Putting Hazardous Events in Sequence:

How the Historical Context of Events Influences Human Responses

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Abstract

Human responses to hazardous events have long been a mainstay of social science and policy interest. New big data sources have created innovative opportunities to study human responses to hazardous events and enabled a vision of automated event-identification systems that could recognize such events in near real-time. However, empirical studies show variation in response to many kinds of events, including large, small, or even no behavioral changes. In this study, we draw on psychological and behavioral theory to examine how human responses might change over a sequence of events that unfold over time. Using Twitter data and a sequence of earthquakes in Nepal, we find decreased responses to subsequent earthquakes, suggesting habituation. Our results indicate a need to account for the historical context of an event when examining human responses, with substantial relevance for event identification systems and effective messaging for warning and evacuation prior to repeated dangerous events.

Introduction

The social world is one of change and adaptation and social science has consequently always been a science of social change. Key questions of concern for policy-makers, the public, and academics alike include—how do humans respond to climate change (Carleton and Hsiang, 2016, Hunter et al., 2015), how do peaceful countries turn into warring countries (Walter, 2017, Wimmer and Min, 2006), and how did many countries in the world move from very high fertility to below replacement levels (Lesthaeghe, 2010, Van De Kaa, 1987). Some social and environmental changes are slow and occur over years, decades, or centuries and from a scientific perspective make it hard to disentangle consequent human responses to one change from responses to other processes that concurrently unfold over time. Other changes are more discrete in time, occur over short periods of days, weeks, or even hours, like new laws and policies, earthquakes, floods, and bomb blasts at the macro level and marriages, births, graduations, and new jobs at the micro-level. From a scientific perspective, these *events* that occur discretely in time make it much easier to convincingly identify human responses that are caused by the events and separate them from human responses to concurrent events. Identification of these human responses to discrete events can then be applied to develop insights about human adaptive capacity and interactions in more general terms. As such, the science of human responses to *events* has gained momentum over the last several decades and become a core enterprise of the social sciences (Abbott, 1995).

As conceptual and theoretical interest in the social sciences has moved towards events, the advent of big data has made possible substantial advances in measuring a variety of human behaviors minute-by-minute, for millions of people, and without any recall or other sources of response bias inherent in more traditional methods of data collection. Big data has pushed the possibilities of the social science of events into a new realm and has been met with much excitement as we explore the new possibilities for learning about human behaviors and adaptation to social change. For example, studies using big data have found changes in human mobility and communication behaviors after political protests, violence against civilians, earthquakes, floods, oil spills, and even holidays (Dobra et al., 2015, Bengtsson et al., 2011, Lu et al., 2012, Sutton et al., 2013).

One of the visions that big data has enabled is that of near real-time event identification systems. Multiple scholarly groups and U.S. Government Agencies, including the National Science Foundation (which funded this study) are currently developing algorithms that would use geospatial information from big data sources with the intent to accurately identify hazardous events as they happen, with the aim to mitigate threats before they fully develop and limit the impact once they occur. Although still in the early development stages, there is much excitement surrounding these efforts.

Regardless of the excitement and potential, the sophisticated data and state-of-the-art modeling now available, and the attention of top scientific minds, clear insights on how humans respond to events remains frustratingly elusive. For example, some studies of climate-related migration show clear increases in migration after weather disasters (Bohra-Mishra et al., 2014, Mastrorillo et al., 2016), while others show weak or no discernible response (Entwisle et al., 2016, Gray and Mueller, 2012, Loebach, 2016, Lu et al., 2016), and still others show decreased migration (Call et al., 2017, Cattaneo and Peri, 2016, Gray and Wise, 2016, Hirvonen, 2016, Nawrotzki and Bakhtsiyarava, 2017, Thiede and Gray, 2017). Research shows that armed conflict results in decreased marriage and fertility behaviors (Agadjanian and Prata, 2001, Agadjanian and Prata, 2002, Heuveline and Poch, 2007, Jayaraman et al., 2008, Lindstrom and

Berhanu, 1999, Neal et al., 2016, Shemyakina, 2009, Williams et al., 2012), but other research shows that it increases marriage and fertility (De Smedt, 1998, Neal et al., 2016, Williams et al., 2012, Urdal and Che, 2013).

For a detailed example of quizzical variation in human responses to events, consider an earthquake (the location of which will be identified later). When examining the frequency of tweets during the earthquake, as shown with the solid “ratio” line in the upper panel of Figure 1, we find more than five times the usual number of tweets and about five times the usual number of people sending tweets. This is precisely what we would expect after a hazardous event and we could use this as evidence that people increase social connections and information sharing during and for several hours after earthquakes. However, consider another earthquake (location to be identified later). Using the same methods and Twitter data, as you can see in the lower panel of Figure 1, we find no discernible effect of the earthquake on the number of tweets or tweeters. This could easily be attributed to different social connection and information sharing behaviors between the populations of the first earthquake and second earthquake. We might then warn policy makers in the country where the second earthquake took place that their people are not communicative or socially altruistic and send a bevy of anthropologists, psychologists, and sociologists to try a better understand why one society is more social attuned. Except, both of these graphs represent data from the same country (Nepal), in the same year (April and July 2015); they show data from the same population yet suggest dramatically different conclusions.

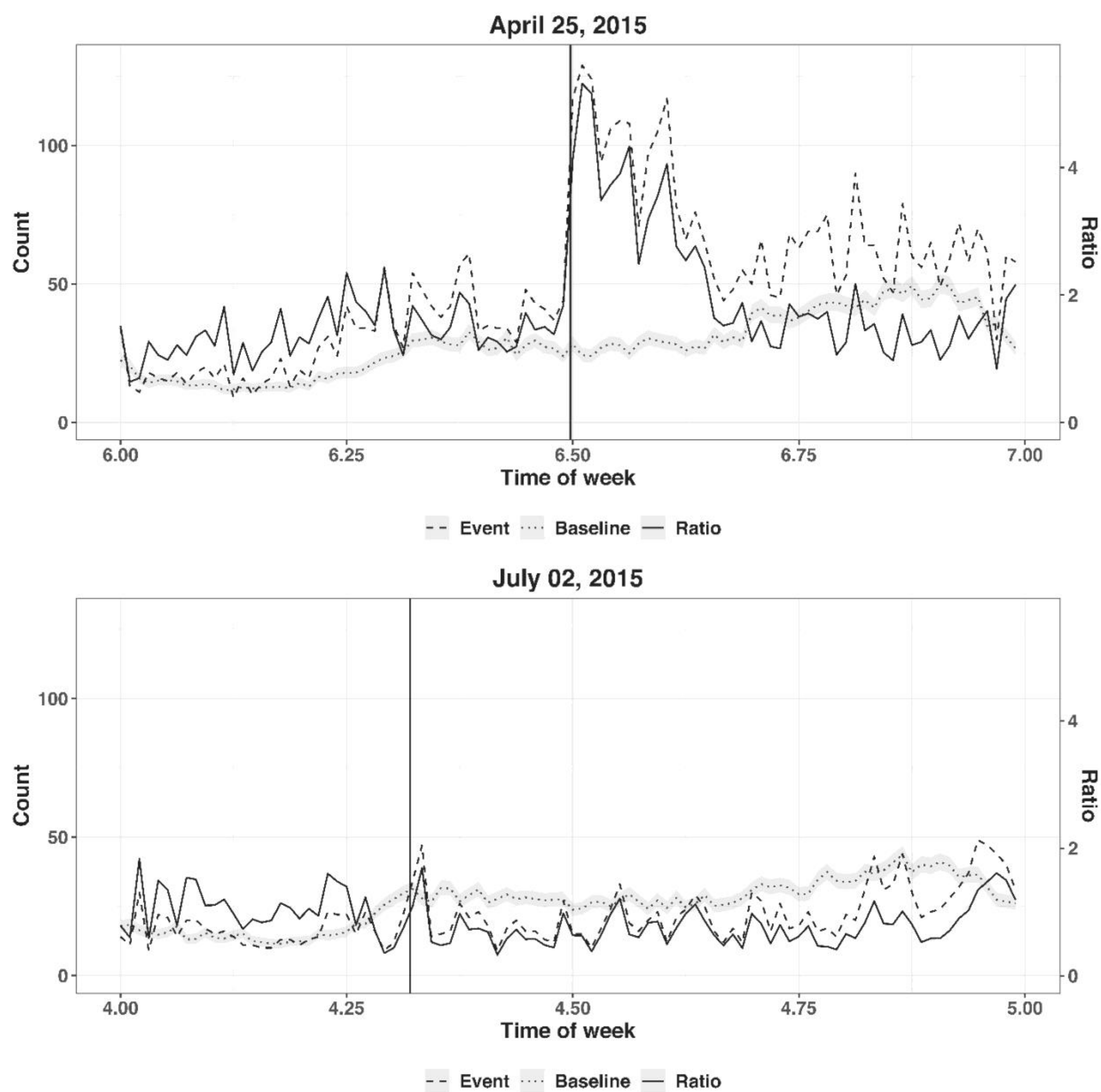

Figure 1. *Twitter responses to earthquakes in Nepal. Upper panel: Tweet counts (dashed line) based on 15-minute time intervals recorded before and after the Gorkha earthquake that took place in Nepal on April 25, 2015 at 11:56am. Lower panel: Tweet counts recorded before and after the Sindhupalchowk earthquake that took place in Nepal on July 2, 2015 at 7:41am. The time when the earthquake occurred is marked with a vertical line. The dotted line gives the estimated intensity of a Poisson model that was fit based on Tweet counts from the same weekly*

time interval in days in which no earthquake took place. This can be interpreted as the expected tweet count if there had not been an earthquake. The grey band gives the 95% CI of the intensity estimates. The solid line gives the ratio between the actual Tweet counts from the event day and the corresponding Poisson intensities (the expected Tweet counts for a non-earthquake day). The units of time are days after Sunday midnight Nepal time. See Table 1 for the time of day and magnitude of these earthquakes.

These disparate empirical results bring into question whether event detection systems using big data, which are sought after by many scholars and public agencies, would even be possible. If responses to a single type of event vary from negative, to positive, to null, then it is hard to imagine how an algorithm could detect such an event. Indeed, as noted in a recent article in *Disasters*, human behavior after hazardous events has historically been treated as a "black box", with assumptions (both dangerous and empirically contradicted) that such behavior is unpredictable and driven primarily by panic (Savage, 2019).

In this study, we follow Savage (Savage, 2019) and many underlying studies in assuming that human behavior after hazardous events is not entirely unpredictable. We seek to contribute to shedding light on the black box of hazard behavior, with relevance for the social science of this topic as well as the development of effective event detection systems using big data.

Of course, the reasons for these quizzical results, for responses to earthquakes, weather disasters, and armed conflict are likely many. In this study, we address one—experiential knowledge. We argue that a single discrete event is not an isolated occurrence, but one of a sequence of many events that unfold over time and the life courses of humans. We already have evidence that humans are extremely adaptive creatures, learning from experiences and changing their behavior over the life course (Kahn, 1988, Osbahr et al., 2008, Sam et al., 2008, Smit and Wandel, 2006, Smithers and Smit, 1997). As such, we can guess that humans might have different behavioral responses to events, depending on the timing of an event in the sequence of events that occur within the life course of a human. Social science has made great strides in putting people into context, by examining the meso- and macro-level social and environmental situations that influence health, well-being, and behavioral outcomes (Chetty et al., 2016, Entwisle, 2007, Sampson et al., 2002). With the present-day move towards the social science of human response to events, it is now time to *put events into context*, by examining the longer-term history in which any singular discrete event occurs. This paper seeks to catalyze this move. We approach this task by first collecting existing theory that relates to human learning and adaptation to singular hazardous events. We then present empirical evidence of changes in human responses over a sequence of hazardous events.

Social-Psychological Background on Adaptation to Events

There has never been a question of whether humans might respond to hazardous events. Evidence has long showed that humans respond in many ways, from psychological reactions such as heightened stress and increased mental health disorders (Galea et al., 2002, Rubin et al., 2005a) to behavioral reactions such as escape, migration, decreased driving and use of public transportation, avoidance of public establishments and many other changes to daily routines (Borell, 2008, López-Rousseau, 2005, Siman-Tov et al., 2016, Stecklov and Goldstein, 2004a, Stecklov and Goldstein, 2010, Spilerman and Stecklov, 2009). That said, multiple studies find reactions that are not as dramatic as might be expected. For example, studies find relatively moderate and short-lived changes (López-Rousseau, 2005, Rubin et al., 2005b) in public transportation use after train bombings in London and Spain. Several studies show short-lived behavioral changes to the Sept. 11 attacks in New York City (Council, 2002, Smelser, 2007, Spilerman and Stecklov, 2009). The key question then is—why actual responses are not as big as we might expect. One hypothesis is that people become habituated to events and therefore their response to earlier events in a sequence will be strong and later events in a sequence weak or non-responsive.

Psychological theory certainly provides strong support for a habituation hypothesis. Several studies show that familiarity with an event decreases perceived risk (Rohrmann and Renn, 2000, Slovic, 2000, Waxman, 2011, Zinn and Taylor-Gooby, 2006). In a similar manner other studies suggest that people overreact to events that are rare or unfamiliar (Blalock et al., 2008, Sivak and Flannagan, 2003, Sunstein, 2003). Still others use the concept of adaptive learning and show that humans adapt their responses to stimuli that are repeated (del Rosal et al., 2006, Thompson, 1986, Thompson and Spencer, 1966). Another study shows that people who experienced losses from a large flood in Australia were more likely to engage in riskier behavior (Page et al., 2014). From a behavioral perspective, studies of behavior in Israel and Lebanon after terrorist attacks show that people modify their routines, from driving on highways to visiting coffees shops, to lessen their vulnerability to subsequent terrorist attacks (Becker and Rubinstein, 2011, Borell, 2008, Spilerman and Stecklov, 2013, Waxman, 2011). Together, these studies provide a strong argument for a pathway from repeated events, to adaptive behaviors, decreased risk perception, and adaptive cognition, to decreased behavioral response to later events in a sequence. In other words, there are multiple strong theoretical and empirical studies that support the habituation hypothesis.

Alternately, psychological and behavioral research also provides theoretical reasons for a possible heightened response to repeated events, what we will call the sensitization hypothesis. Several psychological studies show that when faced with repeated stimuli, people experience heightened sensitivity, develop hyperexcitable fear circuits, ultimately creating strong responses to later stimuli (Kandel 1976; Thompson 1986; Rosen and Schulkin 1998). Other studies show that individuals who experienced earthquakes in Indonesia and the 2004 tsunami in Thailand exhibited greater risk aversion (Cameron and Shah, 2015, Cassar et al., 2017). From a behavioral perspective, studies show that people often exhibit pro-social behavior, including warning behaviors, in potential panic situations after dangerous events or natural hazards (Quarantelli 2001). This explicitly links psychological sensitization and behavioral adaptations to the possibility of increased pro-social behaviors after subsequent events in a sequence.

After this theoretical review, we are then left with good reasons to believe that human responses might change over the course of time, to sequences of events. Further, we have good reasons to believe that responses might decrease and similarly good reasons to believe that responses might increase over a sequence. Turning to empirical evidence does not help to give us a clear path to predict either habituation or sensitization. The studies we cite above that show smaller than expected responses to terrorist attacks in Spain and London surmise that their unexpected results might be due to habituation (López-Rousseau, 2005, Rubin et al., 2005b), but through analyzing only one event, they are not able to test the assertion. Two studies of Israeli responses to terror attacks (Spilerman and Stecklov, 2013, Stecklov and Goldstein, 2004b) explicitly test for habituation to sequences of terror attacks. They find hints, but no strong evidence for habituation. This leaves us with the possibilities that 1) there was no habituation in these cases, 2) both habituation and sensitization occurred, or 3) there was one or the other process but the measurement and testing strategies did not reveal it. In any case, we are left with strong theoretical support for habituation and sensitization and but little empirical evidence, primarily due to a lack of explicit testing. In the remainder of this paper, we take up the search for empirical evidence of either (or both) type of human adaptive response to sequences of events.

Data and Methods

In this study, we take the theoretical ideas above and seek to find a situation that provides demonstration of concept. In other words—can we find empirical evidence of human responses changing over time with increasing exposure to hazardous events? If this is the case, then further work will be necessary to better conceptualize, measure, and analyze (with more traditional hypothesis testing methods) how and why human responses change over sequences of events. To avoid pre-determining our results, we took a blinded approach of choosing a sequence of hazardous events based on clear criteria, and then examining whether human responses varied across the sequence.

Our first criterion is that all events in the sequence must be similar in type. Theory suggests that response to one event might be conditioned on the experience of and learning from all prior events of any type that occurred in a person's life. However, we would expect a different response to different types of events, like a bomb blast or a political protest. Thus, in this initial attempt to identify adaptations, our criteria that a sequence must include similar types of events makes it more likely that any differences we find in response to each event are due to sequencing and not event type. This criterion can later be relaxed as the science of event response becomes more sophisticated.

Second, all events must be in the same general geographic area. We use this criterion for similar reasons to the first one. If all events in a sequence are in the same area, then responses are from the same population. This makes it more likely that any differences we find in responses to each event are due to sequencing and not to different population characteristics.

Third, the sequence must not be preceded in recent time by similar events. This is necessary to create a relatively clean slate in the population that is exposed to the event sequence and could possibly respond. Alternately, if we begin our analysis in the middle of a sequence of events, it is possible that the adaptation has already occurred. In this case, we could incorrectly conclude that there is no adaptation in response, when the adaptation in fact occurred before our study period began.

Fourth, the sequence of events must occur in a time and place for which we have appropriate data of human response. We chose to use data from Twitter. Geo-located tweets provide the location and time of every tweet sent out and a unique identifier for each tweet sender. This data allows us to analyze behaviors of a large number of people and in extremely small temporal units (e.g. 15 minutes). Additionally, this organically collected data is not subject to recall or other type of response bias. Of course, Twitter data is selective of those who use Twitter, and research has shown that these people tend to be younger, wealthier and more likely to live in urban areas (Leetaru et al., 2013). However, given that our purpose here is demonstration of concept that some human responses to hazardous events adapt over time, this selection is not a problem. Further, Twitter is often used as a method to communicate about significant events, for an individual (e.g. 'I got a new haircut!') or at the macro-level (e.g. 'There was a bomb blast!'). Research has shown that social media users turn to platforms like Twitter to report on exceptional events such as political protests, hurricanes, bomb blasts, and even sporting events (Starbird, 2012, Abdelhaq et al., 2013, Guan and Chen, 2014, Khanwalkar et al., 2013, Kraft et al., 2013, Neubauer et al., 2014, Neubauer et al., 2015, S. Schaust, 2013), making this platform a useful data source on information sharing behaviors about events that are considered significant. Accordingly, if we find an increase in aggregate population-level tweet behavior after an event, we can be fairly confident in assuming the increase was because people felt the event was significant. If we do not find an increase, we can assume that on aggregate, people did not feel the event was significant enough to share with others.

The sequence of events we identified that fit our criteria is a series of earthquakes and aftershocks in Nepal that occurred from April 25-July 2, 2015.

Twitter data

We obtained our database of geolocated tweets directly from Twitter through GNIP, a reseller of social data owned by Twitter, as part of a no-cost collaborative research agreement between the University of Washington and Twitter. We acquired all the tweets with explicit geolocation (latitude and longitude) information from mobile devices with GPS sensors that were posted from Nepal between January 1, 2015 and October 31, 2016. Our database comprises 3,378,637 geolocated tweets, posted by 22,148 Twitter users. We discarded the actual tweets after we extracted tuples of the form <user key, time of the posting, latitude, longitude> from the rich content of each tweet. To assure privacy protection, each Twitter user is identified by a randomly generated key which replaces their Twitter identifier. Additional filtering steps were performed to eliminate any non-human activity (e.g., Twitter bots) or any geotweets with coding errors. We discarded all the tweets whose latitude and longitude coordinates do not fall within Nepal's geographical boundaries. We note that this database comprises only public information which can be viewed online, and replicated using the APIs provided by Twitter or downloaded directly from a third party provider of social media data such as GNIP.

Analytical Methods

We divided our observation period (January 1, 2015 and October 31, 2016) into 15-minute time intervals starting with midnight. For each time interval, we calculated the number of geolocated tweets that were posted and determined whether the time interval was on a day in which an earthquake occurred or a day that when there was not an earthquake. To create a baseline estimate of the Twitter activity that could be expected when there were no earthquakes, we fitted Poisson models for counts associated with 15-minute time intervals of every day of the week (Monday to Sunday). The counts we used for a particular time interval (e.g., for Monday between 8:00am – 8:15am) include all the Tweets that were recorded on the same day of the week (e.g., Monday) and the same time interval (e.g., 8:00am – 8:15am) on non-earthquake days during the entire January 2015-October 2016 observation period. With this, for each 15-minute interval, we have an actual count of the number of Tweets during an earthquake-affected time (shown with dashed lines in Figures 1 and 2), an estimated expected Tweet count for the same time period if there were not an earthquake (shown with dotted lines), and 95% confidence intervals for the estimated response (shown in shaded grey). For our primary measure of Twitter response to an earthquake, we created a *response ratio*, which was the actual earthquake response for each time period (dashed) divided by the estimated non-earthquake response from the same time period (dotted) and present this with solid lines.

We undertook the same procedure on Twitter users. Instead of counting and estimating the number of Tweets per 15-minute time period, this analysis counted and estimated the number of unique users of Twitter. We do not present the results from our analysis of Twitter users because they are substantively equivalent to the Tweet count results in Figures 1 and 2.

Results

At 11:56 am on April 25, 2015, a 7.9 magnitude earthquake hit north-central Nepal. With severe shaking in Kathmandu, the capital and most populous area of the country, the earthquake left an estimated 8,891 dead, 22,303 seriously injured, and millions of people homeless (Ministry of Home Affairs, 2015). While the initial earthquake was publicized worldwide, what is less well known is that it was followed by a series of aftershocks, from the same day until July 2. As shown in Table 1, most of the aftershocks were in the range of 5.x magnitude, but the May 12 aftershock was a substantial 7.3 magnitude, which is categorized as a major earthquake. Because responses to any of these events could last for several hours, response to one aftershock might be contaminated by response to an aftershock earlier on the same day. As such, for our analysis, we use only the 11 events that were the first to occur on the day of event. These are shown in Table 1. Prior to 2015, the most recent major earthquake to occur in Nepal was in 1988 and before that in 1934.

Table 1. List of the Gorkha earthquake and aftershocks in Nepal, 2015. We list only the 11 earthquakes that were first to take place during each day out of the 27 earthquakes that took place during this time period. Source: National Seismological Centre, Nepal (http://www.seismonepal.gov.np/).

	Date	Time	District	Magnitude
1	April 25, 2015	11:56	Gorkha	7.9
2	May 12, 2015	12:50	Dolakha	7.3
3	May 25, 2015	3:23	Gorkha	5.0
4	May 26, 2015	22:52	Rasuwa	5.0
5	May 29, 2015	15:44	Dhading	5.2
6	June 11, 2015	21:57	Sindhupalchowk	5.3
7	June 13, 2015	7:06	Dolakha	5.2
8	June 17, 2015	6:14	Sindhupalchowk	5.2
9	June 20, 2015	18:08	Rukum	5.4
10	June 29, 2015	5:42	Ramechhap	5.0
11	July 2, 2015	7:41	Sindhupalchowk	5.0

As shown in the upper panel of Figure 1 the Twitter response to the first April 25 earthquake was substantial. The response ratio (solid line) shows five times as many Tweets were sent and five times as many people tweeted in the three hours following the initial earthquake (during which aftershocks also occurred), compared to our estimate of a baseline day with no earthquake. When we look at the May 12 aftershock (see Figure 2), recalling that it was notable 7.3 magnitude, we find that the Twitter response is lower, with only about three times as many tweets and tweeters. The elevated responses to these two earthquakes occurred over about 3.25 hours on April 25 and a slightly shorter 2.75 hours on May 12. Moving ahead in time, the twitter response to aftershocks generally decreases in both magnitude and time (Figure 2). We see only two additional earthquake events (May 26 and June 17) where the response ratio reaches 2.0 and appears higher than the presumably random peaks of the baseline throughout the day. In addition, the response ratio peaks for only about 30 minutes during these two additional events, much shorter than the three-hour peak in the response ratio after the April 25 and May 12 earthquakes. Besides these four earthquakes with elevated response ratios, we see six earthquake events where there is no peak in response ratio at the time of event that is discernibly different from the normal variance in response ratios throughout the day. This pattern of general decreasing response on Twitter suggests habituation to the earthquakes.

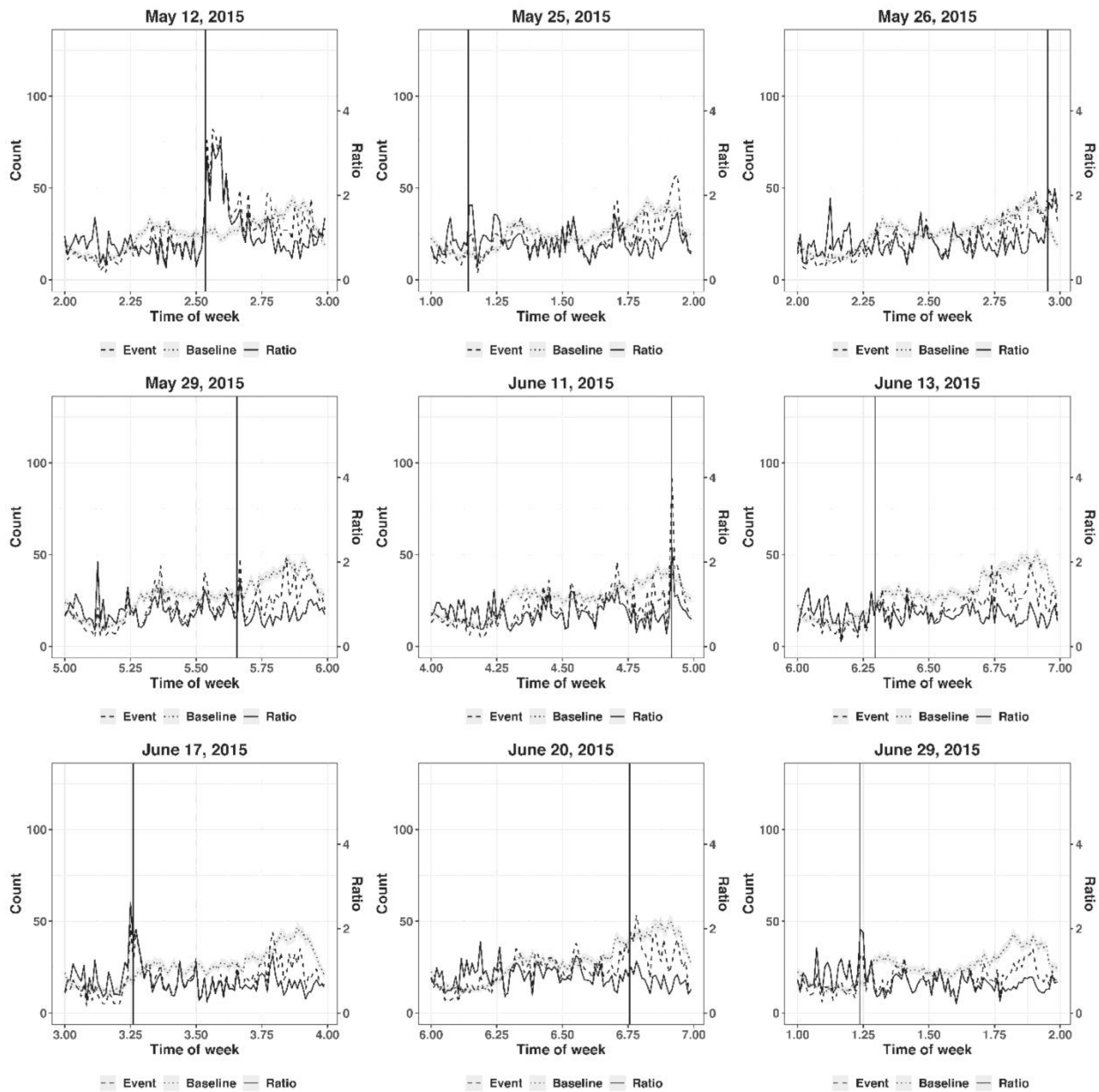

Figure 2. Actual earthquake day (dashed), estimated, non-earthquake days (dotted), and response ratio (solid) of Tweet counts associated with earthquakes that took place in Dolakha (May 12, 2015), Gorkha (May 25, 2015), Rasuwa (May 26, 2015), Dhading (May 29, 2015), Sindhupalchowk (June 11, 2015), Dolakha (June 13, 2015), Sindhupalchowk (June 17, 2015), Rukum (June 20, 2015), and Ramechhap (June 29, 2015). See Table 1 for the time of day and magnitude of these earthquakes.

Of substantial importance is that the magnitude of the earthquakes generally decreased over time, from the initial 7.9 on April 25 to 5.0 on July 2. At the same time, the magnitude of the Twitter response decreased over time, raising the possibility that the decreasing Twitter responses were due to the decreasing earthquake magnitudes and not to a pattern of habituation. The sequence of 11 events here does not allow us to use statistical analysis to disaggregate the cause of response changes over time into event magnitude versus habituation. However, let us focus on just the first two earthquake days: April 25 and May 12. The May 12 earthquake had a smaller magnitude, 7.3 compared to 7.9. But a magnitude 7.3 is arguably still a strong, destructive earthquake that would be large enough to cause concern and fear among the affected population. Yet, we find a subdued response on Twitter, with a response ratio of 5.32 on April 25 and 3.38 on May 12. Now move to July 2, with the 5.0 earthquake. Again, the earthquake is much smaller in magnitude, but it is still an earthquake. In a situation where there was no habituation, we would expect increased use of Twitter after this earthquake. Instead, we find a much smaller response ratio of 1.83, which is no higher than the response ratio peaks that occurred earlier in the day and were thus not affected by earthquake activity. Together, we argue that this pattern is a clear indication that the Nepali population of Twitter users became habituated to earthquakes during the period between April 25 and July 2, 2015.

Discussion

In this study, we described empirical hints and strong theoretical reasoning that supports the concept that human responses to hazardous events might change over a sequence of events. In other words, humans might respond differently the first time they experience an event, compared to the fifth or tenth time they experience that same type of event. We next used empirical data to examine if there was any validity to our conceptual proposition. Our examination of Twitter use during a sequences of earthquakes in Nepal revealed that human responses did change over the course of 27 earthquakes on 11 different days. Specifically, we show that the Twitter response generally decreased over time, from a response ratio of five to the first earthquake, to three for the second quake, and down to one (indicating no discernible difference from the average Twitter frequency on days with no earthquakes). We also find that the length of time that the Twitter response was elevated was longer in earlier earthquakes and shorter for earthquakes later in the sequence. This pattern supports the habituation hypothesis, suggesting that through experience with earthquakes earlier in the sequence, Nepali people likely became familiar, felt decreased sense of risk, adapted their behaviors and cognition, and subsequently responded less to subsequent earthquakes.

In conclusion, our analysis of the 2015 earthquake sequence in Nepal serves demonstration of the concept we introduce that the historical context of a single hazardous event can substantially influence human responses. We hope this will encourage future studies to develop this concept and examine human adaptation to hazardous events further.

This conceptualization of adaptive responses to events has broad significance across the social sciences and relevance for policy and programming as well. From an academic perspective, this study should encourage future researchers to interrogate empirical results that show little or no response to hazardous events. In addition, this concept informs the development of event identification systems that are based on big data sources. If a system assumes consistent human responses to all events, regardless of the historical context, then we believe it is doomed to fail. Instead, designers must find social scientifically informed ways to incorporate adaptive responses to sequences of events.

From a policy perspective, this study has important implications for warning, evacuation, and disaster response efforts. Our results suggest that humans likely experience higher levels of risk and give accord significance to first-time hazardous events, but risk and significance perceptions might decrease for later events of the same type. Consequently, the messaging in warnings and evacuation orders for repeated events (like hurricanes) might need to be different in order to result in the same outcome (e.g. orderly and safe evacuation) as first-time events.

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