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Identifying joint impacts of sun radiation, temperature, humidity, and rain duration on triggering mental disorders using a high-resolution weather monitoring system

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ABSTRACT

Background: Mental disorders (MDs) are behavioral or mental patterns that cause significant distress or impairment of personal functioning. Previously, temperature has been linked to MDs, but most studies suffered from exposure misclassification due to limited monitoring sites. We aimed to assess whether multiple meteorological factors could jointly trigger MD-related emergency department (ED) visits in warm season, using a highly dense weather monitoring system.

Methods: We conducted a time-stratified, case-crossover study. MDs-related ED visits (primary diagnosis) from May-October 2017–2018 were obtained from New York State (NYS) discharge database. We obtained solar radiation (SR), relative humidity (RH), temperature, heat index (HI), and rainfall from Mesonet, a real-time monitoring system spaced about 17 miles (126 stations) across NYS. We used conditional logistic regression to assess the weather-MD associations.

Results: For each interquartile range (IQR) increase, both SR (excess risk (ER): 4.9%, 95% CI: 3.2–6.7%) and RH (ER: 4.0%, 95% CI: 2.6–5.4%) showed the largest risk for MD-related ED visits at lag 0–9 days. While temperature presented a short-term risk (highest ER at lag 0–2 days: 3.7%, 95% CI: 2.5–4.9%), HI increased risk over a two-week period (ER range: 3.7–4.5%), and rainfall hours showed an inverse association with MDs (ER: −0.5%, 95% CI: 0.9-(-0.1)%). Additionally, we observed stronger association of SR, RH, temperature, and HI in September and October. Combination of high SR, RH, and temperature displayed the largest increase in MDs (ER: 7.49%, 95% CI: 3.95–11.15%). The weather-MD association was stronger for psychoactive substance usage, mood disorders, adult behavior disorders, males, Hispanics, African Americans, individuals aged 46–65, or Medicare patients.

Conclusions: Hot and humid weather, especially the joint effect of high sun radiation, temperature and relative humidity showed the highest risk of MD diseases. We found stronger weather-MD associations in summer transitional months, males, and minority groups. These findings also need further confirmation.

1. Introduction

Mental disorders (MDs) were estimated to be the most costly health issue in the U.S. in 2013 at approximately $201 billion (Roehrig, 2016). The global burden of MDs accounts for 32.4% of years lived with disability (YLDs) and 13.0% of disability-adjusted life-years (DALYs), respectively (Vigo et al., 2016). MDs are behavioral or mental patterns that cause distress or impairment of personal functioning (Bolton,

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2013). Specifically, emergency departments (EDs) have become the de facto primary and acute care providers for patients with MDs in the U.S (Larkin et al., 2009) due to the Emergency Medical Treatment and Active Labor Act (EMTALA), MD insurance carveouts, and deinstitutionalization resulting in fewer psychiatrists and psychiatric inpatient beds (Larkin et al., 2009). In addition, emergency medicine is being used more and more frequently to provide primary and acute mental health care to patients with MDs ranging from substance abuse to suicide attempts (Larkin et al., 2009). Notably, the etiology of MDs is multifactorial. Environmental factors, including hurricanes, floods, and heat stress, have been linked to MDs (Palinkas and Wong, 2020).

Scientific evidence over the past 20 years indicates that climate change is associated with MDs (Patz et al., 2014). Climate change has caused more frequent and intense local weather extremes such as heatwaves, which have caused substantial economic losses and claimed many human lives in recent decades (Olmos et al., 2021; Cappucci, 2021). Previous studies found that high temperature (Almendra et al., 2019; Lee et al., 2018; Peng et al., 2017; Vida et al., 2012; Zhang et al., 2020) and high humidity (Vida et al., 2012; Ding et al., 2016) may be associated with healthcare utilization for MDs. As temperature and relative humidity (RH) rise, stress levels and symptoms of MDs could be exacerbated. Lee et al. (Lee et al., 2018) estimated that 14.6% of MD-related ED admissions could be attributed to extremely hot temperatures (Lee et al., 2018). As for humidity, Ding et al. (Ding et al., 2016) found that a one-unit increase in vapor pressure was associated with a 0.1% increase in distress (Ding et al., 2016). Specifically, the "felt temperature" in summer is often different than the actual air temperature, mainly because humidity amplifies the feeling of heat (Extreme Heat, 2022). Heat index (HI) combines air temperature and relative humidity, reflecting the real "felt" temperature. However, this indicator has been seldomly used in investigating its relationship with MDs. In addition, two previous studies presented an association between solar radiation (SR) and bipolar disorders and schizophrenia (Gu et al., 2019; Aguglia et al., 2019) Furthermore, Matthew et al. (2021) observed a positive association between MDs and rainfall in summer (Yap et al., 2021). These findings suggested the potential associations between these meteorological factors and MDs.

Importantly, previous studies (Lee et al., 2018; Peng et al., 2017; Basu et al., 2018; Chan et al., 2018; Carlsen et al., 2019; Wang et al., 2014; Yi et al., 2019) have mainly focused on temperature, while limited studies examined other meteorological factors such as SR and rainfall, especially the joint exposure to multiple meteorological factors. In addition, previous studies (Gu et al., 2019; Aguglia et al., 2019; Lee et al., 2018; Peng et al., 2017; Vida et al., 2012; Chan et al., 2018; Carlsen et al., 2019; Wang et al., 2014; Yi et al., 2019; Niu et al., 2020) utilized very few weather monitoring stations (one or two), and the subsequent exposure misclassification may impact the validity of their conclusions (if the impacts were non-differential, it underestimated the real association). Many studies also used annual data (Lee et al., 2018; Peng et al., 2017; Gu et al., 2019; Aguglia et al., 2019; Chan et al., 2018; Carlsen et al., 2019; Wang et al., 2014; Yi et al., 2019; Niu et al., 2020), but the impact of increased temperature in warmer seasons is quite different from that in colder seasons. Although some studies reported more substantial impacts of heat on several health outcomes in transitional months compared to summer (Qu et al., 2021), we found no similar studies looking at MDs. Furthermore, few studies have analyzed the impact of meteorological factors on different subtypes of MDs.

In this study, we aimed to address these knowledge gaps by assessing how multiple meteorological factors (SR, temperature, relative humidity (RH), heat index (HI), and rainfall) individually and jointly affect MD-related ED visits overall and by lags, MD subtypes, demographics, and in summer and transitional months, using a highly-dense monitoring system (17 * 17-mile grid).

2. Method

2.1. Outcome definitions and data sources

We used a time-stratified case-crossover design (Janes et al., 2005) to estimate the short-term health associations between exposure to various meteorological factors and MD-related ED visits. The case-crossover design is essentially a matched case-control study design where each individual serves as his/her own control, which is commonly used to identify associations between acute environmental triggers and health outcomes. Specifically, for each ED visit reported, we defined the date of the visit as a case day and identified control days as the same day of the week set two weeks apart in the same calendar month before or after the case day.

We obtained ED visit data from the New York Statewide Planning and Research Cooperative System (SPARCS), a mandatory hospital discharge database covering ~ 95% of hospitals in New York State (NYS). The database includes individual-level data on principal /other diagnoses, admission date, patient address, race, ethnicity, sex, age, and type of insurance. Each ED record was geocoded to the street level. We obtained ED visits (N = 547,540) between May and October in 2017 and 2018 that reported a principal diagnosis of MD (International Classification of Diseases 10 (ICD-10): F00-F99; intentional self-harm problems ICD-10: X60-X84).

2.2. Definition of exposures and data sources

We obtained meteorological data from the NYS Mesonet (http://nysmesonet.org). The NYS Mesonet is a dense weather monitoring system deployed statewide. Spaced an average of 17 miles (25 km) apart, the 126 stations collect and process data every 5 min in real-time (Brotzge et al., 2020) (See map in supplemental Fig. A.1). We focused on five meteorological variables (daily scale): total SR, average RH, average temperature, average HI, and rainfall hours (total number of hours of rainfall per day) as described in supplemental Table A.4). In addition to rainfall hours, we also evaluated the consequence of rainfall quantity (i.e., "precipitation") on MDs. We assigned the same-day value of each meteorological factor from the nearest weather station to each health record (matching with ED visit date). Inter-quartile range (IQR) was used as the risk measurement unit. Air pollutant ($PM_{2.5}$ and Ozone) data were obtained from a validated chemical transport model with size-resolved particle microphysics, GEOS-Chem/APM (Yu and Luo, 2009).

2.3. Statistical analysis and confounders

We used a moving average method to calculate the cumulative and individual lagged associations. To examine reference values and joint associations, we selected the lag days with the most significant MD risk for each meteorological factor because the lag effect structures of each meteorological factor are different. For instance, temperature and HI seemed to have an immediate effect with a short lag time, but RH and SR had a relatively long lag effect on mental health disorders. Therefore, identifying different lag effects not only catch the sensitive time window with the highest health risk but also provide a clue for policymakers to plan future intervention or response efforts during extreme weather events. We used the "crosspred" function from the "DLNM" package in the conditional logistic regression to identify the reference values (Gasparrini, 2011). We used natural cubic spline method for each meteorological factor in the models. Since the associations were linear, we then used the medium level of each meteorological factor as the standard reference (normal weather conditions). As for the joint association, we dichotomized the exposures as either low or high level based on the reference values and ran a model with a categorical variable indicating different combination of weather conditions. The associations were assessed overall and by month (May to October) to compare summer and transitional month effects. The selection of lag days was

Table 1
Cumulative excess risk for each IQR[a] increase of meteorological factors on ED visits for MDs, NYS (N = 547,540)[b].

Lag	IQR	SRER (95% CI)	IQR	RHER (95% CI)	IQR	TemperatureER (95% CI)	IQR	HIER (95% CI)	IQR	Rainfall HoursER (95% CI)
0–1	9.5	0.3 (−0.9, 1.5)[c]	18.6	1.5 (0.6, 2.4)	7.1	3.6 (2.5, 4.7)	7.5	4.0 (3.0, 5.0)	1.8	−0.5 (−0.9, −0.1)
0–2	8.3	0.8 (−0.4, 2.1)	16.3	1.5 (0.6, 2.3)	7	3.7 (2.5, 4.9)	7.7	4.4 (3.3, 5.5)	1.5	−0.3 (−0.7, 0.2)
0–3	7.6	1.9 (0.6, 3.2)	15	1.5 (0.5, 2.4)	7	3.7 (2.4, 5.0)	7.5	4.5 (3.3, 5.7)	1.3	−0.2 (−0.7, 0.3)
0–4	7.2	3.0 (1.6, 4.5)	14.6	1.8 (0.8, 2.8)	6.9	3.2 (1.8, 4.6)	7.4	4.3 (3.1, 5.5)	1.3	−0.3 (−0.8, 0.2)
0–5	6.9	3.8 (2.3, 5.3)	14.1	2.2 (1.1, 3.3)	6.7	2.8 (1.4, 4.3)	7.2	4.3 (3.0, 5.5)	1.2	−0.3 (−0.9, 0.2)
0–6	6.6	4.3 (2.8, 5.9)	13.7	2.7 (1.5, 3.9)	6.6	2.5 (1.0, 4.1)	7.1	4.3 (3.0, 5.6)	1.2	−0.5 (−1.1, 0.1)
0–7	6.5	4.7 (3.0, 6.4)	13.4	3.3 (2.0, 4.6)	6.5	2.2 (0.7, 3.9)	7	4.5 (3.2, 5.9)	1.1	−0.5 (−1.1, 0.1)
0–8	6.2	4.7 (3.0, 6.4)	12.8	3.6 (2.3, 5.0)	6.5	1.8 (0.2, 3.5)	7	4.5 (3.1, 5.9)	1.1	−0.3 (−1.0, 0.3)
0–9	6.2	4.9 (3.2, 6.7)	12.7	4.0 (2.6, 5.4)	6.5	1.3 (−0.5, 3.1)	7	4.3 (2.9, 5.8)	1	−0.4 (−1.0, 0.2)
0–10	6.1	4.5 (2.7, 6.3)	12.3	3.7 (2.3, 5.2)	6.5	1.2 (−0.7, 3.1)	7	4.2 (2.6, 5.7)	1	−0.3 (−0.9, 0.4)
0–11	5.8	4.3 (2.5, 6.1)	11.9	3.6 (2.1, 5.1)	6.4	1.1 (−0.8, 3.1)	7.1	4.2 (2.6, 5.9)	1	−0.2 (−0.9, 0.4)
0–12	5.4	4 0.3 (2.6, 6.1)	11.5	3.5 (2.0, 5.0)	6.5	1.0 (−1.1, 3.1)	7.2	4.2 (2.5, 6.0)	0.9	−0.2 (−0.8, 0.5)
0–13	5.2	4.8 (3.1, 6.6)	11	3.7 (2.2, 5.2)	6.4	0.3 (−1.9, 2.5)	7	3.7 (2.0, 5.4)	0.9	−0.2 (−0.9, 0.5)

[a] IQR units: SR (MJ/m^2), RH (%), Temperature (°C), HI (No units), and Rainfall Hours (hour).
[b] For each meteorological factor, model controlled for other three meteorological factors (except for heat index), holiday, $PM_{2.5}$, and Ozone. For heat index, besides holiday, $PM_{2.5}$, and Ozone, only solar radiation and rainfall hour on the same lag day were included in the model.
[c] Presented as ER (95 %CI).

determined by if the elevated risks effect started to decrease.

We used conditional logistic regression to assess the risk associations between meteorological factors and MD-related ED visits. All four meteorological factors, such as SR, RH, temperature, and rainfall (except for HI), were simultaneously put in the models as well as $PM_{2.5}$, O_3, and time-varying variables (holidays). For HI, we excluded the temperature and relative humidity in the models to avoid the over-control problem. Generally, we controlled all other weather factors in the models simultaneously for individual lag and cumulative lag analyses. Other inherit confounders including age, gender, insurance, education, and other demographical variables were controlled by the time-stratified case-crossover study design, where each individual is served as their own control. Stratified analyses were conducted by MD subtypes and demographic groups as well. The excess risk (ER) per each IQR increase was calculated as (exp(beta*IQR)-1)*100%, where beta was the regression coefficient.

We conducted several sensitivity analyses: 1) using the interpolation method to obtain the meteorological exposures at 1 km × 1 km and reran the analysis to check if the further refinement of exposure would change the results; 2) redefining the control days as all other same weekdays in the same calendar month, 3) using different reference values (40th, 60th, and 70th) to compare with 50th to assess the robustness of the original findings using the median (50th), and 4) estimating the joint effect of exposure to multiple meteorological factors

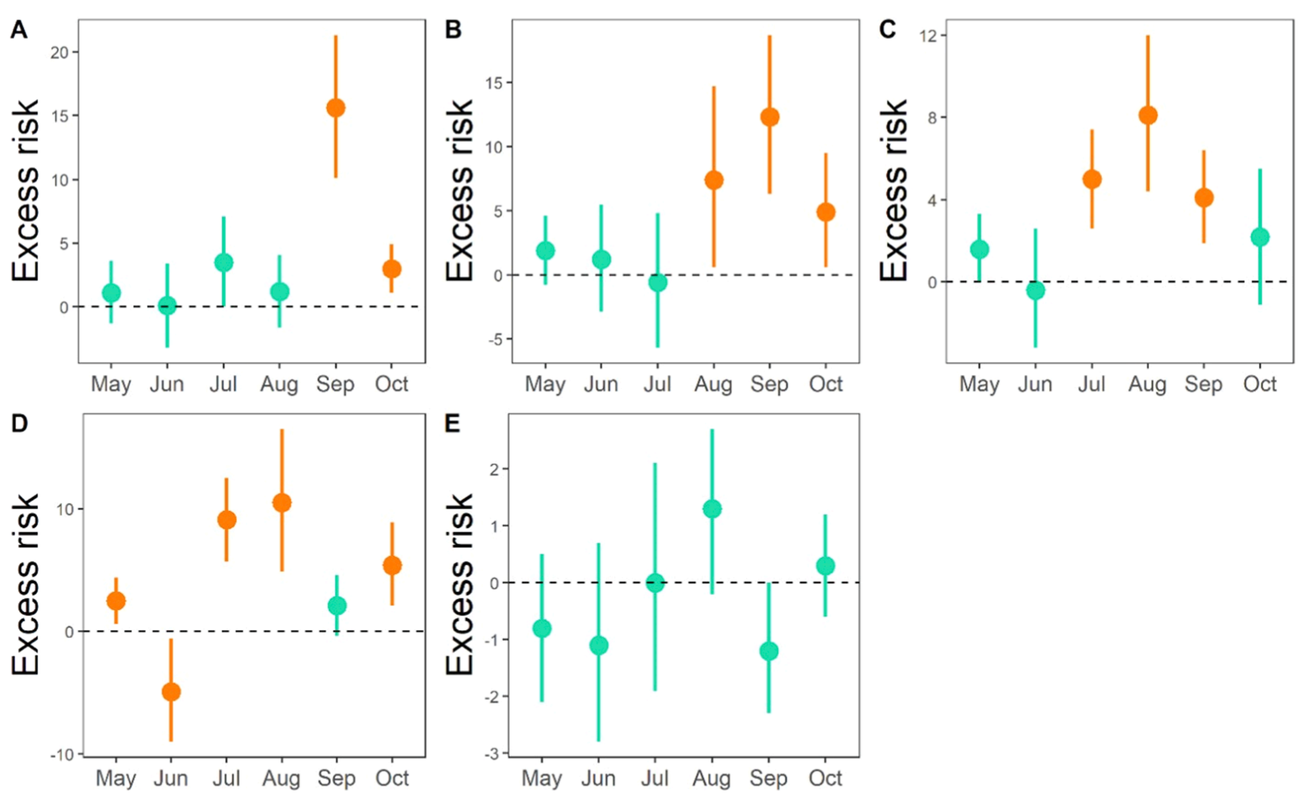

Fig. 1. Cumulative excess risk for each IQR increase of meteorological factors on ED visits for MDs by month, NYS (N = 547,540). Green is not statistically significant; Orange is statistically significant. A is for SR; B is for RH; C is for temperature; D is for HI; E is for Rainfall hours. SR is on lag 0–9 day; RH is on lag 0–9 day; Temperature is on lag 0–2 day; HI is on lag 0–7 day; Rainfall hours is on lag 0–1 day. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

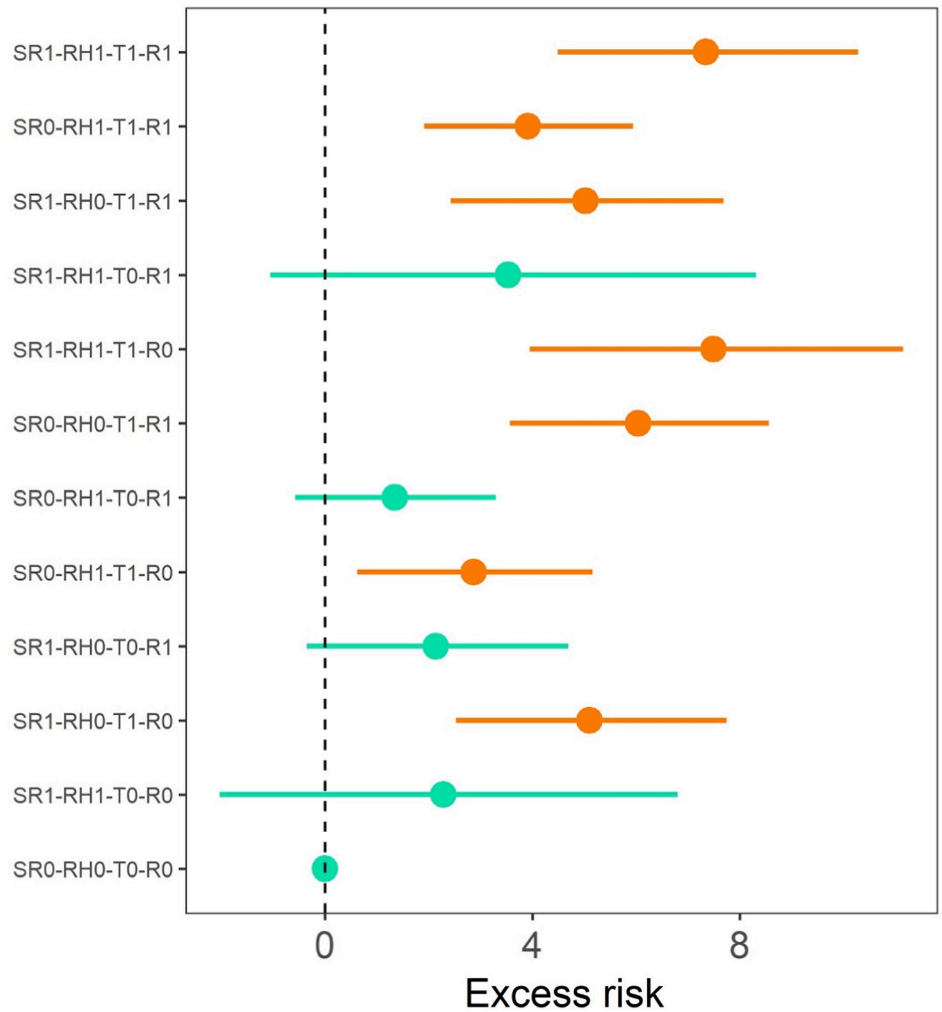

Fig. 2. Comparison of different combinations of meteorological factors on ED visits for MDs, NYS (N = 547,540). Green is not statistically significant; Orange is statistically significant. SR is on lag 0–9 day; RH is on lag 0–9 day; Temperature (T) is on lag 0–2 day; Rainfall hours (R) is on lag 0–1 day (1: high level, 0: low level). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

by using mixture analysis with Quantile G-Computation (Keil et al., 2020). All analysis was conducted using R 4.0.3.

3. Results

In total, 547,540 ED visits (mean age (SD) = 39.47 (17.71), 61.7% male, 38.3% female) from May to October in 2017 and 2018 were included. Table 1 presents the cumulative ER for an MD-related ED visit per IQR increase in each meteorological factor. From lag 0–1 to lag 0–13 days, SR, RH, temperature, and HI were associated with increased ED visits for MDs (SR: ER range = 0.3–4.9%, RH: ER range = 1.5–4.0%, Temperature: ER range = 0.3–3.7%, HI: ER range = 3.7–4.5%). The impact of temperature decreased over time, while the impact of RH increased slightly over time. These two factors led to an overall elevated risk from HI over a two-week period. The lag 0–9 for SR was the moving average from lag 0 to lag 9 days. The impact of SR peaked at lag 0–9 days; rainfall hours yielded a consistently negative association in both the short and long-term. Consistently, by using mixture analysis with Quantile G-Computation, temperature, RH, and SR had positive weights (risk effects) and rainfall hours had negative weights (protective effect). The overall joint effect of the mixture exposure with one quantile increase was ER = 2.90, 95% CI = 1.66–4.15 (See in supplemental Fig. A8). Individual lagged associations are described in supplemental Table A.1. In addition, the Table A.2 shows the results of a sensitivity analysis we conducted using daily rainfall quantity instead of rainfall hours. Unlike rainfall hours, daily rainfall quantity was not significantly associated with MD-related ED visits.

Fig. 1 shows the cumulative ER associated with each meteorological factor on MD-related ED visits by month. We used lag 0–9 days for SR and RH, lag 0–2 days for temperature, lag 0–7 days for HI, and lag 0–1 day for rainfall hours based on Table 1. Generally, the risk associated with SR, RH, temperature, and HI peaked in August and September. SR and RH had the greatest ER in September (SR: ER = 15.6%, 95 %CI = 10.1–21.3%; RH: ER = 12.3%, 95 %CI = 6.3–18.7%), while the ERs of temperature and HI peaked in August (Temperature: ER = 8.7%, 95 %CI = 2.4–15.4%; HI: ER = 8.6%, 95 %CI = 3.2–14.2%). The ERs of rainfall hours did not vary seasonally.

Fig. 2 compares different combinations of meteorological factors on MD-related ED visits. We adopted different lag days for different meteorological factors to assess the joint effects on MDs. SR is on lag 0–9 day; RH is on lag 0–9 day; Temperature is on lag 0–2 day; HI is on lag 0–7 day; Rainfall hours is on lag 0–1 day. The cut-off values were identified using the reference points from the trend of association in the Fig. 3 (SR = 17 MJ /m^2, RH = 70%, Temperature = 20 °C, Rainfall hours = 0.5 h). Meteorological factors were dichotomized into high level (denoted as 1) and low level (denoted as 0). High levels of SR, RH, temperature (T), and lower level of rain hour (R) (SR1-RH1-T1-R0) led to the greatest ER (ER = 7.49%, 95 %CI = 3.95–11.15%). In general, hot weather had the

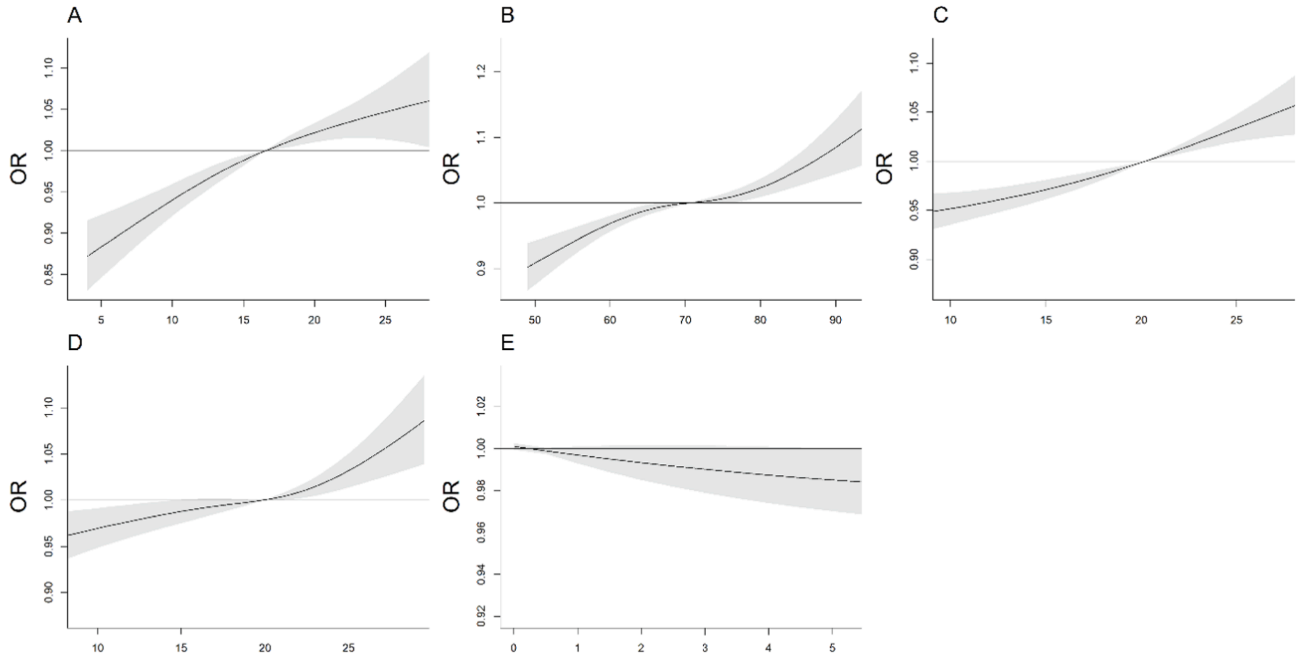

Fig. 3. Trend of association between meteorological factors and ED visits for MDs, NYS (N = 547,540); A is for SR (MJ/m^2); B is for RH (%); C is for temperature (°C); D is for HI; E is for Rainfall hours (hours). SR is on lag 0–9 day; RH is on lag 0–9 day; Temperature is on lag 0–2 day; HI is on lag 0–7 day; Rainfall hours is on lag 0–1 day.

greatest impact on MDs, while rain and cool temperatures mitigated those associations.

The ER for several MD subtypes associated with an IQR increase of each meteorological factor are described in Table 2. Generally, four subtypes of MDs (psychoactive substance usage (ICD-10 = F10-F19), mood disorders (ICD-10 = F30-F39), stress-related disorders (ICD-10 = F40-F48), and adult behavior disorders (ICD-10 = F60-F69)) were significantly impacted by meteorological factors. Among them, ED visits for psychoactive substance usage were related to higher levels of SR, RH, temperature, and HI (ER range = 2.4–5.3). ED visits for mood disorders were associated with lower SR but higher temperature (SR: ER = -3.6%, 95 %CI = -6.9-(-0.2)%, Temperature: ER = 5.4%, 95 %CI = 2.4–8.5%). ED visits for stress-related disorders were related to higher temperature and HI (ER range = 3.2–4.1%). ED visits for adult behavior disorders were related to higher RH (ER = 11.7%, 95 %CI = 1.6–22.9%).

As shown in Table 3, the ERs for MD-related ED visits by meteorological factor and demographic group are described. MD-related ED visits among Hispanics were significantly associated with RH, temperature, and HI (ER range = 4.0–4.2%). ED visits among African Americans were significantly associated with SR and RH. ED visits among individuals aged 46–65 were consistently associated with SR, RH, temperature, and HI (ER range = 3.0–6.9%). The association of ED visits among males with SR, RH, and HI was stronger than among females (ER range = 2.4–2.6%). ED visits among individuals with Medicare were significantly associated with SR and RH (ER range = 4.5–4.9%), whereas ED visits among those with Medicaid or no insurance were significantly associated with temperature and HI (ER range = 4.3–7.3%).

4. Discussion

4.1. Strengths and lags of the weather-MD associations

In this study, all four meteorological factors were found to be significantly associated with MDs. Surprisingly, besides temperature, which most previous studies reported associated with adverse health outcomes, SR demonstrated the greatest risk of visiting the ED for MD-related reasons (ER: 4.8), followed by HI, RH, and temperature (ER range from 4.5 to 3.7%). Interestingly, rainfall hours were negatively associated with MDs, whereas rainfall quantity was not. Consistently, by using mixture analysis (Quantile G-Computation), we found adverse effects for temperature, RH, and SR, but protective effects for rainfall hours. No prior literature assessed all these meteorological factors simultaneously to compare with our findings.

SR and RH showed significantly delayed but lasting associations with MD-related ED visits (highest on 0–9 days) in our study. Consistent with our findings, Shaohua et al. (2019) reported a significant association between sunlight and hospital admissions for schizophrenia on lag 0–21 days (Gu et al., 2019). Another study led by Shia et al. (2009) compared the same-day and two-week average sunlight exposures on MDs and found that only two-week sunlight exposure was related to cognitive function among depressed participants (Kent et al., 2009). As for RH, Salib et al. (2002) found a delayed association between RH and MD admissions at lag 14 days, which was greater than the same-day association (Salib and Sharp, 2002).

Contrastingly, our study found an immediate but short-term response (0–3 days) on MDs after high-temperature exposure. Additionally, HI, a similar indicator as apparent temperature by combining the air temperature and RH (US Department of Commerce), led to significant increases in MD-related ED risks over a two-week period. Our findings are consistent with four previous studies investigating apparent temperature-MDs association (Basu et al., 2018; Yi et al., 2019; Niu et al., 2020; Min et al., 2019). For instance, Basu et al. (Basu et al., 2018) found that the risk of apparent temperature on MDs could last>1 week [19]. The other three studies (2019–2020), conducted in China, suggested that the associations between apparent temperature and MDs could last for 1–2 weeks (Yi et al., 2019; Niu et al., 2020; Min et al., 2019), but these studies (Yi et al., 2019; Niu et al., 2020; Min et al., 2019) used a very low apparent temperature as a reference (-3.4 °C, −2.4 °C, 3.3 °C), which may be inappropriate to investigate the effect of heat. For example, the immediate response of HI may come from temperature, and the lasting association could come from RH.

We could not find any prior studies that evaluated the impacts of precipitation on MDs. Our study found an immediate protective effect of rainfall hours on MDs, which the cooling effect of rain may explain. However, we did not find a similar protective effect between MDs and rainfall quantity, suggesting that the duration of rain may be more

Table 2
Excess risk for each IQR[a] increase of meteorological factors on ED visits by MD subtypes, NYS (N = 547,540)[b.]

Excess Risk[c]	SR	RH	Temperature	HI	Rainfall Hours
	ER (95 %CI)	ER (95 %CI)	ER (95 %CI)	ER (95 %CI)	ER (95 %CI)
Physiological disorders	−2.4 (−11.3, 7.4)	1.6 (−6.0, 9.9)	−1.4 (−9.0, 6.8)	−2.5 (−8.7, 4.1)	−1.1 (−3.7, 1.5)
Psychoactive substance usage	5.3 (3.0, 7.7)	3.0 (1.2, 4.9)	3.4 (1.5, 5.4)	2.4 (0.8, 3.9)	−0.5 (−1.1, 0.1)
Schizophrenia	2.2 (−2.0, 6.5)	2.2 (−1.0, 5.6)	0.3 (−3.1, 3.8)	2.3 (−0.4, 5.2)	0.9 (−0.3, 2.0)
Mood disorders	−3.6 (−6.9, −0.2)	−0.8 (−3.5, 2.0)	5.4 (2.4, 8.5)	2.0 (−0.4, 4.4)	0.0 (−0.9, 1.0)
Stress-related disorders	−1.3 (−4.7, 2.3)	1.5 (−1.4, 4.5)	4.1 (1.0, 7.2)	3.2 (0.8, 5.7)	0.1 (−0.9, 1.1)
Behavioral syndromes	−16.8 (−38.2, 12.0)	−7.8 (−27.3, 17.0)	27.2 (−2.0, 65.0)	3.2 (−15.5, 26.0)	−0.7 (−8.8, 8.0)
Adult behavior disorders	8.1 (−3.9, 21.7)	11.7 (1.6, 22.9)	−3.2 (−12.4, 6.9)	3.9 (−4.1, 12.6)	−0.1 (−3.4, 3.4)
Intellectual disabilities	−4.3 (−28.4, 27.9)	−8.3 (−28.2, 16.9)	−1.9 (−24.9, 28.3)	−7.9 (−25.2, 13.5)	−2.7 (−11.1, 6.4)
Developmental disorders	0.0 (−16.1, 19.3)	−8.0 (−20.0, 5.8)	13.3 (−2.5, 31.7)	2.7 (−8.6, 15.3)	1.6 (−3.2, 6.7)
Behavioral and emotional disorders related to childhood	−2.5 (−11.0, 6.9)	3.0 (−4.1, 10.6)	6.2 (−1.7, 14.7)	3.6 (−2.6, 10.1)	−1.4 (−3.8, 1.1)
Unspecified mental disorder	−1.9 (−35.3, 48.9)	−4.2 (−30.7, 32.6)	16.4 (−16.9, 63.2)	5.8 (−18.6, 37.6)	−11.0 (−21.8, 1.2)
Intentional self-harm	4.4 (−7.1, 17.4)	1.1 (−8.3, 11.4)	5.5 (−4.3, 16.3)	0.6 (−7.2, 9.0)	−1.1 (−4.4, 2.3)

[a] IQR units: SR (MJ/m^2), RH (%), Temperature (°C), HI (No units), and Rainfall Hours (hour).
[b] For each meteorological factor, model controlled for other three meteorological factors (except for heat index), holiday, $PM_{2.5}$, and Ozone. For heat index, besides holiday, $PM_{2.5}$, and Ozone, only solar radiation and rainfall hour on the same lag day were included in the model.
[c] SR is on lag 0–9 day; RH is on lag 0–9 day; Temperature is on lag 0–2 day; HI is on lag 0–7 day; Rainfall hours is on lag 0–1 day.

important than the total amount of precipitation. In addition, in the sensitivity analysis, we redefined the control days as 0–6 lag days and found that the results were similar to the original results (0–13 lag days), although there were slight differences (<1% change). Also, we found similar results in other sensitivity analyses by using interpolation method and different reference values for combination effects.

4.2. Weather-MDs risks in transitional months

Surprisingly, we found that the highest risks for MDs associated with SR and RH occurred in September, and those associated with temperature and HI occurred in September and October. Although no previous studies examined weather-MD associations in transitional months, Andrea et al. (2019) (Aguglia et al., 2019) reported that the hospital admission rates of MDs started to increase in July and peaked in October. Other studies (Geoffroy et al., 2014; Jahan et al., 2020; Lee et al., 2007) found more frequently reported MD-related hospital admissions during the transitional periods from summer to fall. This phenomenon was not unique for MDs. Yanji et al. (2021) also found that the association between extreme heat exposure and pregnancy complications was stronger in transitional months compared to summer (Qu et al., 2021).

4.3. Joint effects of meteorological factors

The combination of high levels of SR, RH, and temperature showed the greatest risk for ED utilization for MDs in our study, specifically when SR > 17 MJ/m^2, RH > 70%, and temperature > 20 °C (potential reference values). To our knowledge, no prior studies have assessed the joint impacts of meteorological factors on MDs. Andrea's study (2019) reported that hospital admissions among patients with bipolar disorders increased in response to higher temperatures, higher humidity, and high SR, separately (Aguglia et al., 2019). In addition, Ding et al. (Ding et al., 2016) reported that the effect of heat on MDs could double when humidity exceeded the 99th percentile [14]. We found that the estimated combined associations were much stronger than the estimated individual associations from each exposure, suggesting a potential synergistic effect. Our results were robust. By changing the reference values (40th, 50th, 60th and 70th), we still found that the combination of higher SR, higher RH, and higher T tended to have greater risk (Fig. A.3). Therefore, focusing on individual meteorological factors may mask the more complex, non-linear impacts associated with environmental exposures, and combined effects should be considered.

4.4. Associations and mechanisms by MD subtype and demographics

SR was associated with increased ED utilization for psychoactive substance use and decreased ED utilization for mood disorders. MDs are biologically affected and regulated by neurotransmitters such as dopamine. Aubert et al. (Aubert et al., 2016) reported that dopamine release was related to ultraviolet radiation in addicted sunbed users [38), and evidence showed that dopamine homeostasis is closely related to psychoactive substance usage and mood disorders (Romeo et al., 2018; Kim et al., 2017; Shiref et al., 2021). In addition, studies have reported a molecular link between circadian rhythm and mood regulation via the dopamine system (Kim et al., 2017).

RH and/or temperature were associated with ED utilization for psychoactive substance usage, mood disorders, and adult behavior disorders (violence-related such as antisocial personality disorder and pyromania). As temperature and humidity rise, the stress and symptoms of those who have MDs could be exacerbated (Basu et al., 2018). Jari et al. (2017) found that for each 2 °C increase in average temperature, the violent crime rate increased by>3% (Tiihonen et al., 2017). In addition, past studies have shown that serotonin and dopamine react differently to body temperature (Yamawaki et al., 1983). Abnormal melatonin, serotonin, and dopamine responses may increase impulsivity and alter adult activities (Tiihonen et al., 2017; Bijlenga et al., 2013; Satyanarayanan et al., 2018), which are closely related to psychoactive substance usage, mood disorders, and adult behavior disorders.

Our findings suggest that Hispanics, African Americans, individuals aged 46–65, and males utilize the ED for MDs more than their counterparts, especially when exposed to high SR and RH. Unfortunately, no previous studies were available for comparison. However, consistent with our temperature-related results, Rupa et al. (2018) reported that MD-related ED visits for Hispanics and females were associated with higher temperature (Basu et al., 2018). In addition, Eun-hye's (2021) results suggested that individuals with MDs aged 20–64 were at greater risk during extreme heat (Yoo et al., 2021).

4.5. Strengths and limitations

This study has several strengths. First, it is one of the few studies that has comprehensively investigated the relationship between ED visits for MDs and multiple meteorological variables. Second, this is the first study

Table 3
Excess risk for each IQR[a] increase of meteorological factors on ED visits for MDs by demographics, NYS (N = 547,540)[b].

Excess Risk[c]		SR	RH	Temperature	HI	Rainfall Hours
		ER (95 %CI)	ER (95 %CI)	ER (95 %CI)	ER (95 %CI)	ER (95 %CI)
Ethnicity	Non-Hispanic	1.2 (−0.4, 2.9)	1.2 (−0.1, 2.5)	3.3 (1.9, 4.7)	1.9 (0.8, 3.0)	−0.1 (−0.6, 0.3)
	Hispanic	3.6 (−0.1, 7.5)	4.2 (1.3, 7.2)	4.1 (1.0, 7.4)	4.0 (1.6, 6.6)	−0.3 (−1.3, 0.6)
Race	White	0.4 (−1.7, 2.6)	0.9 (−0.9, 2.7)	4.1 (2.3, 6.0)	2.0 (0.5, 3.5)	0.0 (−0.6, 0.7)
	African American	4.1 (1.1, 7.2)	3.4 (1.0, 5.8)	−0.6 (−3.0, 1.8)	0.5 (−1.4, 2.5)	−0.7 (−1.4, 0.1)
	Other	1.3 (−1.5, 4.1)	1.6 (−0.5, 3.8)	5.8 (3.4, 8.3)	4.1 (2.2, 6.0)	−0.1 (−0.9, 0.6)
Age	0–5	−25.6 (−44.3, −0.6)	−5.9 (−24.2, 16.8)	7.5 (−16.8, 38.8)	10.2 (−9.2, 33.8)	−3.4 (−10.8, 4.6)
	6–17	−8.6 (−12.7, −4.2)	0.1 (−3.5, 3.8)	3.1 (−0.8, 7.2)	0.6 (−2.4, 3.7)	−1.5 (−2.8, −0.3)
	18–45	0.6 (−1.4, 2.7)	0.6 (−1.0, 2.2)	4.3 (2.5, 6.1)	2.6 (1.2, 4.0)	0.1 (−0.5, 0.7)
	46–65	6.9 (4.1, 9.8)	4.2 (2.0, 6.4)	3.4 (1.2, 5.7)	3.0 (1.2, 4.8)	0.2 (−0.5, 1.0)
	>65	2.4 (−3.2, 8.4)	3.8 (−0.8, 8.5)	−0.3 (−4.8, 4.5)	0.9 (−2.8, 4.8)	−2.1 (−3.6, −0.6)
Gender	Female	0.3 (−2.1, 2.7)	0.4 (−1.5, 2.3)	4.2 (2.2, 6.3)	1.8 (0.2, 3.5)	−0.1 (−0.7, 0.6)
	Male	2.4 (0.5, 4.4)	2.6 (1.1, 4.1)	2.9 (1.3, 4.5)	2.5 (1.2, 3.8)	−0.2 (−0.7, 0.3)
Insurance	Self-paid	−1.2 (−5.2, 3.0)	−0.1 (−3.2, 3.2)	7.3 (3.7, 11.0)	4.4 (1.7, 7.3)	−0.2 (−1.3, 0.9)
	Medicare	4.9 (1.1, 8.9)	4.5 (1.4, 7.6)	2.7 (−0.4, 5.9)	2.8 (0.2, 5.4)	−0.3 (−1.3, 0.8)
	Medicaid	1.1 (−1.4, 3.6)	1.7 (−0.2, 3.7)	5.3 (3.1, 7.5)	4.3 (2.6, 6.0)	0.1 (−0.5, 0.8)
	Company	1.7 (−1.1, 4.5)	1.8 (−0.5, 4.1)	−0.7 (−3.0, 1.6)	−1.9 (−3.8, −0.1)	−0.9 (−1.7, −0.1)
	Other	1.8 (−3.2, 7.0)	−0.7 (−4.7, 3.4)	4.7 (0.5, 9.1)	2.2 (−1.2, 5.8)	1.1 (−0.3, 2.5)

[a] IQR units: SR (MJ/m^2), RH (%), Temperature (°C), HI (No units), and Rainfall Hours (hour).
[b] For each meteorological factor, model controlled for other three meteorological factors (except for heat index), holiday, $PM_{2.5}$, and Ozone. For heat index, besides holiday, $PM_{2.5}$, and Ozone, only solar radiation and rainfall hour on the same lag day were included in the model.
[c] SR is on lag 0–9 day; RH is on lag 0–9 day; Temperature is on lag 0–2 day; HI is on lag 0–7 day; Rainfall hours is on lag 0–1 day.

to evaluate meteorological exposures using the refined data from the highly-dense statewide weather system, NYS Mesonet. Previous studies (Gu et al., 2019; Aguglia et al., 2019; Lee et al., 2018; Peng et al., 2017; Vida et al., 2012; Chan et al., 2018; Carlsen et al., 2019; Wang et al., 2014; Yi et al., 2019; Niu et al., 2020) used data collected from relatively few (usually just one) weather stations, resulting in misclassification exposure. Additionally, this study included data on ED visits across almost all hospitals (>95%) in NYS with good representativeness of different urbanicity, various sociodemographic status, and residents living in different micro-weather regions in NYS. Previous studies were generally confined to a single city or a single hospital (Gu et al., 2019, Aguglia et al., 2019, Chan et al., 2018, Carlsen et al., 2019, Salib and Sharp, 2002, Hu et al., 2020). Finally, this study deals with a large sample size of MDs (547,540).

However, there are also several limitations of this study: 1) We could not control for all air pollutants, but the major pollutants in summer, such as $PM_{2.5}$ and ozone were included. 2) Some potential confounder information such as personal activity patterns and air conditioner use were not available. Nevertheless, the case-crossover design we used has automatically controlled for some inherent variables, including age, gender, race, ethnicity, family history of MDs, and health status. 3) Only ED visits for MDs were included in this study, which may reflect the tip of the iceberg, and included the most severe and acute cases of MDs. Therefore, our findings may not be generalized to moderate and mild MH cases which limits the generalizability of this study. 4) Another limitation was that we did not consider air pressure in this current study. We only focused on the heat effects in the warm seasons. We will investigate the health impacts of air pressure in the future. 5) Unfortunately, the data for the onset of MDs was unavailable. We tried to address this limitation by using multiple lag days, i.e., the number of days when meteorological exposures occurred before the ED visit day, to offset the unavailability of the actual date of the disease onset. The lag days measured the delay between the onset and the visit dates. In addition, we used ED visits as the health outcome rather than common outpatient records. ED visits specifically were considered as severe cases and often need immediate treatments; therefore, they are not scheduled. 6) A potential concern could be the harvest effect, i.e., a phenomenon where a period of excess deaths (or morbidity in this study) is followed by a period of mortality/cases deficit. We purposely used multi-day/cumulative lag and extended the lag period to two weeks so that the pattern and potential harvest effect could be observed.

5. Conclusion

Our findings showed that SR and RH had delayed but lasting impacts on MDs, while temperature had an immediate but short-term impact. Meanwhile, rainfall hours had an immediate protective effect on MDs. The increased risks were stronger in September and October compared to summer months, and among males and minority groups. A combination of high SR, RH, and temperature demonstrated the greatest risk of ED utilization for MDs. While further studies need to validate our findings, our findings may provide important and earliest evidence regarding the joint effect of multiple meteorological factors on MD and the potential exposure-health reference values (medium level) for potential planning, intervention, and education for public health agencies and clinical facilities.

CRediT authorship contribution statement

Xinlei Deng: Conceptualization, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Jerald Brotzge:** Conceptualization, Data curation, Writing – review & editing. **Melissa Tracy:** Conceptualization, Writing – review & editing. **Howard H. Chang:** Conceptualization, Writing – review & editing. **Xiaobo Romeiko:** Conceptualization, Writing – review & editing. **Wangjian Zhang:** Writing – review & editing. **Ian Ryan:** Writing – review & editing. **Fangqun Yu:** Writing – review & editing. **Yanji Qu:** Writing – review & editing. **Gan Luo:** Writing – review & editing. **Shao Lin:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2022.107411.

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