associations certainly exist between asthma and temperature or humidity, what are the *synergistic* effects of temperature, humidity, wind speed, cloud cover, precipitation, pressure, and other weather variables on asthma? How do different *weather types* (*WTs*) impact asthma admissions? These questions are best approached using synoptic climatological methods.

The field of synoptic climatology is based on statistically relating the atmosphere to a particular surface event (Yarnal 1993). By creating classifications of meteorological variables over a wide spatial scale and/or a long time scale, synoptic climatologists define distinct, holistic atmospheric states that can be easily interpreted and associated with a surface event of interest. Synoptic climatological methods have been employed in myriad research papers looking at the relationship between climate and human health (e.g., Kalkstein and Greene 1997; McGregor 1999; Sheridan and Dolney 2003; Morabito et al. 2006; de Pablo et al. 2009; Davis et al. 2012; Sheridan et al. 2012). Despite the utility of synoptic methods in climate research on human health, however, very little research has been undertaken specifically looking at the relationship of asthma to different synoptic climatological WTs (Jamason et al. 1997; Nastos et al. 2006; Hanna et al. 2011).

Using the Spatial Synoptic Classification (SSC) (Sheridan 2002) and incorporating 6 days of lagged effects, the goal of this paper is to examine the relationship between ARHAs and WTs throughout all of NYS across all seasons. This research could help public health officials prepare for days with potentially high numbers of ARHAs.

Data and Methodology

Asthma Admissions Data and Considerations

Respiratory-related hospital admissions data were provided by the New York State Department of Health for the period 1995–2006. All cases with a principal diagnosis ICD code of 493.xx were defined as asthma related and were included in further analyses. Each individual ARHA case was first partitioned into one of two age groups: under 18 (U18) and 18 and over (O18). Each case in these two age groups was then grouped into one of seven regions based upon the county in which the patient resided (Figure 1), and summed by date, to get a daily tally of ARHAs for each region for both age groups. The last 7 days of 2006 were omitted from further analysis due to data quality issues. Cases with missing county or age information were also omitted from further analysis (representing 0.6% of all cases).

Two age groups were selected to maintain an adequate average daily sample size of ARHAs. The cut-off point between the two age groups examined herein was chosen in order to group the school-aged population separately from the older population as previous research suggests the timing of the autumn peak in admissions could be linked to the beginning of the school year (Johnston and Sears 2006; Lin et al. 2011). Regions were selected by each county's proximity to the weather stations for which the SSC (described below) is available, and seven regions were

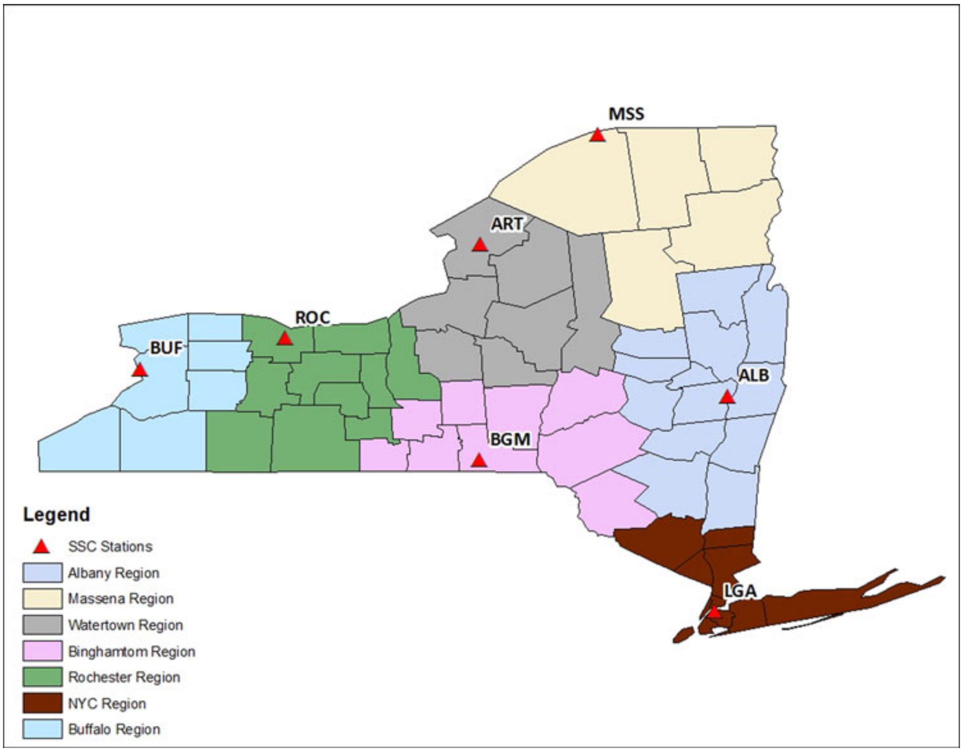

Figure 1. The locations and airport codes of the SSC stations used in the research and the delineation of the regions in NYS, United States.

ultimately created: Albany (ALB), Binghamton (BIN), Massena (MAS), Buffalo (BUF), NYC, Rochester (ROC), and Watertown (WAT; Figure 1).

Climate Data and Considerations

Synoptic climatological relationships to ARHAs are based upon the SSC—a specific type of synoptic climatological method (outlined in Sheridan 2002). The SSC uses a suite of six meteorological variables at a 4-time daily resolution to classify distinct daily WTs on a station-by-station basis. Although cloud cover, pressure, wind speed, and wind direction are also included in the classification process, the WTs are most weighted by their temperature and humidity characteristics, and are named as such—dry polar (DP), dry tropical (DT), dry moderate (DM), moist polar (MP), moist tropical (MT), moist moderate (MM), and a transitional (TR) WT. While used in some previous SSC research, across NYS as a whole, the moist tropical "plus" (MT+) subdivision—a very warm subset of MT days—is relatively rare, and hence all MT+ days were simply re-coded to be MT. In addition, the definition of these WTs is relative to the season and the location of the station. Daily SSC classifications for each of the seven stations (one for each region of NYS) were obtained from the SSC website (http://sheridan.geog.kent.edu/ssc.html) for the 1995–2006 time period.

Exposure Indicators

Two indicators were used in order to examine the WT-to-ARHA relationship—spike days in ARHAs and anomalous ARHAs. These two indicators together represent a robust gauge of the WT-to-ARHA relationship and assist in comparison purposes with previous literature (namely Jamason et al. 1997). These two metrics were examined on a season-by-season basis (March–May is spring, June–August is summer, September–November is autumn, and December–February is winter), and separately for each age group and each WT.

Spike days in ARHAs indicate dates on which there are substantial (defined below) increases in ARHAs above the average number of ARHAs for that date. This metric is expressed in the results as a standardized spike day ratio (SSDR) of *actual* spike days over *expected* spike days. Thus, an SSDR of 2.00 would indicate that the number of spike days that *actually* occurred under that WT is twice the *expected* number of spike days (calculated from the equation below).

Anomalous ARHAs indicate the total number of raw daily asthma admissions above or below the average number of admissions for that date. Average numbers of daily ARHAs are computed separately for each region as well, and are explained below. This metric is expressed as a percentage difference from the mean over a 3-day period (3dARHAs; explained in "Incorporation of a Lagged Effect" section below).

Calculation of Average Daily ARHAs and Anomalous ARHAs

A primary focus of the current study is on anomalous ARHAs in each region. However, due to strong seasonality in the ARHA data, a large undertaking in the research was to develop a methodology to accurately derive a seasonal signal from which anomalous ARHAs could be calculated; the results presented below are highly dependent on the specific methodology chosen. These cycles, however, are not consistent across all age groups, as the strongest cycle is noticed in children, and the seasonality decreases with age to the point of almost no seasonal cycle in the elder age groups (Chen et al. 2006; Baibergenova et al. 2005).

The seasonal signal of average daily ARHA values was calculated separately for each age group and region according to the following method. First, a 14-day centered moving average of ARHAs (14Davg) was found for each day to help account for both the seasonal trend and a time-series trend in the data. This moving average was comprised of the 7 days before and the 7 days after Day 0 (the day being analyzed), excluding Day 0. The exclusion of Day 0 in the 14Davg helps to mitigate the possibility of a high number of ARHAs on Day 0 from unduly affecting the moving average (and thus, the daily anomaly as well). Further, the average daily value not only needed to be derived equally from days before Day 0 and days after Day 0 but also needed to remain a multiple of 7 to prevent the introduction of an artificial day-of-the-week (DOW) bias into the data.

While the selection of a multiple-of-7 smoother does prevent the introduction of further (artificial) DOW bias in the anomaly calculation, it does not explicitly remove a significant DOW bias that already exists in the ARHA data. Thus, in order to completely account for this DOW cycle in ARHAs, the second step in the method was to calculate DOW multiplier (DOWm) for each of the 7 DOW. The DOWm was derived by finding the average daily value of ARHAs for each DOW in the time series and dividing that number by the average daily value of all ARHAs in the time series. Thus, if Mondays had twice as many ARHAs as the actual average, then the standardized value of each Monday was multiplied by two. Like the 14Davg, the DOWm was also derived separately for each region and age group.

The third step in the process was then to multiply the DOWm by the 14Davg for each day in the time series to get the mean daily values (MDV). In the final step of the process, MDV was subtracted from each of the raw daily ARHA values to obtain the anomalous number of ARHAs for each day.

This entire four-step process was iterated separately for each age group and region. While being analyzed in the results themselves, these anomalous ARHAs are also used in the calculation of spike days.

Calculation of Spike Days in ARHAs for NYC

Due to very small daily ARHA sample sizes in all other regions outside of NYC, spike days in ARHAs are only analyzed for NYC. Spike days in ARHAs are determined by finding the standard scores (*z*-scores) of NYC's anomalous ARHAs that are greater than 1.5. Several permutations were assessed, and the 1.5 threshold was chosen to preserve an adequate sample size of spike days in each season, while also representing a realistically substantial 1-day increase in ARHAs that might stress the healthcare system. The spike day metric is expressed as the SSDR of the number of actual spike days over the number of expected spike days. Although not explicitly shown in the results, expected spike days are statistically important as a baseline from which the SSDR calculation can be made and are based on the seasonal frequency of each WT. Expected spike days are calculated as

$$E_{\mathrm{ws}} = \frac{P_{\mathrm{s}}}{D_{\mathrm{s}}}(D_{\mathrm{ws}})$$

where E_{ws} is the expected number of spike days for WT w in season s, P_{s} is the total number of spike days in season s (summed for the entire time series), D_{s} is the total number of days in season s (summed for the entire time series), and D_{ws} is the total number of days classified into WT w for season s (summed for the entire time series). This calculation is repeated for each lag day in each season.

Incorporation of a Lagged Effect

One of the major complicating factors in assessing the effect of weather on ARHAs is that of time—or a lag effect. That is, weather conditions that may be related to increased admissions might occur up to 3 or more days before a patient goes to the hospital. Ehara et al. (2000) found that the mean time of onset of asthma symptoms was 1.8 days before patients were admitted to the hospital. Thus, finding a relationship between weather and asthma admissions must incorporate a lag into the analysis.

To account for this effect, 1-day through 6-day lags (Lag 1–Lag 6) were created for each station's SSC WT in order to find the WT that occurred up to 6 days beforehand. Previous research has suggested that the majority of increases in ARHAs in relationship to WTs occurred anywhere from 1 to 3 days after a cold and dry WT in the autumn (Jamason et al. 1997)—the peak of the ARHA season, or that an asthma epidemic was preceded by the passage of a cold front 1–3 days beforehand (Goldstein 1980). Consideration of these studies, along with preliminary results (Figure 2) led to the focus being on the summed number of anomalous ARHAs occurring in this 1- to 3-day lag period (for the anomalous ARHA indicator) after the occurrence of a WT (hereafter referred to as 3dARHAs). This number is expressed as a percent of the raw total daily ARHAs for each region and season multiplied by 3.

Statistical Analyses

The one-sample difference of means t test was employed to evaluate statistically significant changes in 3dARHAs (difference from zero) by WT for each region and age group. Two-sample difference of proportion tests were used to examine whether the proportion of spike day occurrences for each WT was significantly different than the proportion of all days in each WT for each season in NYC—effectively testing the significance of the difference between *actual* and *expected* spike days (or the SSDR). Chi-square tests were also used to find whether the actual number of spike days was significantly different from the expected number of spike days across a season—effectively determining whether the amount of partitioning of spike days among WTs was significant. That is, if spike days were equally frequent across all WTs in a season, then weather typing would not be a very useful measure to gauge ARHA spike days. However, if spike days only occurred when one or two WTs were present, then WTs would be a good measure of increased spike day occurrence. Significant results at the $P \leq 0.05$ level are the main focus of the discussion, though near-significant ($P \leq 0.10$) results are also highlighted.

To account for temporal autocorrelation, all t tests with the 3dARHA indicator were performed with an effective sample size, whereby the sample size was reduced based on the following equation (from von Storch and Zwiers 2003):

$$N' = (N)\frac{1-r}{1+r}$$

where N' is the effective sample size, N is the original sample size, and r is the Pearson correlation coefficient at lag1 for each variable. Spike days, however, were calculated from anomalous ARHAs (which have $r < 0.09$ in all cases) rather than 3dARHAs, and thus, significance testing for the SSDR was not adjusted for temporal autocorrelation.

In an effort to create a larger sample size representing the entire state (outside of NYC), a NYS aggregate was also computed by summing all 3dARHA anomalies from the six regions (excluding NYC) for each WT within each season. Although additional aggregates were also created for dry (DP, DM, DT) and moist (MP, MM, MT) WTs, the results are not displayed and are only discussed where relevant.

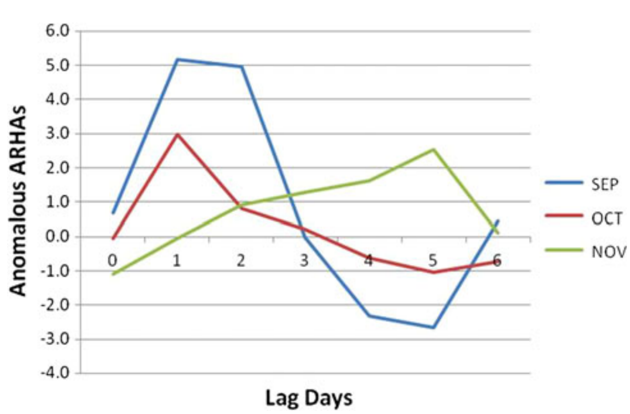

Figure 2. Effect of lag on anomalous ARHA admissions 0 to 6 days after the occurrence of a Dry Polar (*DP*) weather type in the New York City (*NYC*) region during three autumn months.

Results

Seasonal Trends and Demographics of Asthma Admissions

Among the 518,164 cases that contained county of residence and age data for the admitted patient, 82% of all admissions in the state were from the NYC region. Seasonal trends in the two age groups exhibit many similarities that follow the meteorological seasons quite well (Figure 3). ARHAs in both age groups demonstrate a trough in the summer before a sharp increase in September and October, along with a more muted rise in admissions in March and

May. The main differences between the age groups are the opposing trends displayed in December—while the U18 age group experiences a slight drop in admissions, the O18 age group exhibits an increase from November to December. There is also a difference in the relative steepness of the autumnal increase between the two age groups—in the U18 age group, the number of AHRAs in September is more than double those in August, while in the O18 age group, September ARHAs are only 25% more than August admissions. Overall trends by age (Figure 4) indicate that ARHAs are more common in males until about age 15, with female ARHAs becoming more common thereafter. Overall county-by-county spatial patterns of asthma admissions are displayed in Figure 5—with only the NYC region showing any spatial clustering.

Spike Days in ARHAs in the NYC Region

The analysis of spike days in admissions (Tables 1, 2) yields more significant results than the analysis of anomalous

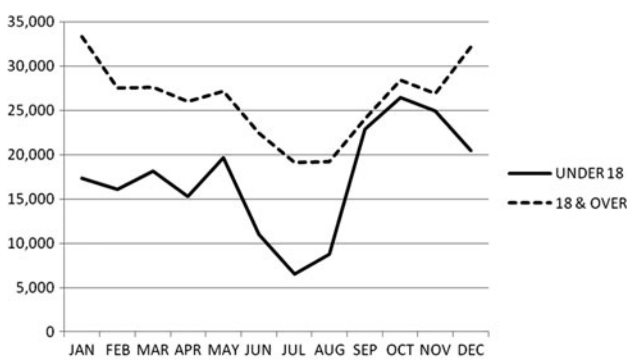

Figure 3. Seasonal trends in NYS ARHAs for the two age groups used in this research (monthly sums 1995–2006).

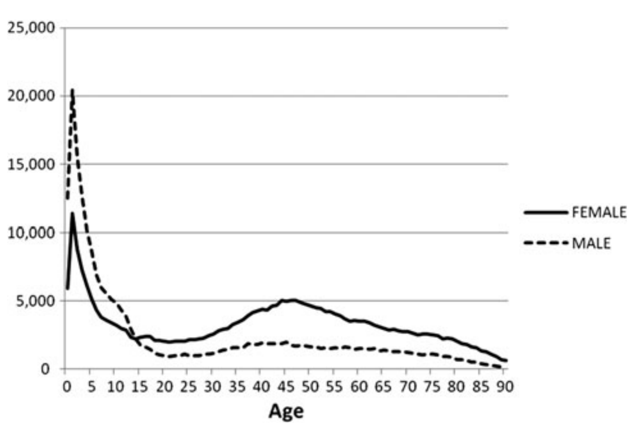

Figure 4. Male and female NYS ARHAs by age (1995–2006).

ARHAs (Tables 4, 5). In the U18 age group, the most consistent results are for the autumn DP WT, which shows an above average number of spike days in ARHAs for Day0 through Lag6 after occurrence; including Lags 3, 4, and 6, where the difference is significant (Table 1). Winter DP also shows a substantial increase in spike days for all but Lag1—including on Lag 6, which is significant. Although infrequent in summer (less than 3%), when MP does occur in this season, it yields high SSDRs, especially at longer lag times. Summer MM has a similar affect, though is much more frequent. The largest increase in spike days occurred with summer DT on Lags 2 and 3, both accounting for an SSDR of over 3.3 ($P < 0.001$), although total spike day occurrence was only six days. Only about 2.0% of summer days qualified as spike days of ARHAs (22 of 1104), which most likely led to many large SSDRs, despite low overall occurrence. Other seasons varied considerably in the relationship between WT and spike days among the U18 age group.

In looking at the spike days for the O18 age group for NYC, results are considerably different from the younger age group. The most consistent results in the older age group are for the spring DT WT 3–5 days after occurrence (Table 2); each of which has a SSDR of at least 2.1. Overall, summer WTs show the most similarity to the U18 age group, as summer DT exhibits increases in spike days from Day 0 through Lag 4, with Day 0 and Lag 1 being nearly significant ($P \leq 0.10$). Summer MM and summer MP also show substantial results at longer lag times, much like the U18 results. In autumn, DP corresponds to an increase in spike days from Day 0 to Lag 2, although only Lag 1 (SSDR = 1.93) is significant.

Chi-square results in Table 3 detail the discriminatory power of spike days in being partitioned across all WTs by lag day within a season. Using the Chi-square test with the U18 age group, summer Lag2; summer and autumn Lag6; and spring, summer, and autumn Lag3 showed significant differences in actual spike day occurrence versus expected spike day occurrence across all the WTs as a whole (Table 3). With the O18 age group, only spring Lag4 showed a significant difference in observed spike days versus expected across WTs.

Anomalous Admissions (3dARHAs)

Though the 3dARHA analysis does yield some large anomalous percentages, it is important to note than none are significant at $\alpha = 0.05$. In the U18 age group in autumn

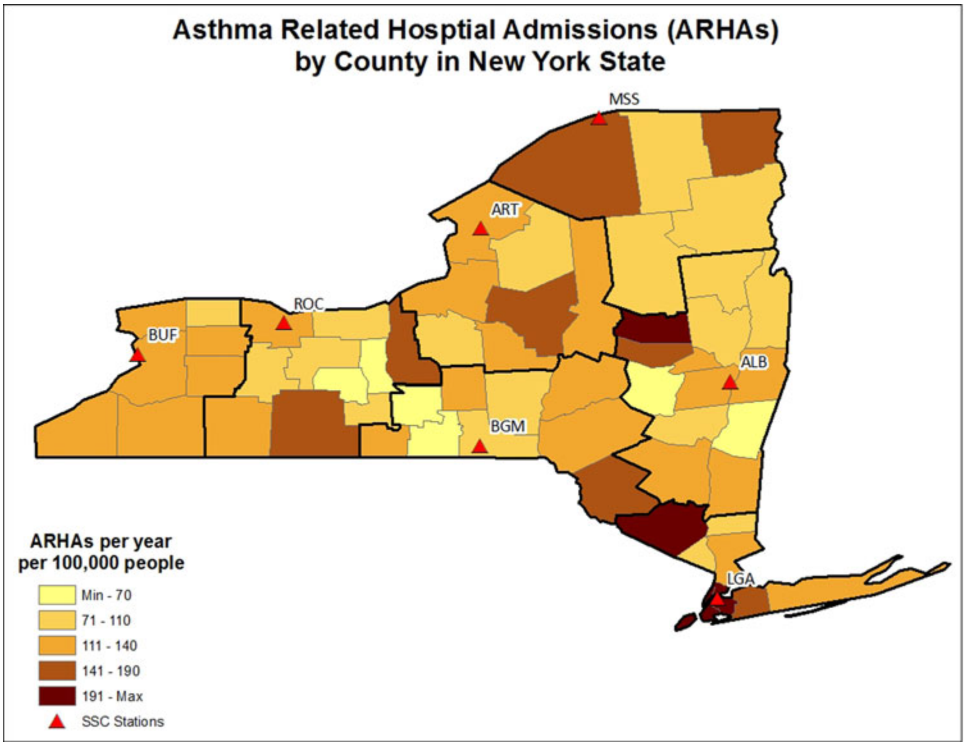

Figure 5. Mean annual ARHA rate by county in NYS. Rate is calculated as the mean total number of admissions per 100,000 population per year.

in the NYC region, of the seven WTs, only DP and DT have substantial anomalous mean 3dARHAs, at +2.6 and +3.3%, respectively (Table 4). After aggregating all dry WTs together (DM, DP, and DT), there is a positive 0.9% anomaly in autumn (not shown) for NYC. Of the other three seasons, only summer has any WTs with any noteworthy anomalous 3dARHAs in this region, with DP, DT, and MM accounting for −3.4, +4.1, and −3.8% anomalous admissions, respectively.

The aggregate of the rest of the state for the U18 age group is rather different from NYC. In autumn, only the MM type has a positive anomaly greater than 0.5%, standing in stark contrast to the DP and DT types in NYC. Only three WTs showed consistent positive anomalies throughout most of the state (at least 6 of 7 regions) in the U18 age group—spring MM, autumn DM, and winter MT.

Despite the sample size in the NYC region, generally the 3dARHA trends from the U18 age group are not consistent with those in the O18 age group (Table 5). The lone exception is autumn DP, which has substantial anomalous 3dARHAs with a mean of +2.1%. The trend noticed above (toward drier air corresponding to an increase in admissions in autumn) *does* hold true for the O18 age group in the region, as the aggregate of the three dry WTs are associated with a positive anomaly of 0.8%, and the aggregated moist WTs account for a negative anomaly of 1.1% in autumn for this age group as well. The summer and spring seasons have no markedly positive changes. While the winter shows a 5.1% increase in ARHAs for the DT WT and a 2.0% increase for the winter MT WT, both DT and MT occur quite infrequently in the winter season.

Outside of winter DT and MT, NYS as a whole shows little similarity between age groups or with the NYC O18 results. Besides these types, for this age group, there are three WTs that showed consistent positive anomalies throughout most regions of the state: summer DT, autumn DM (as in the U18 age group), and winter DM.

Discussion

Overall, these results show a markedly varied spatial relationship between ARHAs and WTs. While one of the original goals of the research was to examine any type of spatial homogeneity between the relationship of WTs and asthma admissions, small daily sample sizes due to multiple stratification likely led to these varied spatial results. One of the primary results is that while examining the relationship of anomalous 3dAHRAs to WTs yielded poor results in NYC (and overall), results with *spike days* in ARHAs were clearer.

Table 1. Standardized Spike Day Ratios (SSDRs; Observed Spike Days Over Expected Spike Days) for the U18 Age Group by Lag Day (Rows) and Weather Type (Columns) for Each Season in the NYC Region (1 is Considered Normal)

	DM	DP	DT	MM	MP	MT	TR
Spring							
0	1.20	0.94	0.58	0.71	0.81	1.46	0.97
1	0.86	1.22	1.15	0.87	1.02	1.07	1.06
2	0.94	1.29	0.28	1.04	1.02	1.25	0.74
3	1.20	0.82	0.84	0.65	0.80	0.42	**1.91**
4	1.17	0.88	1.38	1.06	0.91	0.58	0.95
5	0.90	1.16	0.81	0.98	1.15	0.58	1.25
6	0.90	1.16	0.81	1.30	0.95	0.44	1.14
Summer							
0	1.30	1.50	1.14	0.49	**3.14**	1.00	0.00
1	1.52	0.74	0.56	0.24	0.00	1.25	1.34
2	0.88	0.00	**3.35**	0.48	0.00	1.13	0.67
3	0.44	0.71	**3.31**	0.48	0.00	1.13	1.36
4	0.87	0.70	0.55	1.47	1.48	1.01	0.67
5	0.65	1.36	0.00	**2.17**	*2.79*	0.52	1.34
6	0.88	**2.68**	0.00	*1.69*	**3.67**	0.52	0.00
Autumn							
0	1.10	1.03	0.66	0.66	1.54	1.24	0.72
1	0.94	1.24	0.88	0.99	1.28	1.02	0.91
2	0.95	1.05	1.10	1.22	1.67	0.73	1.04
3	0.95	**1.73**	1.10	1.12	0.32	0.59	0.99
4	1.10	**1.48**	1.10	1.05	1.00	0.57	0.71
5	1.13	*1.37*	0.44	1.15	1.00	0.59	0.80
6	0.98	**1.54**	0.22	1.14	1.04	0.50	*1.39*
Winter							
0	1.07	1.05	1.54	0.95	0.64	1.09	0.90
1	1.06	0.90	0.82	0.95	0.81	1.01	1.25
2	0.95	1.15	0.92	1.03	1.29	0.49	0.80
3	0.80	1.22	1.98	0.76	0.97	*1.67*	1.00
4	1.02	*1.28*	0.00	0.85	0.97	0.72	0.79
5	1.13	1.13	1.15	0.52	0.81	1.38	0.89
6	0.86	**1.49**	1.15	0.69	0.65	0.70	1.12

Bold values indicate significant at the $P < 0.05$ level and italicized values indicate near-significant ($P < 0.10$).

Table 2. Standardized Spike Day Ratios (SSDRs; Observed Spike Days Over Expected Spike Days) for the O18 Age Group by Lag Day (Rows) and Weather Type (Columns) for Each Season in the NYC Region (1 is Considered Normal)

	DM	DP	DT	MM	MP	MT	TR
Spring							
0	0.74	1.25	0.00	1.43	0.70	1.33	1.08
1	0.65	*1.54*	0.58	0.80	1.37	1.09	1.08
2	1.00	0.92	0.57	1.14	1.14	0.56	1.29
3	1.27	1.06	**2.28**	0.33	0.23	0.85	1.51
4	1.27	1.34	*2.23*	0.33	0.46	*1.76*	0.21
5	1.00	0.88	*2.19*	**1.66**	0.23	0.89	0.64
6	1.00	0.59	1.64	0.49	1.44	0.89	*1.68*
Summer							
0	1.19	0.41	*1.88*	0.54	0.86	0.89	1.77
1	0.84	1.22	*1.86*	1.06	1.73	0.96	0.00
2	0.96	0.80	1.23	0.53	1.67	*1.31*	0.37
3	0.97	0.78	1.21	1.33	0.00	1.11	0.00
4	0.60	0.38	1.21	0.94	1.62	1.25	1.10
5	0.83	0.37	0.61	1.19	*2.30*	1.07	1.10
6	0.61	1.47	0.91	*1.46*	**2.69**	0.79	0.73
Autumn							
0	0.92	1.28	1.63	1.28	1.53	0.91	0.36
1	0.97	**1.93**	1.08	0.58	1.58	0.69	1.04
2	0.83	1.46	1.08	1.04	0.82	0.68	*1.55*
3	0.98	0.66	1.63	1.04	**3.17**	0.78	1.05
4	0.94	0.66	1.08	1.25	1.65	0.98	1.06
5	1.00	0.51	0.54	1.13	0.00	*1.46*	0.90
6	0.94	0.69	1.08	1.01	1.72	1.04	1.27
Winter							
0	1.12	0.96	0.87	0.88	0.54	*1.85*	0.89
1	1.12	1.02	0.00	0.88	1.46	0.57	0.77
2	0.95	**1.36**	1.04	0.68	1.09	1.37	0.52
3	1.12	1.09	2.24	0.58	1.27	0.27	1.01
4	1.15	0.93	0.00	0.77	0.91	0.27	*1.53*
5	0.98	1.22	1.30	0.58	1.10	0.26	1.39
6	1.18	1.28	1.30	0.69	0.92	0.26	0.63

Bold values indicate significant at the $P < 0.05$ level and italicized values indicate near-significant ($P < 0.10$).

The most substantial result is that DP in autumn is associated with increases in asthma admissions—an outcome that is in agreement with previous literature (Jamason et al. 1997; Nastos et al. 2006). However, this result was most apparent in the NYC region, and did not hold true across all seven regions examined, or in an aggregate of the rest of NYS. Spike days in asthma occurred with greater than average frequency up to 2 days after the occurrence of the autumn DP type in the O18 age group and up to 6 days after occurrence with the U18 age group as well. These results coincide with biological research which has shown that cooler and drier conditions can decrease air flow in the lungs of asthmatics (Mathur et al. 1993); though ARHAs in the current study include both asthmatics and non-asthmatics admitted for asthma. Jamason et al. (1997) also found that three cool/cold and dry *winter* WTs showed

Table 3. *P* Values for Chi-Square Test to Test Differences in Observed Spike Days from Expected Spike Days Across All Weather Types in Each Season (Columns) for Each Lag Day (Rows) for the NYC Region for U18 and O18

	Spring	Summer	Autumn	Winter
Under 18				
0	0.613	0.390	0.340	0.959
1	0.966	0.496	0.962	0.979
2	0.661	**0.038**	0.657	0.868
3	**0.036**	**0.038**	**0.033**	0.487
4	0.846	0.938	0.157	0.743
5	0.845	*0.051*	0.163	0.610
6	0.649	**0.009**	**0.018**	0.273
18 and over				
0	0.563	0.315	0.577	0.659
1	0.611	0.412	0.222	0.709
2	0.950	0.555	0.596	0.445
3	0.116	0.527	0.251	0.410
4	**0.040**	0.688	0.935	0.397
5	0.204	0.625	0.504	0.414
6	0.366	0.198	0.951	0.391

Bold values indicate significant at the $P < 0.05$ level and italicized values indicate near-significant ($P < 0.10$).

significant increases in admissions 1–2 days after occurrence in NYC. While this result held true for winter DP spike days for the O18 age group in this research, only Lag 2 was statistically significant, while for the U18 age group the impact of winter DP on spike days in ARHAs was significant only at a longer lag. Other regions of NYS did not exhibit a significant relationship between anomalous ARHAs and winter DP in either age group.

While the inconsistent spatial relationship noticed between WTs and asthma admissions in all seasons could be partially attributable to sample size issues in these regions, previous research in NYS has shown that access to medical care and the differing socio-economic status of various zip codes can impact asthma admissions rates as well (Lin et al. 1999)—potentially confounding any relationship between ARHAs and WTs in these regions. Differing concentrations of a variety of pollutants and/or allergens that are associated with a particular WT in different regions may also lead to inconsistent spatial results.

In comparison to previous synoptic literature looking at NYC (Jamason et al. 1997), with the exception of the general agreement with the autumn DP type, the results herein differ quite substantially. In their research, no summer WTs showed significant associations to increased admissions. In the current research, however, one of the most consistent results found is that some summer WTs—primarily DT (hot and dry)—were associated with increased asthma admissions and more spike days, especially in the U18 age group in NYC and the O18 age group throughout the rest of NYS—a result consistent with research from Hanna et al. (2011) in North Carolina (though they did not stratify by season). A possible reason for this is due to this WT's association with increased pollen levels and increased levels of a variety of pollutants—a known trigger for asthma exacerbation (Hanna et al. 2011). However, Lin et al. (2009) find that extreme heat (greater than 32°C) by itself is a significant risk factor for increased asthma admissions in NYC. Another possible reason behind the significant summer results herein is that the number of daily ARHAs and the number of spike days in summer are both substantially less than what occurs in most other seasons, in essence, making small absolute differences become large percentage differences. Summer MP and summer MM also exhibited strong associations to spike days in ARHAs at extended lag times (4–6 days) in both age groups. The fact that there is such consistency between age groups for the summer season (when school is not in session) more so than other seasons, supports results from Lin et al. (2011) and Johnston and Sears (2006) that suggest the timing of the school year and the associated asthma triggers (indoor allergens, pet dander, pollutants, etc.) that are suddenly introduced to children in the classroom may play a role in the autumnal increase in ARHAs (in summer, both adults and the school-aged population are presumably subjected to more similar environmental conditions—while in other seasons, this is not the case).

The conclusions of this study must be understood in the context of its limitations. Sample size was a limiting factor in two ways. First, despite a seemingly large total sample size (over 518,000 cases), the average number of ARHAs was fewer than 4 per day for the O18 age group, and fewer than 2 per day for the U18 age group for every region except NYC (Table 6). In some seasons, this likely created substantial anomalous admissions and/or a spike day out of a day when only one extra person was admitted (hence the reason for selecting NYC as the only region to examine spike days). While perhaps statistically relevant, in a practical sense, this is unlikely to result in an increased burden to the local medical facilities. This said, for a variety of reasons, the vast majority of ARHA cases are from dense urban areas—nearly 82% in this research—and thus, the results found herein may be quite relevant for a large

Table 4. Average Anomalous ARHAs Summed for the U18 Age Group for the 1- to 3-Day Period After Air Mass Occurrence (3dARHAs) as a Percent of the Raw Average for Each Season and Each Region (3-DAY AVG)

3dARHAs	DM (%)	DP (%)	DT (%)	MM (%)	MP (%)	MT (%)	TR (%)	3-DAY AVG
Spring								
NY City	0.4	0.8	0.5	0.3	−0.1	0.4	0.1	121.1
ALB	−0.4	0.1	−4.5	11.4	−0.8	3.2	−3.0	5.6
BUF	−0.3	−2.8	11.6	7.7	0.3	−10.2	3.2	5.9
WAT	4.7	−5.6	−1.0	3.7	3.2	−0.1	−4.4	4.0
BIN	−4.1	−3.9	14.8	0.5	−4.4	25.9	−1.6	2.2
ROC	−2.5	−1.5	6.4	4.3	2.9	5.1	−4.4	3.7
MAS	−6.9	0.1	0.9	1.0	−5.3	18.8	2.6	0.9
NY State	−0.1	−0.4	0.7	1.0	0.1	0.2	−0.2	22.3
Summer								
NY City	0.5	−3.4	4.1	−3.8	−3.7	0.2	−2.4	59.2
ALB	1.5	−2.3	−2.3	−9.4	7.8	2.8	−5.1	2.6
BUF	−4.6	1.0	3.5	−4.9	1.4	2.7	0.1	3.3
WAT	4.6	−10.3	8.5	4.9	−3.8	−5.1	0.1	2.1
BIN	2.5	−3.6	−21.8	0.1	1.0	1.6	−14.9	1.1
ROC	−4.3	3.2	24.2	3.0	−3.1	−1.5	−6.6	2.0
MAS	−6.8	−5.2	−26.6	8.0	−7.4	3.0	16.9	0.4
NY State	−0.1	−0.3	0.3	−0.2	0.0	0.1	−0.5	11.5
Autumn								
NY City	0.2	2.6	3.3	−0.4	−1.4	−0.6	−1.0	170.6
ALB	0.0	3.0	7.8	−3.2	−2.2	2.9	1.8	7.7
BUF	1.4	1.7	−4.4	6.7	−5.4	−2.3	−3.8	9.0
WAT	1.5	1.7	2.7	1.8	−2.8	−0.5	−8.6	5.7
BIN	2.2	−2.2	1.6	2.1	4.5	−4.1	−3.7	3.1
ROC	−2.0	−1.5	−5.8	6.2	−0.3	1.0	−0.1	5.5
MAS	2.1	−1.4	14.0	2.4	1.6	−10.1	−2.5	1.2
NY State	0.1	0.2	0.3	0.5	−0.4	−0.1	−0.5	32.2
Winter								
NY City	−0.7	−0.4	−0.4	−0.1	0.0	0.8	0.3	127.0
ALB	2.5	−1.3	−18.8	0.5	−2.4	0.5	0.6	5.7
BUF	−0.8	−0.8	−1.2	5.0	−2.7	5.5	−5.5	5.6
WAT	−0.9	−0.4	40.7	−3.4	2.8	3.9	5.8	3.6
BIN	−3.2	0.7	−16.8	3.6	1.1	1.5	−3.8	2.3
ROC	−1.2	−2.7	74.3	2.9	−4.7	11.4	2.9	3.6
MAS	4.2	4.0	–	−8.1	−1.2	−44.1	−0.1	0.8
NY State	0.0	−0.1	1.1	0.3	−0.3	0.6	0.0	21.6

NY State region is all regions aggregated except for the NY City region. Positive values indicate positive anomalies and negative values indicate negative anomalies.

percentage of ARHA cases. Second, due to inherent seasonality in different WTs, effective sample sizes in statistical testing (where N was the number of days in each WT by season) were sometimes quite small.

It should also be noted that in some seasons for each age group the issue of multiple comparison testing may also need to be taken into consideration when interpreting the probability of the significant spike day results being due to random chance. However, the a priori knowledge of the fundamental relationships between weather and asthma discovered in previous research does help to substantiate some of these results.

Table 5. Average Anomalous ARHAs Summed for the O18 Age Group for the 1- to 3-Day Period After Air Mass Occurrence (3dARHAs) as a Percent of the Raw Average for Each Season and Each Region (3-DAY AVG)

3dARHAs	DM (%)	DP (%)	DT (%)	MM (%)	MP (%)	MT (%)	TR (%)	3-DAY AVG
Spring								
NY City	0.1	0.4	0.0	−0.7	−0.3	−0.4	1.2	174.0
ALB	1.6	−0.6	−2.6	1.3	−1.8	0.8	2.6	10.0
BUF	−0.6	−2.5	6.0	−1.3	−2.9	10.4	−1.0	10.5
WAT	0.3	−0.4	9.3	1.1	−2.0	−3.5	−0.5	7.8
BIN	2.5	−3.3	−8.9	3.9	2.8	−6.0	3.4	4.4
ROC	−2.1	−0.2	−2.3	−6.1	3.0	8.3	1.0	8.9
MAS	−0.5	−3.7	−3.6	3.4	1.9	7.4	−4.7	2.7
NY State	0.0	−0.2	0.0	−0.1	−0.1	0.7	0.1	44.3
Summer								
NY City	−0.2	−1.8	1.6	−1.5	−0.2	0.8	−2.1	134.4
ALB	−2.7	−1.9	9.8	−0.9	3.7	1.0	−0.8	6.7
BUF	−2.8	3.6	22.9	−1.0	−5.7	2.7	−5.5	7.2
WAT	0.9	−1.1	11.2	−0.4	−8.0	3.9	−0.4	5.2
BIN	−1.9	2.6	2.8	0.1	−12.7	−1.4	8.6	2.8
ROC	2.4	−6.5	23.0	0.8	−5.1	−0.5	−5.3	6.3
MAS	−3.2	−14.8	5.5	−1.4	2.4	3.2	9.9	1.7
NY State	−0.2	−0.3	2.1	−0.1	−0.6	0.3	−0.3	29.9
Autumn								
NY City	0.4	2.1	0.7	−1.3	0.7	−1.1	0.7	175.9
ALB	0.4	0.6	−3.4	0.9	1.9	−1.0	−3.7	9.8
BUF	3.2	−4.3	5.1	1.7	−3.7	1.7	0.5	9.3
WAT	4.2	−1.3	5.4	−1.8	−4.5	−5.5	0.9	7.1
BIN	−1.8	1.4	−6.2	4.0	−0.3	3.1	−0.5	3.9
ROC	0.8	0.9	2.2	−1.2	−3.7	2.7	3.2	8.2
MAS	1.1	−2.5	3.2	0.0	−2.4	2.4	2.0	2.3
NY State	0.2	−0.1	0.0	0.1	−0.4	0.1	0.0	40.7
Winter								
NY City	−1.1	0.4	5.1	0.1	1.4	2.0	−1.3	207.6
ALB	0.8	−1.0	7.2	−2.3	2.1	3.2	−0.8	12.1
BUF	0.6	−0.7	9.2	0.1	−0.1	5.1	1.9	11.4
WAT	8.4	−0.6	9.8	−0.5	1.0	1.5	−4.1	8.4
BIN	0.3	0.3	−6.2	−0.7	−0.4	6.7	−2.1	4.8
ROC	1.1	−0.9	19.8	3.2	−0.4	0.6	−2.7	10.0
MAS	5.2	0.0	–	0.7	−3.6	13.3	1.2	2.9
NY State	0.3	−0.1	1.2	0.0	0.1	0.6	−0.2	49.6

NY State region is all regions aggregated except for the NY City region. Positive values indicate positive anomalies and the negative values indicate negative anomalies.

The aforementioned effects of lag present another complicating factor. In an effort to capture the most substantial anomalous ARHAs, the present study purposely chose an "ideal lag period" (from 1 to 3 days after WT occurrence; based on initial examination and previous research) in order to evaluate the ARHA response to a WT. While choosing one "ideal lag day" might help better identify a relationship, it was discovered that the peak period/day of anomalous admissions after a WT occurs differs for each season/month, each region, and each WT, and would likely result in even more heterogeneous results spatially, and less intuitive results in a qualitative manner. On the opposite end, the inclusion of too many lag days into a single period may effectively cancel out positive and

Table 6. Average Daily Raw ARHAs by Region and Season for the Under 18 Age Group and the 18 and Over Age Group

	ALB	MAS	WAT	BIN	ROC	NYC	BUF
Under 18							
Spring	1.9	0.3	1.3	0.7	1.2	40.4	2.0
Summer	0.9	0.1	0.7	0.4	0.7	19.7	1.1
Autumn	2.6	0.4	1.9	1.0	1.8	56.9	3.0
Winter	1.9	0.3	1.2	0.8	1.2	42.3	1.9
Annual	1.8	0.3	1.3	0.7	1.2	39.8	2.0
18 and Over							
Spring	3.3	0.9	2.6	1.5	3.0	58.0	3.5
Summer	2.2	0.6	1.7	0.9	2.1	44.8	2.4
Autumn	3.3	0.8	2.4	1.3	2.7	58.6	3.1
Winter	4.0	1.0	2.8	1.6	3.4	69.2	3.8
Annual	3.2	0.8	2.4	1.3	2.8	57.6	3.2

negative anomalies. Future research on this topic will have to account for these issues with lagged ARHA responses to WTs. The issue of temporal autocorrelation when examining anomalous ARHA data merited the examination of spike days in the current research, which may prove to be a more valuable avenue of investigation in future studies.

This study also aggregates results by seasons instead of months (or a shorter time period) in order to have a sample size large enough to attain some substantial results in regions other than NYC. So while the results herein are analyzed by season, WT-to-ARHA relationships likely vary on monthly or shorter time scales as well, and deserve future attention. Future research may also benefit from looking at certain meteorological variables within a WT (as examined in Jamason et al. 1997). As drier WTs in general were found to be related to increased admissions in this study, investigating the role of the within-type humidity levels of DP, DT, or DM WTs in affecting ARHAs could prove useful in further explaining ARHA variability.

Conclusions

The utilization of synoptic WTs in the present study allowed for the analysis of the entire weather situation to which an individual is exposed, as opposed to just individual weather variables. Among other significant results, cold and dry autumn WTs, along with a variety of summer WTs at different lags (including a hot and dry type) were associated with spikes in ARHAs in NYC. Consistent, but non-significant, positive anomalies in admissions were related to these same types across NYS as a whole, though results differed between age groups. While total anomalous ARHAs were examined as well, results were less conclusive than with spike day analyses. This research also highlights the need for further examination of the relationship between synoptic WTs and asthma admissions in non-urban settings.

Although synoptic climatological methods are becoming an increasingly valuable tool for climate change impacts research (Sheridan and Lee 2010; Lee and Sheridan 2012), before accurate future projections of changes (in relation to climate change) in ARHAs can be made, further research still needs to be undertaken to better understand the association between WTs and asthma admissions across a broader spatial scale. With contemporary forecasting capabilities, as was suggested by Jamason et al. (1997), ample warning can be provided to public health officials in these cities to prepare for an increase in admissions and increased stress on the system, while the susceptible population can also take appropriate measures in order to decrease their exposure to adverse environmental conditions.

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