Article

Environment and Behavior
2021, Vol. 53(7) 787–805

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/0013916520937455
journals.sagepub.com/home/eab
SAGE

In Cold Weather We Bark, But in Hot Weather We Bite: Patterns in Social Media Anger, Aggressive Behavior, and Temperature

Heather R. Stevens[1], Petra L. Graham[1], Paul J. Beggs[1], and Ivan C. Hanigan[2]

Abstract

Hotter weather is associated with aggressive crime. However, it is not well known if similar relationships apply to online aggression. This study uses anger counts derived from Twitter posts (tweets) and assault counts in New South Wales, Australia, to investigate if they share a similar relationship with temperature, and to determine if online anger is a predictor of assault. Results indicated that the relationships were largely inverse—assault counts were higher in summer than winter, while angry tweet counts were lower. As daily maximum temperatures rose, assault counts increased while angry tweet counts decreased. Angry tweet counts were inversely associated with assaults, with an increase in tweets signaling decreasing assaults. There are several plausible explanations for the dissimilarities including the impact of temperature on behavior, socio-demographic differences, and data collection

[1]Macquarie University, Sydney, New South Wales, Australia
[2]The University of Sydney, New South Wales, Australia

Corresponding Author:
Heather R. Stevens, Department of Environmental Sciences, Faculty of Science and Engineering, Macquarie University, 12 Wally's Walk, Level 4, Sydney, New South Wales 2109, Australia.
Email: heather.stevens@hdr.mq.edu.au

methods. The findings of this study add to the growing literature in social media emotion and its relationship with temperature.

Keywords
Twitter, emotion, anger, assault, heat hypothesis

The heat hypothesis states that hot temperatures can increase aggressive motives and behaviors (Anderson, 2001; Anderson et al., 1997), specifically those that are affective (emotional) and that are intended to harm the target in some way (Anderson, 1989). The hypothesis has been demonstrated through numerous studies that have used crimes such as assault as a proxy for aggressive behavior (Anderson et al., 2000; Burke et al., 2015; Stevens et al., 2019). Very few studies however have explored aggressive online behavior and its relationship with changing temperature.

Of Australia's 24.6 million people, 18 million (73%) are active social media users (We Are Social, 2019), with 4.7 million (19%) using the microblogging service Twitter (Cowling, 2019). The widespread use of social media by the general public has created an opportunity not only to share but also a means to gather information. Because tweets are publicly and widely available they are becoming a popular source to track moods (positive or negative) or emotions (short lived feelings) of the users, and to collectively infer these spatially and temporally (Giachanou & Crestani, 2016; Larsen et al., 2015). Analyzing Twitter sentiment is generally done using a lexicon-based approach by which tweets are scanned for predetermined emotional terms, or by machine learning where an algorithm can classify a whole tweet (Giachanou & Crestani, 2016).

Very few studies have looked at the relationship between online aggressive emotions and temperature. Li et al. (2014) examined 2 years of tweet counts from urban areas in the USA against a range of meteorological conditions and found that as daily average temperature increased, so did anger. Baylis et al. (2018) used US based Twitter and Facebook data to examine how temperature affected either positive or negative emotion, finding that negative emotions increased with decreasing temperatures and very high temperatures (beyond 30°C) and that there was less negativity for temperatures between 20°C and 30°C.

A larger number of studies have looked at how temperature relates to a one dimensional measure of mood (incorporating negative and positive) with mixed results. Baylis (2015) developed a mood metric ranging from negative to positive from Twitter data from the US and tested it against temperature. The study found no relationship between the mood metric and cooler temperatures but found that temperatures above 21°C caused a sharp decline in mood. The difference between temperature bands of approximately 16°C to 21°C and 27°C to 32°C were comparable to the average difference in mood between Sundays and Mondays (weekends generally having higher positive mood, see Golder & Macy, 2011 and Larsen et al., 2015). Hannak et al. (2012) found that season (using month as a proxy) and weather variables (including temperature, humidity, precipitation, and others) significantly predicted an aggregated sentiment of positive and negative moods, whereby higher temperatures were associated with more positive sentiment though this decreased with increasing humidity. In a global study, Golder and Macy (2011) analyzed Twitter content across 84 countries over 2 years finding that absolute day length (as a proxy for season) was not significant to mood. Likewise, Li et al. (2014) found that mood was not significantly impacted by daily average temperature. The problem with studies that use a single mood metric is that positive and negative moods have been found to be independent of each other—that is, having low positive mood indicates the absence of positive feelings, not necessarily the presence of negative feelings (Clark et al., 1989; Golder & Macy, 2011).

Tweet content has also been used to predict crime. Wang et al. (2012) combined tweets that related to traffic or roads with a traditional crime prediction model for “hit and run” events. The addition of Twitter analysis outperformed the baseline model uniformly across all days. A subsequent study by Gerber (2014) also applied Twitter content to traditional crime prediction methods and found that, for 19 of the 25 crime types studied, the addition of Twitter data improved crime prediction performance versus a standard approach. This was specifically true for aggressive crimes such as criminal damage, burglary, and assault.

This study investigates if angry emotions extracted from tweets display similar seasonality and temperature patterns to those of assault. The study also considers if anger in social media can act as a predictor of aggressive crime. The (dis)similarities between assault and angry tweets will be discussed in the context of temperature—behavior theories.

Method

Data

Social media data were collected from the publicly available “We Feel” tool (wefeel.csiro.au), a collaboration between the Australian Commonwealth

Scientific and Industrial Research Organisation (CSIRO) and the Black Dog Institute (Larsen et al., 2015). We Feel collects all English language tweets that contain one or more words from a select list of emotional words from the publicly available Twitter Application Programming Interface (API). The vocabulary list was drawn from the Affect Norms for English Words (Bradley & Lang, 1999) and the Linguistic Inquiry and Word Count (Pennebaker et al., 2001). The words were then organized against Parrott's hierarchy of emotions (Parrott, 2001) and Shaver's Emotion Tree (Shaver et al., 1987) into six primary and 25 secondary emotion categories. For this study, the data collected from We Feel included a daily count of the six primary emotions (joy, sadness, love, surprise, anger, and fear), and "other," for the self-selected time zone of "Sydney, Australia GMT +10" (the capital city of New South Wales) between January 1, 2015 and December 31, 2017. Over the study period, the We Feel program had 14 days (not necessarily consecutive) of system downtime, so angry tweet counts for those dates were interpolated to be the mean of the counts on adjoining days.

Assault data, including incidents of domestic violence-related assault, non-domestic violence-related assault, and assault against police were obtained from the New South Wales (NSW) Department of Justice, Bureau of Crime Statistics and Research (BOCSAR; BOCSAR reference NM1715202). Single incident assault data were aggregated to daily count.

Temperature exposure estimates were created using the gridded meteorological datasets for Australia from the Australian Water Availability Project (AWAP), a partnership of the Australian Bureau of Meteorology, Bureau of Rural Sciences, and CSIRO. Temperature is estimated for each pixel of a grid with a resolution of 0.05×0.05 decimal degrees (approximately 5×5 km) using a spatial model (Bureau of Meteorology, 2018; Jones et al., 2009). The Twitter spatial scale was the time zone encompassing the state of NSW, which has an area of 809,444 km^2 and a population and temperature that varies greatly—suburb population average 45,128, range 1,061 to 301,125, standard 30-year average daily maximum temperature range 6°C to 30°C (Bureau of Meteorology, 2016). When data on meteorological conditions are aggregated to large study regions it is important that exposure estimates are representative of the conditions experienced by the majority of the population (Hanigan et al., 2006). To provide an optimal representation of the meteorological conditions where the Twitter users were likely to reside, a population weighted maximum daily temperature average was generated. The AWAP data were retrieved from the Centre for Air Pollution, Energy and Health Research (CAR) data platform. The R package Velox (Hunziker, 2017) was used to attach spatially weighted averages of AWAP grids cells to the 2,625 suburbs within NSW. The population weighted average daily average maximum temperature was created using weights for the population that live in each suburb, as per the 2016 census (Australian Bureau of Statistics, 2018). The equation used to calculate the population weighted daily average maximum temperature was $\frac{\sum w_i \times t_i}{\sum w_i}$, where w_i is the population for each of the $i=1$ to 2,625 suburbs, and t_i is the daily average maximum temperature for suburb i. Herein, daily average maximum population weighted temperature is referred to as daily maximum temperature.

Analysis

The 10 highest and lowest angry tweet count days within the study period were identified, and newsworthy events that occurred on or immediately prior to that day were obtained from the Australian Broadcasting Commission archive tool (abc.net.au/archives; ABC, 2019). The 10 highest and lowest daily maximum temperature days were also identified and compared against the daily count and difference from the daily mean for all and angry tweets, and assaults.

Negative binomial regression models for all days were used to explore the relationship between daily angry tweet counts and assault counts by either season or daily maximum temperature, after adjusting for trend over time, day of the week, and if it was a public holiday (including New Year's Eve and Day, Australia Day, Anzac Day, Easter Friday and Monday, June long weekend, Labor Day, and Christmas and Boxing Day). The standard Southern Hemisphere seasons were used; summer (December, January, February), autumn (March, April, May), winter (June, July, August), and spring (September, October, November). Polynomial terms for temperature were also examined.

Spearman's correlation was used to measure the strength of the relationship between daily assault counts and daily angry tweet counts. Negative binomial regression models were used to determine whether angry tweet counts were a significant predictor of daily assault counts with and without adjusting for maximum temperature, trend over time, day of the week, and if it was a public holiday. The Akaike Information Criterion (AIC) was used to compare the adjusted model to the model that did not include angry tweet counts. Smaller AIC indicates better model fit.

Data were visualized using scatter plots with fitted lines included from the relevant regression models. Data were summarized using means and standard deviations (*SD*).

Analysis was done using R version 3.5.2 (R Core Team, 2018) and RStudio version 1.1.463 (R Studio Team, 2016). Significance was taken to be p-values $<.05$.

Results

Descriptive Statistics

Over the 3-year period (2015–2017) a total of 74.2 million tweets were counted, of which 2.87 million (3.87%) were angry. On average there were 67,657 (SD = 13,530) tweets per day of which 2,621 (SD = 523) were angry. During the same period there were a total of 188,678 incidents of assault, with a daily average of 172 (SD = 33).

Average angry tweet counts were highest on a Monday (2,759 per day) and lowest on weekends (Saturday 2,373 and Sunday 2,499 per day). Seasonally, average angry tweet counts were highest in winter closely followed by autumn (2,777 and 2,747 per day, respectively) and lowest in spring (2,415 per day). Assault counts were highest on weekends (Saturday 202 and Sunday 204 per day) and lowest on a Wednesday (150 per day). Assault counts were highest in summer (191 per day) and lowest in winter (153 per day). Full descriptive statistics are available in Table A in the Online Supplemental Material. The daily average population weighted maximum temperature over the 3-year period was 23.55°C (SD = 5°C).

On the 10 days with the highest angry tweet counts there appeared to be an observable major negative or divisive news event that correlated to each day (e.g., a political leadership spill, mass shooting, or extreme cold weather event; see Table B in the Online Supplemental Material). The average daily temperature for these 10 days was 19.79°C, 3.76°C below the study period average. Of the days in which angry tweet counts were lowest, 8 of the 10 corresponded to public holidays and the average daily temperature was 28.57°C, 5.02°C above study period average (Table B in the Online Supplemental Material).

Of the 10 days with the highest daily maximum temperature, the average angry tweet count was 2,482 per day (SD = 316, range 866). Of the 10 coldest days the average angry tweet count was higher, at 3,354 per day and had much larger variability (SD = 607, range 2,006). Corresponding daily assault counts for the 10 hottest days were 195 per day (SD = 33, range 104) on average, and were an average of 154 per day (SD = 21, range 65) for the 10 coldest days (Table C in the Online Supplemental Material).

Table 1 shows the results of negative binomial regression modeling of angry tweet counts or assault counts by season, controlling for trend over

Table 1. Negative Binomial Model for the Relationship Between Daily Average Angry Tweets or Assaults and Season in New South Wales, 2015 to 2017 With Coefficient and Standard Error (*SE*), Incidence Rate Ratio (IRR) and 95% Confidence Intervals (CI).

	Angry tweets			Assaults		
	Coefficient (*SE*)	IRR (95% CI)	*p* value	Coefficient (*SE*)	IRR (95% CI)	*p* value
Intercept	8.198 (0.014)		<.001	4.942 (0.014)		<.001
Season (ref = Winter)						
Spring	−0.101 (0.011)	0.904 (0.884, 0.924)	<.001	0.138 (0.010)	1.148 (1.125, 1.172)	<.001
Summer	−0.113 (0.011)	0.893 (0.873, 0.913)	<.001	0.211 (0.010)	1.235 (1.210, 1.261)	<.001
Autumn	−0.051 (0.011)	0.950 (0.930, 0.971)	<.001	0.105 (0.010)	1.111 (1.088, 1.134)	<.001
Time	−0.00039 (0.00001)	0.99961 (0.99958, 0.99963)	<.001	0.0000162 (0.00001)	1.00002 (0.99999, 1.00003)	.166
Day (ref = Monday)						
Tuesday	−0.019 (0.015)	0.981 (0.953, 1.010)	.194	−0.029 (0.014)	0.971 (0.945, 0.998)	.034
Wednesday	−0.018 (0.015)	0.982 (0.954, 1.011)	.222	−0.056 (0.014)	0.945 (0.919, 0.971)	<.001
Thursday	−0.032 (0.015)	0.969 (0.941, 0.997)	.033	0.004 (0.014)	1.004 (0.977, 1.032)	.779
Friday	−0.054 (0.015)	0.948 (0.921, 0.976)	<.001	0.072 (0.014)	1.075 (1.046, 1.104)	<.001
Saturday	−0.152 (0.015)	0.859 (0.834, 0.884)	<.001	0.239 (0.014)	1.270 (1.237, 1.304)	<.001
Sunday	−0.100 (0.015)	0.905 (0.879, 0.931)	<.001	0.249 (0.014)	1.283 (1.249, 1.317)	<.001
Holiday	−0.064 (0.025)	0.938 (0.894, 0.985)	.010	0.190 (0.022)	1.209 (1.158, 1.262)	<.001
AIC		15,891			9,736	

time, day of the week, and holiday days. The models indicated that daily angry tweet counts were significantly lower in all seasons compared with winter ($p < .001$), with summer having an estimated incidence rate ratio (IRR) of 0.893 (95% CI 0.873, 0.913) compared to winter. On the other hand, daily assault counts were significantly higher in all seasons compared to winter ($p < .001$), with an IRR of 1.235 (95% CI 1.210, 1.261) for summer versus winter. The models also indicated that daily angry tweet counts were significantly lower on weekends ($p < .001$) with Saturday having an estimated IRR of 0.859 (95% CI 0.834, 0.884) compared to Monday. Daily assault counts were significantly higher on weekends ($p < .001$) with an incidence rate ratio of 1.283 (95% CI 1.249, 1.317) for Sunday compared to Monday. Significantly lower angry tweet counts ($p = .010$) and higher assault counts ($p < .001$) were found if the day was a holiday. The fitted models are shown in Figure 1 for (a) daily angry tweets and (b) assaults. The red lines are the fitted values of the model involving season and holiday and orange for temperature (weekday effect is excluded for clarity). As per Table 1, these graphs show that colder temperatures were associated with higher tweet counts but fewer assaults, and the inverse for hotter temperatures.

Table 2 shows the results of the same model but using temperature instead of season. For both angry tweet counts and assault counts the temperature related terms are highly significant ($p < .001$). Figure 2 shows the relationship between (a) angry tweet count or (b) assault count and temperature, with red fitted lines from the temperature model and 95% confidence intervals shaded. The plots suggest that angry tweets decrease as temperatures increase, with some evidence of an increase after 30°C, while assaults increase with some evidence of a plateau or decrease after 33°C.

The AIC for the temperature model (Table 2) was lower than the seasonal model (Table 1) for both angry tweet counts (15,879 vs. 15,891) and assault count (9,595 vs. 9,736) indicating that temperature was a better fit, especially so for the assault model.

The Relationship Between Anger and Assault

The scatterplot of daily assault counts against angry tweet counts with a red line showing the fitted values from a regression of assault counts against angry tweet counts (including linear and quadratic terms for tweet counts) and 95% confidence intervals (shaded) is shown in Figure 3. The plot indicates a mostly negative and non-linear relationship. Spearman's rank correlation shows a highly significant but weak negative correlation ($\rho = -0.32$, $p < .001$). Because interest is in developing a predictive model for assault counts using angry tweet counts, a negative binomial regression model of

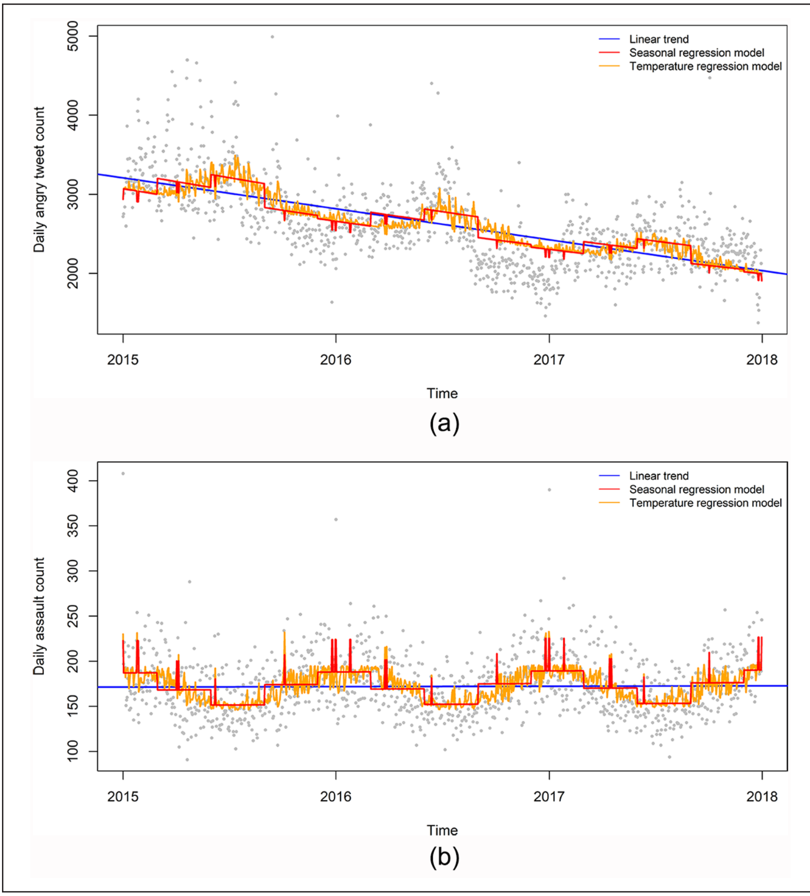

Figure 1. Scatter plots of daily count of (a) angry tweets and (b) assaults by time with linear trend lines (blue) and negative binomial regression model lines for count versus season, time, and holidays (red) and count versus temperature, associated polynomial terms, time, and holidays (orange), New South Wales 2015 to 2017.

daily assaults versus angry tweets, controlling for daily average maximum temperature, trend over time, day of the week and if it was a holiday was developed. Results are shown in Table 3. The results indicate that as angry tweet counts increase the incidence of assaults decreases (IRR 0.954, 95% CI 0.937–0.973 per 1,000 tweets). The AIC of the model including angry tweet counts in Table 3 was lower than that of the model for daily assault by temperature shown in Table 2 (AIC 9,574 vs. 9,595, respectively), indicating that the addition of angry tweet counts improves the prediction of assault.

Table 2. Negative Binomial Model for the Relationship Between Daily Average Angry Tweets or Assaults and Population Weighted Average Maximum Daily Temperature in NSW, 2015 to 2017 With Coefficient, Standard Error (*SE*), Incidence Rate Ratio (IRR), and 95% Confidence Intervals (CI).

	Angry tweets			Assaults		
	Coefficient (*SE*)	IRR (95% CI)	*p* value	Coefficient (*SE*)	IRR (95% CI)	*p* value
Intercept	8.668 (0.071)		<.001	5.309 (0.228)		<.001
Temperature	−0.038 (0.006)	-[a]	<.001	−0.073 (0.029)	-[a]	.011
Temperature^2	0.001 (0.00012)	-[a]	<.001	0.004 (0.001)	-[a]	<.001
Temperature^3			[b]	−0.00006 (0.00002)	-[a]	<.001
Time	−0.00039 (0.00001)	0.99961 (0.99958, 0.99963)	<.001	0.00001 (0.00001)	1.00001(0.99999, 1.00003)	.240
Day (ref = Monday)						
Tuesday	−0.019 (0.015)	0.981 (0.953, 1.010)	.190	−0.027 (0.013)	0.973 (0.948, 0.998)	.037
Wednesday	−0.020 (0.015)	0.980 (0.952, 1.009)	.180	−0.055 (0.013)	0.946 (0.922, 0.971)	<.001
Thursday	−0.033 (0.015)	0.968 (0.940, 0.996)	.014	0.006 (0.013)	1.006 (0.981, 1.032)	.643
Friday	−0.055 (0.015)	0.946 (0.919, 0.974)	<.001	0.075 (0.013)	1.077 (1.051, 1.105)	<.001
Saturday	−0.154 (0.015)	0.858 (0.833, 0.883)	<.001	0.242 (0.013)	1.274 (1.243, 1.307)	<.001
Sunday	−0.101 (0.015)	0.904 (0.879, 0.931)	<.001	0.250 (0.013)	1.283 (1.252, 1.316)	<.001
Holiday	−0.060 (0.024)	0.942 (0.898, 0.988)	<.001	0.192 (0.020)	1.212 (1.165, 1.261)	<.001
AIC		15,879			9,595	

[a]IRR is a function of the polynomial terms and cannot be displayed for individual terms.
[b]A cubic term was found not to be supported by comparing AIC, so excluded from the model.

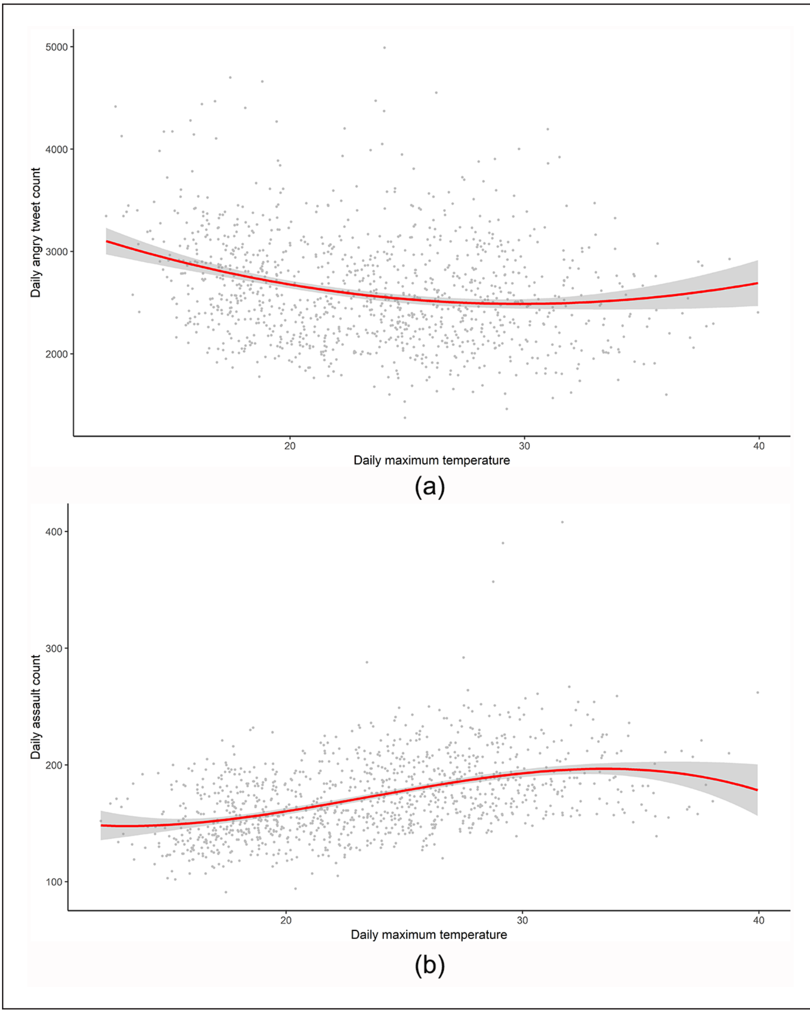

Figure 2. Scatter plots of daily count of (a) angry tweets and (b) assaults by population weighted daily maximum temperature (°C) with negative binomial regression model lines for count versus temperature and associated polynomial terms for temperature with 95% confidence intervals (gray shaded area), New South Wales 2015 to 2017.

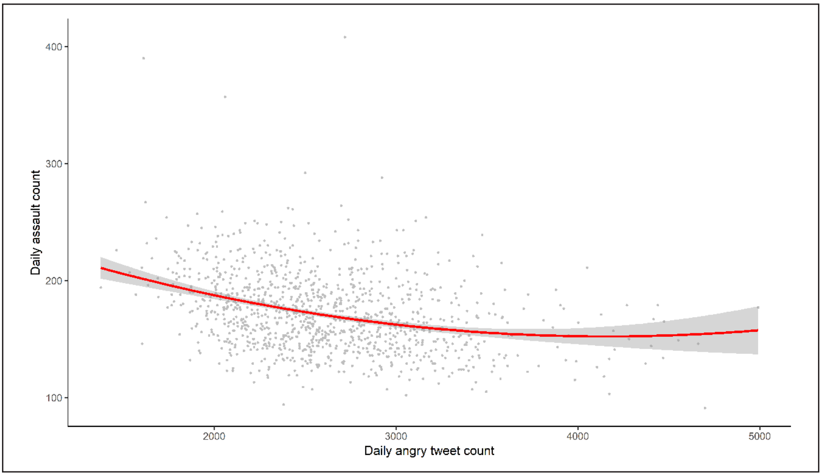

Figure 3. Scatter plot of daily assault count by angry tweet counts with negative binomial regression model line for assault count versus angry tweet counts and associated polynomial terms for angry tweet counts with 95% confidence intervals (gray shaded area), New South Wales 2015 to 2017.

Discussion

This study echoes extant research that found assaults peak in summer and increase with temperature (Anderson et al., 2000; Burke et al., 2015). However, the opposite patterns were seen in social media anger. Similar to observations by Baylis et al. (2018), this study indicated that daily angry tweet counts decreased as temperatures increased. The addition of angry tweets improved the performance of the assault model including temperature, however the association was negative—as angry tweets increased, assaults decreased.

The difference in how temperature affects the likelihood of angry tweets or assaults may be behavioral. The routine activity theory (Rotton & Cohn, 2003) suggests that aggressive crimes increase because warmer weather encourages behavior that fosters assaults. For example, more time spent outdoors, increased social interactions and alcohol consumption all increase in warmer weather and are behaviors associated with increasing assaults (Gotsis & Dobson, 2018). This may explain why this study found assaults are higher on weekends, holidays, and hotter days. However, those same factors of time outdoors and socialization may reduce opportunity or motivation to Tweet, and the effects of alcohol (i.e., reduction in mental clarity and physical precision) make composing a Tweet more difficult and thus less likely. This theory

Table 3. Negative Binomial Model for the Relationship Between Average Daily Assaults and Angry Tweets in NSW, 2015 to 2017 With Coefficient, Standard Error (*SE*), Incidence Rate Ratio (IRR) and 95% Confidence Intervals (CI).

	Assault		
	Coefficient (*SE*)	IRR (95% CI)	*p* value
Intercept	5.598 (0.233)		<.001
Anger count/1,000	−0.047 (0.010)	0.954 (0.937, 0.973)	<.001
Temperature	−0.087 (0.029)	-[a]	.002
Temperature^2	0.00445 (0.00116)	-[a]	.010
Temperature^3	−0.00006 (0.00002)	-[a]	<.001
Time	−0.00004 (0.00001)	0.99996 (0.99993, 0.99999)	.015
Day (ref = Monday)			
Tuesday	−0.030 (0.013)	0.970 (0.946, 0.996)	.021
Wednesday	−0.057 (0.013)	0.944 (0.920, 0.969)	<.001
Thursday	0.002 (0.013)	1.002 (0.977, 1.028)	.888
Friday	0.067 (0.013)	1.070 (1.043, 1.097)	<.001
Saturday	0.224 (0.013)	1.251 (1.220, 1.284)	<.001
Sunday	0.237 (0.013)	1.268 (1.237, 1.300)	<.001
Holiday	0.186 (0.020)	1.204 (1.158, 1.253)	<.001
AIC		9,574	

[a]IRR is a function of the polynomial terms and cannot be displayed for individual terms.

is supported by the finding that both angry tweet counts as well as all tweet counts (as a proxy for overall Twitter use) were lower on weekends, holidays and on the hottest days (See Tables A and C in the Online Supplemental Material).

From a physiological perspective, the general aggression model (GAM) proposes that temperature has a physical impact, and, depending on social, cognitive, personality, and biological responses, can cause aggression (Allen et al., 2018). It is interesting to note that both anger and assault had a non-linear relationship with daily maximum temperature with the trough or peak similar at around 30°C. This temperature is approximately the same as "thermal neutrality," wherein the heat dissipated by human metabolism can create an equilibrium with the surrounding temperature. In humans, this zone is between 29°C to 31°C (American Meteorological Society, 2012). As temperatures approached this range angry tweets decreased. This could indicate that the physical discomfort of moving away from thermal neutrality increases the likelihood of anger. However, why does assault show a possible plateau in extreme heat? The negative affect escape (NAE) theory (Baron, 1972;

Baron & Bell, 1976) may explain. The NAE builds on the GAM, proposing that aggression increases with temperature because of bio-social-cognitive factors, however only up to a certain point, after which the motivation to escape the uncomfortable temperature outweighs the motivation to be aggressive (Bell, 1992). Thus it is possible that assaults peak then plateau as some people retreat from the heat, reducing socialization and activity.

The addition of angry tweets to the assault model including temperature improved model performance, indicating that anger in social media was an important predictor of assaults. It is possible that Twitter users are able to vent their frustrations and hence then be less inclined to commit assault. However, it is more likely that this relationship is confounded by the vast differences in demographics. Previous research has shown that assault offenders are predominately male (3.5–1) and more likely to be young adults (Gotsis & Dobson, 2018), while the sex ratio of Twitter users is roughly even and they are generally middle aged (Perrin & Angerson, 2019). Assault offenders are often associated with poverty (Australian Institute of Criminology, 2011) while the majority of Twitter users sit within the higher income bracket of all social media users (Perrin & Angerson, 2019). It is beyond the scope of the study to theorize as to why these variants in assault offenders and Twitter users differs by temperature except to note that, in light of the aforementioned biophysical theories, it is likely that age, sex, and other socio-demographic factors influence the temperature aggression relationship.

A limitation to this study is the way in which data were collected and its representativeness to the broader population. First, Twitter is not necessarily an accurate representation of all social media users. Twitter content is public while other sites like Facebook and Snapchat are only available to invited viewers. The public nature of tweets could prohibit posting personal or emotional content. Similarly, Twitter is also a preferred medium for politicians (Parmelee & Bichard, 2011), academics (Priem & Costello, 2010), and news agencies (Zhao et al., 2011). Posts from these users could be less emotive and/or express different emotions to that of the general public. For this study, angry tweets were sourced from the We Feel sentiment analysis tool, however calculating emotion from Twitter is an emerging, complex and imperfect methodology (see Giachanou & Crestani, 2016; Kalampokis et al., 2013) and classification errors in We Feel are an inevitable challenge (Larsen et al., 2015). We Feel also didn't provide information on how many unique Twitter accounts contributed to the data. It is possible that different social media platforms and sentiment analysis methodologies would result in different findings. Likewise, assault data were collected from recorded incidents, however it has been noted that assault is an under-reported crime (Smith et al.,

2014) and therefore counts used in this study may not be an accurate representation of assault rates.

The implications of temperature influencing social media anger are broad. Emotional states are transmitted through social networks (Baylis et al., 2018) and of all the emotions, anger is the emotion that spreads through online communities the fastest (Berger & Milkman, 2012; Fan et al., 2014). Thus temperature fluctuations and corresponding social media anger can have an effect on the wider population. Identifying the weak but significant relationship between increasing angry tweets and decreasing assaults may improve studies addressing the predictive powers of social media. The relationship between temperature, social media anger, and aggressive behavior is also relevant when considering global climate change. Climate change is likely to impact both assault rates (Burke et al., 2015) and mood (Rehdanz & Maddison, 2005), so this complex interaction is worthy of further investigation.

In conclusion, assaults and angry tweets had opposing seasonal trends whereby as temperatures increased so too did assaults, while angry tweets decreased. While angry tweet counts were a significant predictor of assaults and improved the assault and temperature model, the association was negative. There are several behavioral and biological theories that can help to explain these dissimilarities such as changes in physiology and routine that affect motivation or opportunity to act aggressively, but also limitations in comparing assault offenders and Twitter users, two relatively different demographics. This is the first study to compare the patterns of assault and social media anger with temperature and extends the understanding of how temperature affects mood and behavior.

Acknowledgments

The authors would like to thank Brian Jin and Stephen Wan of Data61 CSIRO for the development and maintenance of the We Feel system, and the New South Wales Bureau of Crime Statistics and Research for access to crime data. This research was undertaken with the assistance of resources from the Collaborative Environment for Scholarly Analysis and Synthesis (CoESRA) https://coesra.tern.org.au.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iDs

Heather R. Stevens https://orcid.org/0000-0002-8702-6355
Petra L. Graham https://orcid.org/0000-0003-2890-2447
Paul J. Beggs https://orcid.org/0000-0001-9949-1783

Supplemental Material

Supplemental material for this article is available online.

References

ABC. (2019). *Archive*. Australian Broadcasting Commission. Retrieved March 1, 2019, from https://www.abc.net.au/news/archive/

Allen, J. J., Anderson, C. A., & Bushman, B. J. (2018). The general aggression model. *Current Opinion in Psychology*, *19*, 75–80. https://doi.org/10.1016/j.copsyc.2017.03.034

American Meteorological Society. (2012). *Thermal neutrality. American Meteorological Society*. Glossary of Meteorology. Retrieved 1 June, 2019, from http://glossary.ametsoc.org/wiki/Thermal_neutrality

Anderson, C. A. (1989). Temperature and aggression: Ubiquitous effects of heat on occurrence of human violence. *Psychological Bulletin*, *106*(1), 74–96. https://doi.org/10.1037/0033-2909.106.1.74

Anderson, C. A. (2001). Heat and violence. *Current Directions in Psychological Science*, *10*(1), 33–38. https://doi.org/10.1111/1467-8721.00109

Anderson, C. A., Anderson, K. B., Dorr, N., DeNeve, K. M., & Flanagan, M. (2000). Temperature and aggression. *Advances in Experimental Social Psychology*, *32*, 63–133. https://doi.org/10.1016/s0065-2601(00)80004-0

Anderson, C. A., Bushman, B. J., & Groom, R. W. (1997). Hot years and serious and deadly assault: Empirical tests of the heat hypothesis. *Journal of Personality and Social Psychology*, *73*(6), 1213–1223. https://doi.org/10.1037/0022-3514.73.6.1213

Australian Bureau of Statistics. (2018). *2033.0.55.001—Census of population and housing: Socio-economic indexes for areas (SEIFA), Australia, 2016*. Australian Bureau of Statistics. Retrieved April 11, 2019, from http://www.abs.gov.au/websitedbs/censushome.nsf/home/seifa

Australian Institute of Criminology. (2011). *Australian crime: Facts and figures 2011*. Canberra. http://aic.gov.au/publications/current%20series/facts/1-20/2011.html

Baron, R. A. (1972). Aggression as a function of ambient temperature and prior anger arousal. *Journal of Personality and Social Psychology*, *21*(2), 183–189. https://doi.org/10.1037/h0032892

Baron, R. A., & Bell, P. A. (1976). Aggression and heat: The influence of ambient temperature, negative affect, and a cooling drink on physical aggression. *Journal of Personality and Social Psychology*, *33*(3), 245–255. https://doi.org/10.1037/0022-3514.33.3.245

Baylis, P. (2015). *Temperature and temperament: Evidence from a billion tweets*. Energy Institute at HAAS. Retrieved June 1, 2019, from https://ei.haas.berkeley.edu/research/papers/WP265.pdf

Baylis, P., Obradovich, N., Kryvasheyeu, Y., Chen, H., Coviello, L., Moro, E., Cebrian, M., & Fowler, J. (2018). Weather impacts expressed sentiment. *PloS ONE*, *13*(4), e0195750. https://doi.org/10.1371/journal.pone.0195750

Bell, P. A. (1992). In defense of the negative affect escape model of heat and aggression. *Psychological Bulletin*, *111*(2), 342–346. https://doi.org/10.1037/0033-2909.111.2.342

Berger, J., & Milkman, K. L. (2012). What makes online content viral? *Journal of Marketing Research*, *49*(2), 192–205. https://doi.org/10.2139/ssrn.1528077

Bradley, M. M., & Lang, P. J. (1999). *Affective norms for English words (ANEW): Instruction manual and affective ratings*. The Center for Research in Psychophysiology. https://www.uvm.edu/pdodds/teaching/courses/2009-08UVM-300/docs/others/everything/bradley1999a.pdf

Bureau of Meteorology. (2016). *Average annual and monthly maximum, minimum, and mean temperature*. Retrieved July 1, 2019, from http://www.bom.gov.au/jsp/ncc/climate_averages/temperature/index.jsp

Bureau of Meteorology. (2018). *Australian water availability project*. http://www.bom.gov.au/jsp/awap/

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Climate and conflict. *Annual Review of Economics*, *7*(1), 577–617. https://doi.org/10.3386/w20598

Clark, L., Watson, D., & Leeka, J. (1989). Diurnal variation in the positive affects. *Motivation and Emotion*, *13*(3), 205–234. https://doi.org/10.1007/bf00995536

Cowling, D. (2019). *Social Media Statistics Australia—April 2019*. Social Media News. Australian Social Media Statistics. Retrieved May 1, 2019, from https://www.socialmedianews.com.au/social-media-statistics-australia-april-2019/

Fan, R., Zhao, J., Chen, Y., & Xu, K. (2014). Anger is more influential than joy: Sentiment correlation in Weibo. *PloS ONE*, *9*(10), e110184. https://doi.org/10.1371/journal.pone.0110184

Gerber, M. S. (2014). Predicting crime using Twitter and kernel density estimation. *Decision Support Systems*, *61*(1), 115–125. https://doi.org/10.1016/j.dss.2014.02.003

Giachanou, A., & Crestani, F. (2016). Like it or not: A survey of Twitter sentiment analysis methods. *ACM Computing Surveys (CSUR)*, *49*(2), 28. https://doi.org/10.1145/2938640

Golder, S., & Macy, M. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science (Washington)*, *333*(6051), 1878–1881. https://doi.org/10.1126/science.1202775

Gotsis, T., & Dobson, M. (2018). *A statistical snapshot of crime and justice in New South Wales*. NSW Parliamentary Research Service. Retrieved June 1, 2019, from https://www.parliament.nsw.gov.au/researchpapers/Documents/a-statistical-snapshot-of-crime-and-justice-in-n/Crime.pdf

Hanigan, I., Hall, G., & Dear, K. B. G. (2006). A comparison of methods for calculating population exposure estimates of daily weather for health research. *International Journal of Health Geographics*, *5*(1), 38. https://doi.org/10.1186/1476-072X-5-38

Hannak, A., Anderson, E., Barrett, L. F., Lehmann, S., Mislove, A., & Riedewald, M. (2012). *Tweetin'in the rain: Exploring societal-scale effects of weather on mood*. Paper presented at the Sixth International AAAI Conference on Weblogs and Social Media.

Hunziker, P. (2017). *Velox: Fast raster manipulation and extraction R package version 0.2.0*. https://github.com/hunzikp/velox

Jones, D. A., Wang, W., & Fawcett, R. (2009). High-quality spatial climate datasets for Australia. *Australian Meteorological and Oceanographic Journal*, *58*(4), 233–248. https://doi.org/10.22499/2.5804.003

Kalampokis, E., Tambouris, E., & Tarabanis, K. (2013). Understanding the predictive power of social media. *Internet Research*, *23*(5), 544–559. https://doi.org/10.1108/intr-06-2012-0114

Larsen, M. E., Boonstra, T. W., Batterham, P. J., Odea, B., Paris, C., & Christensen, H. (2015). We Feel: Mapping emotion on Twitter. *IEEE Journal of Biomedical and Health Informatics*, *19*(4), 1246–1252. https://doi.org/10.1109/JBHI.2015.2403839

Li, J., Wang, X., & Hovy, E. (2014). *What a nasty day: Exploring mood-weather relationship from Twitter*. Paper presented at the Proceedings of the 23rd ACM International Conference on Information and Knowledge Management, Shanghai. https://doi.org/10.1145/2661829.2662090

Parmelee, J. H., & Bichard, S. L. (2011). *Politics and the Twitter revolution: How tweets influence the relationship between political leaders and the public*. Lexington Books. https://doi.org/10.1093/poq/nft075073916502X

Parrott, W. G. (2001). *Emotions in social psychology: Essential readings*. Psychology Press.

Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2001). *Linguistic inquiry and word count: LIWC 2001*. Lawrence Erlbaum Associates.

Perrin, A., & Angerson, M. (2019). Share of U.S. adults using social media, including Facebook, is mostly unchanged since 2018. Facttank News in the Numbers. Pew Research Centre. Retrieved May 6, 2019, from https://www.pewresearch.org/fact-tank/2019/04/10/share-of-u-s-adults-using-social-media-including-facebook-is-mostly-unchanged-since-2018/

Priem, J., & Costello, K. L. (2010). How and why scholars cite on Twitter. *Proceedings of the American Society for Information Science and Technology*, *47*(1), 1–4. https://doi.org/10.1002/meet.14504701201

R Core Team. (2018). *A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

R Studio Team. (2016). *RStudio: Integrated development for R*. RStudio, Inc. https://www.rstudio.com/

Rehdanz, K., & Maddison, D. (2005). Climate and happiness. *Ecological Economics*, *52*(1), 111–125. https://doi.org/10.1016/j.ecolecon.2004.06.015

Rotton, J., & Cohn, E. G. (2003). Global warming and US crime rates: An application of routine activity theory. *Environment and Behavior*, *35*(6), 802–825. https://doi.org/10.1177/0013916503255565

Shaver, P., Schwartz, J., Kirson, D., & O'Connor, C. (1987). Emotion knowledge: Further exploration of a prototype approach. *Journal of Personality and Social Psychology*, *52*(6), 1061–1086. https://doi.org/10.1037//0022-3514.52.6.1061

Smith, R. G., Jorna, P., Sweeney, J., & Fuller, G. (2014). *Counting the costs of crime in Australia: A 2011 estimate research and public policy series no. 129*. Australian Institute of Criminology. https://aic.gov.au/publications/rpp/rpp129

Stevens, H. R., Beggs, P. J., Graham, P. L., & Chang, H.-C. (2019). Hot and bothered? Associations between temperature and crime in Australia. *International Journal of Biometeorology*, *63*(6), 747–762. https://doi.org/10.1007/s00484-019-01689-y

Wang, X., Gerber, M. S., & Brown, D. E. (2012). Automatic crime prediction using events extracted from Twitter posts. In S. J. Yang, A. M. Greenberg, & M. Endsley (Eds.), *Social computing, behavioral-cultural modeling* (pp. 231–238). Springer. https://doi.org/10.1007/978-3-642-29047-3_28

We Are Social. (2019). *Digital 2019: Global internet use accelerates*. https://wearesocial.com/blog/2019/01/digital-2019-global-internet-use-accelerates

Zhao, W. X., Jiang, J., Weng, J., He, J., Lim, E.-P., Yan, H., & Li, X. (2011). *Comparing Twitter and traditional media using topic models*. Paper presented at the European Conference on Information Retrieval, Dublin, Ireland. https://doi.org/10.1007/978-3-642-20161-5_34

Author Biographies

Heather R. Stevens, MRes, is pursuing a doctoral degree in the Department of Environmental Sciences at Macquarie University. Her research interests include relationships between weather and aggression, including the implications of climate change, and prevention and management strategies. E-mail: heather.stevens@hdr.mq.edu.au.

Petra L. Graham, PhD, is a senior research fellow and biostatistician in the Centre for Economic Impacts of Genomic Medicine (GenIMPACT) at Macquarie University. Petra has research interests in meta-analysis and longitudinal modeling particularly in the areas of cognitive change, hearing, men's health, and intensive care. Her current research is examining the effect of illness and disability on poverty. E-mail: petra.graham@mq.edu.au

Paul J. Beggs, PhD, is an associate professor in the Department of Environmental Sciences at Macquarie University. His research examines the relationships between weather and climate and human morbidity and mortality, including the implications of climate change. E-mail: paul.beggs@mq.edu.au

Ivan C. Hanigan, PhD, is a data scientist specialising in environmental epidemiology with the University of Sydney School of Public Health. Ivan completed his PhD in environmental epidemiology at the Australian National Centre for Epidemiology and Population Health (ANU) where he was also data manager and data analyst from 2001 to 2013. Ivan's research seeks to disentangle health effects of environmental changes from social factors. E-mail: ivan.hanigan@sydney.edu.au