Twitter under Storm: Social Media Response Sensitization in the Caribbean

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Abstract

Climate change has led to rising sea levels and warmer sea surface temperatures. These factors contribute greatly to the intensity of hurricanes and floods they provoke. Projections estimate there will be an increase of 45% to 87% in the frequency of Category >4 hurricanes originating in the Atlantic Basin, which typically impact the Caribbean and Continental United States of America. During the 2019 Hurricane Season, there were 20 depressions, 18 storms, 6 hurricanes and 3 major hurricanes. Through this work, we explored the response on Social Media to these natural phenomena as a function of their trajectory, intensity, and previous exposure of the population to intense natural disasters. Data was collected through the Twitter API. The influences of hurricane proximity and intensity on volume of Social Media production was explored. Hurricane Dorian, with its trajectory strongly threatening the previously exposed Puerto Rico, and eventually causing widespread damage in the Abaco Islands of the Bahamas, presented the strongest case for the evaluation of the dichotomy of responses between populations with differences in previous history of exposure. The landscape of historic hurricane exposure Caribbean has radically changed in recent years. Taking advantage of Big Data to help elucidate these dynamics could be instrumental in the tailoring of emergency preparedness plans and the effective design of mental health first aid strategies.

Keywords: *Social Network Analysis, Computational Linguistics, Disaster Psychology*

Resumen

El cambio climático ha provocado un aumento en el nivel del mar y temperaturas más cálidas en su superficie. Proyecciones estiman que factores contribuirán a un aumento de 45% a 87% en la frecuencia de los huracanes de categoría 4 y 5 que se originan en la cuenca del Atlántico. Durante la temporada de huracanes de 2019, hubo 20 depresiones, 18 tormentas, 6 huracanes y 3 huracanes de alta categoría. A través de este trabajo, investigamos la respuesta en las redes sociales a estos fenómenos naturales en función de su trayectoria, intensidad y exposición previa de la población a desastres naturales intensos. Los datos se recopilaban a través de la API (Interfaces de programación de aplicaciones) de Twitter. Se exploró cómo influye la proximidad y la intensidad de la tormenta tropical de interés, en el volumen del contenido generado en las redes sociales. El huracán Dorian amenazó fuertemente a Puerto Rico y eventualmente causó daños generalizados en las Islas Ábaco de las Bahamas. Esta situación sienta las bases para una evaluación de la dicotomía de respuestas entre poblaciones con diferencias en historia previa de exposición. El panorama de exposición previa a huracanes ha cambiado radicalmente en años recientes. Las estrategias de Macrodatos (Big Data) pudieran ayudar a dilucidar estas dinámicas, lo cual podría ser instrumental en la adaptación de los planes de preparación para emergencias y para el diseño efectivo de estrategias de primeros auxilios de salud mental.

Keywords: *Análisis de redes sociales, Lingüística Computacional, Psicología de Desastres*

Introduction

Tropical cyclones (TCs), most known as hurricanes, are one of the most devastating natural-occurring phenomena. They are the most damaging natural disaster in the US¹. In recent times, it is apparent that TCs have been hitting landfall at much higher intensities than in previous years. To quantify how much more intense TCs have been, the power dissipation index (PDI), serves as a measurement of how destructive a TC is. Through this work, it is shown that the PDI for TCs has been increasing significantly since the 1970s (Emmanuel, 2005). Additionally, sea surface temperatures (SSTs), which have been increasing as a result of global warming², strongly correlate positively to PDI values for TCs in the Atlantic region. Later, Emanuel (2007) went on to determine that additional factors contribute to the PDI, all of which are simulated by global climate models and can be used to project PDI values. Work done by Knutson et al. (2013), for example, further confirms that increasing SSTs leads to higher PDI values. In short, TCs have been, and will continue to be, much more intense because of global warming.

Worth noting, however, is that the frequency of TCs in the Atlantic region is expected to remain the same. Knutson et al. (2013) remarked among their conclusions that, based on their projections, an overall decrease in TC frequency should be expected in the Atlantic region.³ However, Vecchi et al. (2013) present in their work examples of studies with conflicting conclusions⁵; that is, some project an increase in frequency of TCs while others present a decrease. Work followed up by Murakami et al. (2014) for example, conclude that further development of predictive models is required to create more robust predictions regarding the frequency of TCs in the Atlantic region.

Before the 2017 Hurricane season, most nations in the Caribbean had been spared in recent years of significant hurricane damage. However, this rapidly changed beginning with Hurricane's Irma and María of the 2017 Season and has continued with 2019's Hurricane Dorian being the most recent instance (Colón-Zayas, 2018). Natural disasters are an unpredictable and uncontrollable source of anxiety we believe represent a prime candidate for symptomatic onset (Kar, et al. 2006; Orengo-Aguayo, et al. 2019). We posit that the manifested social media response will reflect the level of disaster preparedness of the population, which will vary in function of their recent exposure history and facilitate population level public health monitoring (De Choudhury, 2013).

Language is the social fabric that underlies thoughts, feelings, and emotions, which in turn guide our behavior (Rude, et al. 2004). The choice of words we use to express

ourselves are not arbitrary or accidental, but the contrary. The ways people use words in their daily lives can provide rich information about their beliefs, fears, thinking patterns, social relationships, and personalities (Tausczik & Pennebaker, 2010). In other words, through language use we can access our internal thoughts and emotions into a form that others can understand. This enables us to parse what is considered normal or abnormal in the psychopathology spectrum.

Our current paradigm of diagnosis of mental disorders is limited to language-based assessments in the form of clinical criteria. If the content of what we say is symptomatically loaded, correlations can be drawn as to what that person in particular is experiencing. Although it's been the clinician's job to detect what is symptomatically salient, linguistically speaking, using computer-based text analysis, a whole avenue of large corpuses can be addressed and evaluated through a computational linguistics lens (Mazuz and Yom-Tov, 2020).

Social media applications contain huge volumes of text generated by users themselves. In recent years, researchers have begun to explore linguistic signals deemed relevant of clinical content in internet forums, social media and other online communities. (see, Nguyen et al., 2014; Shen & Rudzicz, 2017). For example, for depression specific symptomatology, not only the content of language (ie. negative valanced words) seemed to be predictive of depression, but also the way or style these people use function words (ie. pronouns, prepositions, etc.) (Rude et al., 2004). Another study found that the use of 'absolute words', and hence, 'absolutist thinking', was indicative of anxiety and depression symptomatology, as well as suicidal ideation in the context of online communities, which would lead to cognitive distortions as established in cognitive-based psychotherapies (Al-Mosaiwi & Johnstone, 2018).

However, application of these approaches to reactions to on-going events has been limited. Though common in the analysis of political discourse, and polarization throughout bipartisan battles, more generalized examples of situational stress have been less commonly examined (Gaspar, et. al, 2016). Therefore, many questions remain on how social network analysis could be implemented beyond politics or binary sentiment. This report lays the foundation to initiate this analysis in the context of the Caribbean and the content dynamics elucidated during the 2019 Atlantic Hurricane Season.

Methods

Data collection

Data was collected from two main sources: the National Oceanic and Atmospheric Administration (NOAA) National Hurricane Center (NHC) and Twitter. Digital historic records of hurricane trajectory and intensity were recollected from 2010 onwards by accessing the records of the NHC (NOAA, 2020). For the duration of the 2019 Hurricane Season, daily tweets where any of the names of the Atlantic Named-Storms was mentioned were sampled as permitted by the Twitter API through Rtweet and stored for future analysis (Kearney, 2019).

Historical hurricane exposure

Utilizing the digital records supplied by the National Hurricane service, each geographically and politically contiguous territory in the Caribbean was registered for their minimal proximity to each hurricane, and their intensity at this minimal proximity.

Data processing-Baseline substraction

Data collected for each major hurricane could vary largely. Dependent on the name, certain collections widely encompassed largely irrelevant material. For example, for Hurricane Karen, there was a large amount of background noise, as Karen is a common name used by many Twitter users. On the other hand, Hurricane Dorian suffered less from this contamination. To remediate this, baseline tweet count levels were calculated, through gaussian fit minimization.

Results

History of Major Hurricanes in the Caribbean

Table 1 presents summary statistics for 10 of the Major Hurricanes studied. Data as far back as 2010 in supplementary information. This includes dates and location for formation, peak intensity and dissipation, as well as code and storm name.

Figure 1 A. Change in exposure to recent Hurricane activity in the Caribbean. illustrates territories with major hurricane exposure history up until the ending of the 2016 Hurricane Season.

Figure 1 B. Change in exposure to recent Hurricane activity in the Caribbean. illustrates territories with major hurricane exposure history up until the ending of the 2019 Hurricane Season.

With this data, the history of hurricane exposure by territory is presented in Figure 1, demonstrating a rapid change in exposure history over the last few years

Storm of Note

As can be shown from the historical analysis captured in Figure 1, the distribution of historical hurricane exposure has been in rapid change in the Caribbean over the past few years.

Puerto Rico and the Abaco Islands, historically largely spared from major Hurricane activity prior to 2017, have now both recently been impacted by major storms. Figure 2, captures some significant differences between what we can denote as 3 particularly interesting storms, with 2 directly related to these 2 territories. The first storm of note is Hurricane Dorian, an extremely powerful storm that impacted the Bahamas, particularly the Abaco Islands, very closely. The second storm, Hurricane Karen, threatened Puerto Rico, however never experienced major intensification. The third storm, Hurricane Lorenzo, one of the most powerful storms we have observed so early in the Atlantic, formed and dissipated without much landfall anywhere at all.

Figure 2. Comparison framework for intensity and proximity. Dissection of the 2019

Excess Determination

Focusing on the three storms of note identified, baseline activity was determined beyond the confines of immediate storm activity. **Figure 3** contains visualizations of the peak and baseline detection process, and **Table 2** summarizes the outcome of this process by comparing baseline tweet activity, peak activity, and total activity before and after excess estimation.

Figure 1. Baseline tweet determination for each storm. Each panel illustrates the highest hourly tweet count, and the baseline as determine by optimal Gaussian fitting for each Storm.

Interaction of Tweet Activity, Hurricane Intensity and Proximity

Statistical analysis included the construction of General Linear Models to explore the influence of two different independent variables: intensity and proximity, on one continuous dependent variable, tweet activity after excess filtering. Results tabulated in **Table 3** and visualized in **Figure 4**.

Figure 2 Multiple comparisons of proximity and intensity with Social Media response. One dimensional illustration of relationship between these variables for each location and storm of interest.

Discussion

As captured in **Figure 1**, the landscape of recent major hurricane exposure in the Caribbean has rapidly changed in the last few years. The extensive repercussions this has brought upon their local health, economic and social infrastructure has been amply documented in the literature (Amadeo, 2020; Doran, et al. 2019). However, this visualization leaves patent how recent the extent of hurricane damage has been across the entire Caribbean.

As we inspect the 10 strongest hurricanes we have had in recent history, summarized in **Table 1**, we can immediately note that two of them were observed in the 2019 Hurricane Season. This led to their immediate inclusion in our following up inspection of Social Media data. Additionally, data for Hurricane Karen was also included, given how close this Hurricane was to impacting Puerto Rico, an island still struggling with recovery from its last major hurricane impact.

This arrangement allows us to parse these 3 major storms in two main domains: intensity and proximity. Most major storms, thankfully, are low intensity and remain at a distance from most human-inhabited territory. However, among these 3 storms, we can see how they deviate from the norm in distinct ways. Hurricane Karen, despite not registering major intensification, did make a close approach to Puerto Rico. On the other hand, Hurricane Lorenzo intensified significantly, but remained in the mid-Atlantic, posing no major threat. Finally, Hurricane Dorian both intensified significantly, and caused widespread damage, particularly in the Abaco Islands. This classification scheme is what is illustrated in **Figure 2** and establishes the foundation for a framework in which to interpret the statistical differences observed during their trajectory.

After correction for baseline activity, we can see in the distinct windows of **Figure 4** that low-dimensional 1 to 1 relationships between these variables do seem to carry some relation. This low-level inspection already heavily suggests that, nor intensity nor proximity are the definite arbiters of Social Media activity. On the contrary, the interaction effect between these reveals that it is their summative presence that potentiates the sensitization of the social media response. We can find p-values for each coefficient in a GLM fixed for each Hurricane and location in **Table 3**. Hurricane Lorenzo, having never approached the Caribbean made comparison in proximity a moot point, for which reason results are only presented inspecting the relation of its intensity with Social Media Activity. Nonetheless, moving beyond just a discussion of alpha levels, inspecting these p-values is informative of the dynamic influence the interaction effect truly has. For example, we can, at an alpha level of 0.10, arbitrarily remark that intensity was statistically significant for Tweet Counts generated by Dorian in Puerto Rico, but not the Bahamas. However, it is of greater interest to observe that, beyond alpha levels, the influence of proximity was equally dynamic, changing between the datapoint of interest, while the interaction

Figure 3 Contrast in usage of Anxiety and 'Ansiedad' during Hurricane Dorian. Visualization of the clear time-domain separation of word usage on Social Media, reflective of underlying geographical and linguistic patterns.

effect, commonly allowed higher alpha levels in the literature, remains stable.

Therefore, Hurricane Dorian presented the opportunity of evaluating the continued Social Media Response in two contexts: on approach to Puerto Rico and on approach to the Abaco Islands. To further explore the differences in these two contexts, future studies could explore content level differences. We exemplify this with a simple contrast between the usage of words “Ansiedad” and “Anxiety”, synonyms in Spanish and English respectively that denote a feeling of unease, such as worry or fear, that can be mild or severe and carry clinical connotations, throughout the course of Dorian in **Figure 5**. We note that these distributions are markedly different, with “Ansiedad” strongly reflecting the fact that, Hurricane Dorian menaced Spanish-speaking Caribbean nations first, before finally devastating the English-speaking populations of the Bahamas, and these two separate populations seem to be the main drivers of the activity at each peak. We would suggest the implementation of non-negative matrix factorization to identify the content-level relevant material, to potentiate the dimensions of linguistic criteria that could be compared in the future (Dao, et al. 2016).

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Table 1. Major Atlantic Storm History. Data extracted from the National Hurricane Center historical archive.

Code	Name	Formation Date and Coordinates		Dissipation Date and Coordinates		Max Wind Intensity, Date and Coordinates		
al052019	Hurricane Dorian	8/24/2019 15:00	[-47.9, 10.4]	9/9/2019 3:00	[-53.4, 52.1]	160	9/1/2019 21:00	[-77.3, 26.6]
al112017	Hurricane Irma	8/30/2017 15:00	[-30.3, 16.4]	9/12/2017 3:00	[-84.9, 32.4]	160	9/6/2017 12:00	[-63.3, 18.1]
al152017	Hurricane Maria	9/16/2017 15:00	[-50.5, 12.2]	9/30/2017 21:00	[-43.9, 42.0]	150	9/20/2017 3:00	[-64.7, 17.3]
al132019	Hurricane Lorenzo	9/23/2019 3:00	[-20.9, 10.8]	10/2/2019 15:00	[-25.8, 44.4]	140	9/29/2019 3:00	[-44.9, 24.2]
al142016	Hurricane Matthew	9/28/2016 15:00	[-60.7, 13.4]	10/9/2016 21:00	[-72.0, 35.4]	140	10/1/2016 3:00	[-72.3, 13.3]
al112010	Hurricane Igor	9/8/2010 15:00	[-23.5, 13.7]	9/21/2010 21:00	[-51.7, 49.3]	135	9/15/2010 3:00	[-53.9, 19.0]
al112015	Hurricane Joaquin	9/28/2015 3:00	[-68.7, 27.5]	10/8/2015 3:00	[-37.0, 42.0]	135	10/3/2015 18:00	[-70.9, 26.4]
al122017	Hurricane Jose	9/5/2017 15:00	[-39.1, 12.3]	9/22/2017 21:00	[-69.1, 39.3]	135	9/9/2017 3:00	[-59.3, 16.9]
al142018	Hurricane Michael	10/6/2018 21:00	[-86.6, 18.0]	10/12/2018 9:00	[-73.1, 38.0]	135	10/10/2018 18:00	[-85.5, 30.0]
al072008	Hurricane Gustav	8/25/2008 15:00	[-70.1, 15.5]	9/2/2008 9:00	[-93.4, 31.7]	130	8/31/2008 0:00	[-83.4, 22.7]
al072010	Hurricane Earl	8/25/2010 15:00	[-30.8, 14.3]	9/5/2010 3:00	[-59.2, 50.7]	126	9/2/2010 12:00	[-74.8, 30.1]
al082014	Hurricane Gonzalo	10/12/2014 17:30	[-58.4, 16.4]	10/19/2014 21:00	[-41.8, 51.6]	126	10/17/2014 0:00	[-67.8, 27.4]
al092008	Hurricane Ike	9/1/2008 15:00	[-39.5, 17.6]	9/14/2008 9:00	[-92.5, 36.4]	125	9/4/2008 9:00	[-55.8, 22.7]
al172008	Hurricane Paloma	11/5/2008 21:00	[-81.8, 14.0]	11/10/2008 3:00	[-78.0, 22.0]	125	11/8/2008 21:00	[-78.5, 20.5]
al162011	Hurricane Ophelia	9/21/2011 3:00	[-40.1, 12.2]	10/3/2011 15:00	[-52.0, 48.1]	122	10/2/2011 6:00	[-62.0, 34.9]

al062018	Hurricane Florence	8/30/2018 15:00	[-18.4, 12.9]	9/16/2018 9:00	[-81.4, 33.8]	120	9/11/2018 21:00	[-67.1, 27.5]
al062010	Hurricane Danielle	8/21/2010 21:00	[-32.1, 11.0]	8/31/2010 3:00	[-47.1, 41.3]	117	8/28/2010 0:00	[-60.4, 27.7]
al032009	Hurricane Bill	8/15/2009 15:00	[-34.0, 11.5]	8/24/2009 9:00	[-50.2, 48.6]	115	8/19/2009 21:00	[-57.6, 19.8]
al092017	Hurricane Harvey	8/17/2017 15:00	[-54.1, 13.1]	8/31/2017 3:00	[-92.3, 31.7]	115	8/26/2017 3:00	[-97.0, 28.0]
al122010	Hurricane Julia	9/12/2010 15:00	[-21.4, 12.7]	9/20/2010 15:00	[-46.4, 34.7]	115	9/15/2010 15:00	[-32.7, 18.2]
al122011	Hurricane Katia	8/29/2011 9:00	[-26.3, 9.4]	9/10/2011 15:00	[-47.7, 44.7]	115	9/6/2011 3:00	[-64.4, 25.8]
al152016	Hurricane Nicole	10/4/2016 15:00	[-60.4, 23.8]	10/18/2016 9:00	[-39.5, 47.1]	115	10/13/2016 9:00	[-65.8, 31.1]
al092019	Hurricane Humberto	9/12/2019 21:00	[-74.8, 23.7]	9/20/2019 3:00	[-58.0, 40.0]	110	9/19/2019 9:00	[-62.2, 35.2]
al152008	Hurricane Omar	10/13/2008 15:00	[-69.6, 14.8]	10/18/2008 15:00	[-50.7, 33.4]	110	10/16/2008 9:00	[-63.2, 19.1]
al022008	Hurricane Bertha	7/3/2008 9:00	[-22.7, 12.6]	7/20/2008 15:00	[-35.7, 51.3]	105	7/8/2008 9:00	[-53.3, 21.4]
al072009	Hurricane Fred	9/7/2009 21:00	[-24.5, 12.5]	9/12/2009 21:00	[-33.7, 17.7]	105	9/9/2009 15:00	[-32.4, 13.9]
al072016	Hurricane Gaston	8/22/2016 21:00	[-29.0, 12.1]	9/3/2016 9:00	[-26.9, 40.5]	105	8/31/2016 3:00	[-50.9, 32.9]
al092011	Hurricane Irene	8/20/2011 23:00	[-58.5, 14.9]	8/29/2011 3:00	[-71.3, 45.3]	105	8/25/2011 3:00	[-75.4, 23.8]
al132010	Hurricane Karl	9/14/2010 21:00	[-84.2, 18.3]	9/18/2010 9:00	[-97.6, 18.5]	105	9/17/2010 15:00	[-95.9, 19.4]
al042015	Hurricane Danny	8/18/2015 15:00	[-36.5, 10.6]	8/24/2015 15:00	[-61.5, 15.9]	100	8/21/2015 21:00	[-49.1, 14.5]
al062014	Hurricane Edouard	9/11/2014 15:00	[-37.1, 16.2]	9/19/2014 21:00	[-37.5, 39.5]	100	9/16/2014 15:00	[-57.8, 31.1]

al132012	Hurricane Michael	9/3/2012 21:00	[-42.2, 25.6]	9/11/2012 21:00	[-45.8, 41.4]	100	9/6/2012 15:00	[-41.3, 30.1]
al142017	Hurricane Lee	9/15/2017 3:00	[-25.4, 10.7]	9/30/2017 9:00	[-35.6, 46.7]	100	9/27/2017 21:00	[-57.1, 31.2]
al172017	Hurricane Ophelia	10/9/2017 9:00	[-39.9, 31.1]	10/16/2017 3:00	[-13.3, 49.2]	100	10/14/2017 21:00	[-23.7, 35.9]
al082012	Hurricane Gordon	8/15/2012 21:00	[-55.1, 29.9]	8/20/2012 21:00	[-20.3, 39.2]	96	8/19/2012 6:00	[-32.7, 34.6]
al162016	Hurricane Otto	11/21/2016 9:00	[-79.4, 11.5]	11/25/2016 6:00	[-86.2, 10.8]	96	11/24/2016 18:00	[-83.9, 11.0]
al182011	Hurricane Rina	10/23/2011 21:00	[-81.9, 15.9]	10/28/2011 21:00	[-86.1, 21.9]	96	10/26/2011 6:00	[-85.0, 17.5]
al182012	Hurricane Sandy	10/22/2012 15:00	[-78.0, 13.5]	10/30/2012 3:00	[-75.4, 39.8]	96	10/25/2012 6:00	[-75.9, 20.1]
al082018	Hurricane Helene	9/7/2018 15:00	[-17.8, 13.1]	9/16/2018 15:00	[-25.7, 43.8]	95	9/11/2018 9:00	[-33.6, 16.0]
al112009	Hurricane Ida	11/4/2009 15:00	[-82.0, 11.6]	11/10/2009 15:00	[-87.6, 30.6]	91	11/9/2009 6:00	[-87.5, 24.4]
al032018	Hurricane Chris	7/6/2018 21:00	[-73.8, 32.2]	7/12/2018 15:00	[-57.7, 44.4]	90	7/11/2018 9:00	[-69.9, 35.3]
al082017	Hurricane Gert	8/13/2017 3:00	[-70.3, 25.3]	8/17/2017 21:00	[-46.0, 44.8]	90	8/17/2017 3:00	[-58.4, 40.1]
al102019	Hurricane Jerry	9/17/2019 15:00	[-44.9, 12.9]	9/25/2019 21:00	[-65.6, 32.2]	90	9/20/2019 6:00	[-57.9, 18.1]
al112012	Hurricane Kirk	8/28/2012 21:00	[-43.9, 23.8]	9/2/2012 21:00	[-32.6, 49.7]	90	8/31/2012 15:00	[-50.8, 31.2]
al132017	Hurricane Katia	9/5/2017 21:00	[-96.7, 22.4]	9/9/2017 12:00	[-97.7, 20.1]	90	9/8/2017 21:00	[-96.5, 21.0]
al162018	Hurricane Oscar	10/27/2018 3:00	[-45.7, 26.7]	10/31/2018 21:00	[-49.6, 39.3]	90	10/30/2018 9:00	[-58.2, 28.6]
al012010	Hurricane Alex	6/25/2010 22:00	[-83.5, 16.5]	7/2/2010 3:00	[-102.4, 23.3]	87	7/1/2010 1:00	[-97.5, 24.3]

al012014	Hurricane Arthur	7/1/2014 3:00	[-79.1, 27.6]	7/5/2014 15:00	[-65.5, 45.0]	87	7/4/2014 7:00	[-75.9, 35.6]
al182010	Hurricane Paula	10/11/2010 21:00	[-84.0, 16.0]	10/15/2010 15:00	[-79.5, 22.8]	87	10/13/2010 12:00	[-85.9, 21.3]
al212010	Hurricane Tomas	10/29/2010 21:00	[-57.5, 11.1]	11/7/2010 21:00	[-69.1, 26.1]	87	10/31/2010 12:00	[-63.3, 14.0]
al042008	Hurricane Dolly	7/20/2008 15:45	[-84.2, 18.4]	7/24/2008 21:00	[-100.6, 28.2]	85	7/23/2008 17:00	[-97.0, 26.2]
al132018	Hurricane Leslie	9/23/2018 15:00	[-46.5, 33.0]	10/13/2018 21:00	[-9.5, 40.5]	80	10/12/2018 9:00	[-31.0, 31.9]
al142012	Hurricane Nadine	9/11/2012 15:00	[-43.1, 16.3]	10/4/2012 15:00	[-26.7, 40.0]	80	9/30/2012 15:00	[-38.6, 37.1]
al162017	Hurricane Nate	10/4/2017 15:00	[-81.9, 12.2]	10/8/2017 15:00	[-87.3, 33.1]	80	10/7/2017 18:00	[-88.9, 27.6]
al172011	Hurricane Philippe	9/24/2011 9:00	[-25.2, 10.7]	10/9/2011 3:00	[-43.9, 38.4]	80	10/7/2011 9:00	[-56.3, 29.6]
al172012	Hurricane Rafael	10/12/2012 23:30	[-63.1, 15.0]	10/17/2012 21:00	[-56.5, 40.2]	80	10/16/2012 15:00	[-64.5, 28.6]
al192010	Hurricane Richard	10/21/2010 3:00	[-81.1, 17.5]	10/26/2010 15:00	[-93.1, 20.4]	80	10/25/2010 3:00	[-88.6, 17.3]
al012016	Hurricane Alex	1/13/2016 21:00	[-30.8, 27.1]	1/15/2016 21:00	[-27.8, 43.0]	75	1/14/2016 21:00	[-27.8, 33.6]
al042014	Hurricane Cristobal	8/23/2014 21:00	[-72.3, 21.8]	8/29/2014 15:00	[-47.1, 45.5]	75	8/29/2014 3:00	[-56.6, 40.2]
al052012	Hurricane Ernesto	8/1/2012 21:00	[-49.0, 12.2]	8/10/2012 15:00	[-99.2, 18.0]	75	8/8/2012 3:00	[-87.7, 18.7]
al062015	Hurricane Fred	8/30/2015 5:30	[-18.4, 12.1]	9/6/2015 21:00	[-42.5, 26.5]	75	8/31/2015 15:00	[-23.7, 16.4]
al072017	Hurricane Franklin	8/6/2017 21:00	[-82.0, 15.6]	8/10/2017 15:00	[-99.2, 19.7]	75	8/10/2017 3:00	[-96.1, 20.2]
al092013	Hurricane Humberto	9/8/2013 21:00	[-20.7, 13.1]	9/19/2013 21:00	[-42.0, 33.6]	75	9/12/2013 9:00	[-28.7, 20.5]

al102013	Hurricane Ingrid	9/12/2013 21:00	[-93.6, 19.7]	9/17/2013 9:00	[-99.9, 23.7]	75	9/15/2013 9:00	[-95.4, 22.4]
al172010	Hurricane Otto	10/6/2010 9:00	[-67.0, 22.2]	10/10/2010 15:00	[-41.1, 37.3]	75	10/9/2010 9:00	[-58.5, 29.2]
al022018	Hurricane Beryl	7/5/2018 15:00	[-41.4, 10.2]	7/16/2018 3:00	[-62.4, 38.6]	70	7/7/2018 0:00	[-48.3, 10.6]
al032014	Hurricane Bertha	8/1/2014 3:00	[-55.5, 12.3]	8/6/2014 15:00	[-62.7, 40.2]	70	8/4/2014 15:00	[-73.6, 27.6]
al052016	Hurricane Earl	8/2/2016 16:00	[-80.2, 16.3]	8/6/2016 15:00	[-98.0, 19.0]	70	8/4/2016 6:00	[-88.3, 17.4]
al082008	Hurricane Hanna	8/28/2008 9:00	[-57.9, 19.8]	9/7/2008 9:00	[-70.0, 42.6]	70	9/2/2008 3:00	[-72.5, 21.8]
al092012	Hurricane Isaac	8/21/2012 9:00	[-51.2, 15.2]	8/30/2012 21:00	[-92.6, 32.7]	70	8/29/2012 5:00	[-90.0, 29.0]
al092016	Hurricane Hermine	8/28/2016 21:00	[-81.7, 23.7]	9/6/2016 18:00	[-72.3, 39.4]	70	9/2/2016 3:00	[-84.3, 29.7]
al112008	Hurricane Kyle	9/25/2008 21:00	[-68.3, 23.5]	9/29/2008 3:00	[-65.9, 44.8]	70	9/28/2008 15:00	[-67.7, 40.4]
al142010	Hurricane Lisa	9/21/2010 3:00	[-31.9, 17.1]	9/26/2010 21:00	[-29.4, 26.1]	70	9/25/2010 3:00	[-27.9, 20.7]
al142011	Hurricane Maria	9/6/2011 21:00	[-37.0, 11.8]	9/16/2011 21:00	[-51.5, 48.5]	70	9/16/2011 9:00	[-60.3, 41.7]
al182019	Hurricane Pablo	10/25/2019 21:00	[-32.2, 35.8]	10/28/2019 15:00	[-17.7, 46.8]	70	10/27/2019 21:00	[-17.2, 44.7]
al022019	Hurricane Barry	7/10/2019 15:00	[-86.4, 28.5]	7/14/2019 21:00	[-93.6, 32.8]	65	7/13/2019 15:00	[-92.0, 29.6]
al032012	Hurricane Chris	6/19/2012 21:00	[-57.7, 39.3]	6/22/2012 15:00	[-46.9, 44.6]	65	6/21/2012 15:00	[-43.2, 41.1]
al072014	Hurricane Fay	10/10/2014 15:00	[-63.7, 23.8]	10/13/2014 21:00	[-49.9, 33.7]	65	10/12/2014 21:00	[-60.7, 34.7]
al092018	Hurricane Isaac	9/7/2018 21:00	[-34.9, 13.6]	9/15/2018 9:00	[-70.8, 14.8]	65	9/10/2018 15:00	[-43.9, 14.7]

al122012	Hurricane Leslie	8/30/2012 15:00	[-43.4, 14.1]	9/11/2012 15:00	[-53.6, 49.4]	65	9/7/2012 0:00	[-62.2, 26.5]
al122015	Hurricane Kate	11/9/2015 3:00	[-73.0, 23.0]	11/12/2015 9:00	[-50.8, 40.7]	65	11/11/2015 15:00	[-60.5, 36.8]
al202010	Hurricane Shary	10/29/2010 3:00	[-63.7, 27.3]	10/30/2010 21:00	[-50.9, 39.2]	65	10/30/2010 15:00	[-55.6, 35.9]
al022012	Tropical Storm Beryl	5/26/2012 3:00	[-74.8, 32.5]	5/30/2012 21:00	[-76.1, 34.9]	61	5/28/2012 0:00	[-80.5, 30.1]
al152011	Hurricane Nate	9/7/2011 21:00	[-92.4, 20.2]	9/12/2011 3:00	[-98.4, 20.5]	61	9/9/2011 6:00	[-92.2, 19.7]
al072018	Tropical Storm Gordon	9/2/2018 21:00	[-77.3, 22.7]	9/5/2018 15:00	[-90.2, 32.3]	60	9/5/2018 0:00	[-87.9, 29.7]
al092009	Tropical Storm Grace	10/5/2009 3:00	[-20.3, 41.2]	10/6/2009 3:00	[-13.4, 49.7]	60	10/5/2009 9:00	[-18.0, 43.0]
al122016	Tropical Storm Karl	9/14/2016 15:00	[-25.0, 17.0]	9/25/2016 15:00	[-47.9, 39.9]	60	9/25/2016 15:00	[-47.9, 39.9]
al012011	Tropical Storm Arlene	6/29/2011 0:00	[-93.7, 21.2]	7/1/2011 3:00	[-99.1, 20.9]	56	6/30/2011 12:00	[-97.5, 21.6]
al032013	Tropical Storm Chantal	7/8/2013 3:00	[-47.2, 9.8]	7/10/2013 21:00	[-73.7, 16.5]	56	7/10/2013 0:00	[-64.9, 15.4]
al102010	Tropical Storm Hermine	9/6/2010 3:00	[-95.2, 20.7]	9/8/2010 3:00	[-99.5, 31.6]	56	9/7/2010 0:00	[-97.1, 24.8]
al122013	Tropical Storm Karen	10/3/2013 13:00	[-87.6, 22.0]	10/6/2013 15:00	[-89.9, 28.1]	56	10/4/2013 0:00	[-88.9, 23.8]
al192011	Tropical Storm Sean	11/8/2011 9:00	[-69.4, 27.2]	11/12/2011 3:00	[-57.7, 36.7]	56	11/10/2011 18:00	[-70.0, 30.5]
al012013	Tropical Storm Andrea	6/5/2013 22:00	[-86.5, 25.3]	6/8/2013 15:00	[-68.8, 43.6]	55	6/6/2013 21:00	[-83.4, 29.5]
al012018	Tropical Storm Alberto	5/25/2018 15:00	[-86.8, 19.7]	5/29/2018 9:00	[-86.8, 32.3]	55	5/28/2018 6:00	[-86.1, 28.6]
al022011	Tropical Storm Bret	7/17/2011 21:00	[-78.2, 27.5]	7/22/2011 15:00	[-64.2, 37.7]	55	7/18/2011 21:00	[-77.0, 28.3]

al032008	Tropical Storm Cristobal	7/19/2008 3:00	[-79.6, 31.9]	7/23/2008 9:00	[-55.9, 44.7]	55	7/21/2008 21:00	[-71.4, 37.1]
al052008	Tropical Storm Edouard	8/3/2008 21:00	[-88.1, 28.2]	8/5/2008 21:00	[-95.2, 30.2]	55	8/5/2008 12:00	[-94.2, 29.6]
al062008	Tropical Storm Fay	8/15/2008 21:00	[-69.4, 18.5]	8/24/2008 3:00	[-87.1, 30.9]	55	8/19/2008 21:00	[-81.0, 27.3]
al082019	Tropical Storm Gabrielle	9/3/2019 21:00	[-32.3, 19.0]	9/10/2019 15:00	[-37.8, 43.9]	55	9/9/2019 3:00	[-49.3, 36.5]
al102008	Tropical Storm Josephine	9/2/2008 9:00	[-23.9, 12.4]	9/6/2008 9:00	[-36.9, 16.8]	55	9/3/2008 15:00	[-28.8, 13.8]
al102016	Tropical Storm Ian	9/12/2016 15:00	[-50.4, 21.8]	9/16/2016 15:00	[-36.2, 48.8]	55	9/16/2016 15:00	[-36.2, 48.8]
al132008	Tropical Storm Marco	10/6/2008 15:00	[-94.1, 19.0]	10/8/2008 3:00	[-97.5, 20.0]	55	10/7/2008 6:00	[-95.7, 19.9]
al142013	Tropical Storm Melissa	11/18/2013 15:00	[-53.6, 29.3]	11/22/2013 3:00	[-29.0, 41.5]	55	11/19/2013 21:00	[-53.7, 33.0]
al142019	Tropical Storm Melissa	10/11/2019 15:00	[-69.6, 38.5]	10/14/2019 15:00	[-51.4, 41.0]	55	10/11/2019 15:00	[-69.6, 38.5]
al152018	Tropical Storm Nadine	10/9/2018 10:00	[-29.7, 10.3]	10/13/2018 3:00	[-39.5, 16.0]	55	10/11/2018 3:00	[-32.7, 13.6]
al202019	Tropical Storm Sebastien	11/19/2019 15:00	[-58.7, 20.1]	11/25/2019 3:00	[-28.9, 41.0]	55	11/24/2019 3:00	[-43.1, 34.4]
al012015	Tropical Storm Ana	5/8/2015 3:00	[-77.6, 31.5]	5/10/2015 21:00	[-78.6, 34.4]	52	5/9/2015 18:00	[-78.1, 32.7]
al022015	Tropical Storm Bill	6/16/2015 3:00	[-94.2, 27.1]	6/17/2015 9:00	[-97.1, 31.0]	52	6/16/2015 18:00	[-96.7, 28.2]
al032016	Tropical Storm Colin	6/5/2016 15:00	[-88.1, 21.9]	6/7/2016 21:00	[-72.2, 36.5]	52	6/7/2016 18:00	[-74.7, 35.3]
al042012	Tropical Storm Debby	6/23/2012 21:00	[-87.6, 26.2]	6/27/2012 21:00	[-78.3, 29.5]	52	6/25/2012 0:00	[-86.0, 28.3]
al062009	Tropical Storm Erika	9/1/2009 21:00	[-57.3, 17.2]	9/4/2009 3:00	[-65.6, 16.8]	52	9/2/2009 6:00	[-58.7, 17.0]

al072011	Tropical Storm Gert	8/14/2011 3:00	[-61.6, 27.9]	8/16/2011 21:00	[-54.7, 39.5]	52	8/15/2011 12:00	[-63.3, 31.5]
al072013	Tropical Storm Gabrielle	9/4/2013 21:00	[-66.2, 16.5]	9/13/2013 21:00	[-64.0, 42.0]	52	9/11/2013 6:00	[-65.3, 32.2]
al082010	Tropical Storm Fiona	8/30/2010 21:00	[-48.7, 14.4]	9/4/2010 3:00	[-64.9, 31.4]	52	9/1/2010 18:00	[-62.2, 19.3]
al082011	Tropical Storm Harvey	8/19/2011 3:00	[-82.1, 15.4]	8/22/2011 15:00	[-97.3, 18.1]	52	8/20/2011 18:00	[-88.3, 17.0]
al132011	Tropical Storm Lee	9/2/2011 0:00	[-91.4, 26.6]	9/5/2011 3:00	[-91.4, 31.0]	52	9/3/2011 18:00	[-91.8, 29.3]
al032011	Tropical Storm Cindy	7/20/2011 21:00	[-53.8, 35.2]	7/23/2011 3:00	[-31.2, 49.2]	50	7/21/2011 15:00	[-47.3, 40.3]
al032017	Tropical Storm Cindy	6/19/2017 21:00	[-88.7, 24.7]	6/22/2017 15:00	[-93.5, 31.0]	50	6/21/2017 9:00	[-91.9, 27.3]
al042010	Tropical Storm Colin	8/2/2010 15:00	[-41.1, 12.6]	8/8/2010 21:00	[-65.6, 32.9]	50	8/6/2010 3:00	[-66.6, 26.3]
al042013	Tropical Storm Dorian	7/24/2013 9:00	[-28.1, 13.9]	8/3/2013 21:00	[-77.6, 31.7]	50	7/25/2013 15:00	[-35.9, 16.0]
al052009	Tropical Storm Danny	8/26/2009 15:00	[-70.3, 24.9]	8/29/2009 9:00	[-74.6, 34.3]	50	8/27/2009 15:00	[-73.1, 27.5]
al062012	Tropical Storm Florence	8/4/2012 3:00	[-27.8, 13.8]	8/6/2012 15:00	[-40.2, 16.4]	50	8/5/2012 9:00	[-34.2, 16.6]
al122008	Tropical Storm Laura	9/29/2008 9:00	[-47.3, 37.2]	10/1/2008 15:00	[-46.5, 46.5]	50	9/30/2008 3:00	[-48.4, 39.0]
al122018	Tropical Storm Kirk	9/22/2018 15:00	[-23.6, 8.3]	9/29/2018 3:00	[-65.8, 15.1]	50	9/26/2018 21:00	[-55.7, 12.7]
al162019	Tropical Storm Nestor	10/17/2019 15:00	[-95.7, 22.4]	10/19/2019 21:00	[-84.1, 30.4]	50	10/19/2019 0:00	[-87.6, 27.6]
al182017	Tropical Storm Philippe	10/27/2017 21:00	[-84.5, 17.5]	10/29/2017 21:00	[-75.0, 31.0]	50	10/29/2017 21:00	[-75.0, 31.0]
al192017	Tropical Storm Rina	11/6/2017 9:00	[-50.2, 28.9]	11/9/2017 15:00	[-45.5, 47.0]	50	11/8/2017 15:00	[-48.7, 39.4]

al012012	Tropical Storm Alberto	5/19/2012 21:00	[-77.7, 32.2]	5/22/2012 15:00	[-74.0, 33.1]	45	5/20/2012 9:00	[-78.9, 31.7]
al012017	Tropical Storm Arlene	4/19/2017 15:00	[-40.9, 31.9]	4/21/2017 15:00	[-49.9, 39.3]	45	4/21/2017 9:00	[-48.0, 40.0]
al032015	Tropical Storm Claudette	7/13/2015 17:00	[-68.1, 37.4]	7/15/2015 3:00	[-57.8, 43.8]	45	7/13/2015 21:00	[-66.9, 38.1]
al042009	Tropical Storm Claudette	8/16/2009 9:00	[-83.9, 27.7]	8/17/2009 12:00	[-87.2, 31.3]	45	8/16/2009 21:00	[-85.6, 29.5]
al042011	Tropical Storm Don	7/27/2011 21:00	[-87.0, 22.2]	7/30/2011 9:00	[-98.8, 27.9]	45	7/29/2011 15:00	[-94.9, 26.2]
al042018	Tropical Storm Debby	8/7/2018 15:00	[-48.5, 38.9]	8/9/2018 21:00	[-40.5, 45.5]	45	8/9/2018 3:00	[-46.5, 42.8]
al052011	Tropical Storm Emily	8/1/2011 23:30	[-62.0, 15.2]	8/7/2011 21:00	[-74.1, 31.1]	45	8/3/2011 21:00	[-71.0, 16.9]
al052014	Tropical Storm Dolly	9/1/2014 21:00	[-93.6, 20.1]	9/3/2014 15:00	[-99.2, 21.7]	45	9/2/2014 15:00	[-96.5, 23.4]
al052015	Tropical Storm Erika	8/25/2015 3:00	[-47.7, 14.4]	8/29/2015 13:30	[-75.9, 21.5]	45	8/28/2015 9:00	[-67.7, 17.7]
al052017	Tropical Storm Don	7/17/2017 21:00	[-52.6, 11.2]	7/19/2017 3:00	[-62.5, 11.9]	45	7/18/2017 12:00	[-57.0, 11.4]
al062013	Tropical Storm Fernand	8/25/2013 21:00	[-95.5, 19.5]	8/26/2013 21:00	[-98.5, 20.6]	45	8/26/2013 3:00	[-96.2, 19.3]
al062016	Tropical Storm Fiona	8/17/2016 3:00	[-34.1, 12.6]	8/23/2016 15:00	[-64.5, 26.1]	45	8/21/2016 3:00	[-50.1, 21.7]
al072015	Tropical Storm Grace	9/5/2015 15:00	[-25.2, 12.3]	9/9/2015 15:00	[-49.0, 14.5]	45	9/7/2015 3:00	[-32.5, 13.3]
al072019	Tropical Storm Fernand	9/3/2019 9:00	[-94.3, 23.5]	9/5/2019 3:00	[-99.0, 25.0]	45	9/4/2019 6:00	[-96.7, 23.0]
al102009	Tropical Storm Henri	10/6/2009 21:00	[-54.0, 17.8]	10/8/2009 21:00	[-62.2, 20.4]	45	10/7/2009 9:00	[-56.1, 18.1]
al102015	Tropical Storm Ida	9/18/2015 15:00	[-36.7, 13.1]	9/27/2015 21:00	[-48.7, 24.5]	45	9/21/2015 15:00	[-48.0, 20.6]

al102018	Tropical Storm Joyce	9/12/2018 21:00	[-41.9, 34.3]	9/19/2018 3:00	[-27.9, 30.4]	45	9/15/2018 9:00	[-42.2, 31.9]
al112013	Tropical Storm Jerry	9/29/2013 3:00	[-50.2, 25.2]	10/3/2013 21:00	[-38.7, 31.8]	45	10/1/2013 3:00	[-43.8, 27.4]
al132013	Tropical Storm Lorenzo	10/21/2013 15:00	[-55.1, 28.0]	10/24/2013 15:00	[-47.6, 30.2]	45	10/23/2013 3:00	[-50.0, 29.6]
al132016	Tropical Storm Lisa	9/19/2016 21:00	[-28.6, 13.6]	9/25/2016 3:00	[-40.8, 25.8]	45	9/22/2016 15:00	[-34.0, 20.0]
al152010	Tropical Storm Matthew	9/23/2010 18:00	[-76.2, 13.9]	9/26/2010 15:00	[-92.9, 17.4]	45	9/25/2010 3:00	[-85.0, 15.2]
al152012	Tropical Storm Oscar	10/3/2012 15:00	[-41.5, 17.3]	10/5/2012 15:00	[-37.1, 24.1]	45	10/5/2012 9:00	[-38.9, 23.0]
al172019	Tropical Storm Olga	10/25/2019 15:00	[-94.4, 25.6]	10/26/2019 3:00	[-92.2, 27.8]	45	10/26/2019 3:00	[-92.2, 27.8]
al192012	Tropical Storm Tony	10/22/2012 21:00	[-51.7, 22.3]	10/25/2012 21:00	[-34.0, 31.2]	45	10/24/2012 21:00	[-42.5, 29.6]
al022013	Tropical Storm Barry	6/17/2013 15:00	[-87.6, 16.2]	6/21/2013 3:00	[-98.2, 19.6]	40	6/20/2013 9:00	[-96.2, 19.6]
al022016	Tropical Storm Bonnie	5/27/2016 21:00	[-74.7, 28.5]	6/5/2016 3:00	[-63.6, 34.7]	40	5/29/2016 3:00	[-79.5, 31.0]
al022017	Tropical Storm Bret	6/18/2017 21:00	[-50.4, 7.5]	6/20/2017 21:00	[-67.3, 12.0]	40	6/20/2017 15:00	[-64.4, 11.6]
al042016	Tropical Storm Danielle	6/19/2016 21:00	[-94.7, 19.9]	6/21/2016 9:00	[-99.3, 20.6]	40	6/20/2016 21:00	[-97.0, 21.3]
al052018	Tropical Storm Ernesto	8/15/2018 9:00	[-45.6, 37.6]	8/18/2018 9:00	[-20.0, 51.9]	40	8/17/2018 9:00	[-36.4, 45.6]
al062011	Tropical Storm Franklin	8/12/2011 21:00	[-63.9, 36.0]	8/14/2011 3:00	[-51.8, 40.5]	40	8/13/2011 15:00	[-57.9, 39.0]
al062017	Tropical Storm Emily	7/31/2017 10:00	[-83.5, 27.7]	8/2/2017 3:00	[-78.0, 30.9]	40	7/31/2017 15:00	[-82.8, 27.6]
al072012	Tropical Storm Helene	8/9/2012 21:00	[-43.8, 13.7]	8/19/2012 3:00	[-99.1, 22.8]	40	8/17/2012 21:30	[-96.1, 20.6]

al102017	Atmospheric System Ten	8/27/2017 21:00	[-80.0, 31.2]	8/29/2017 21:00	[-74.3, 36.0]	40	8/29/2017 21:00	[-74.3, 36.0]
al112011	Tropical Storm Jose	8/28/2011 12:00	[-65.7, 30.8]	8/29/2011 15:00	[-63.1, 39.5]	40	8/28/2011 21:00	[-65.7, 33.2]
al122019	Tropical Storm Karen	9/22/2019 9:00	[-60.2, 11.9]	9/27/2019 21:00	[-58.5, 29.3]	40	9/25/2019 6:00	[-65.1, 19.8]
al162012	Tropical Storm Patty	10/11/2012 15:00	[-72.6, 25.4]	10/13/2012 15:00	[-72.6, 24.8]	40	10/12/2012 3:00	[-72.5, 25.9]
al192019	Tropical Storm Rebekah	10/30/2019 21:00	[-40.7, 38.3]	11/1/2019 9:00	[-29.0, 40.6]	40	10/31/2019 9:00	[-36.7, 39.7]
al012008	Tropical Storm Arthur	5/31/2008 17:00	[-88.5, 18.1]	6/2/2008 3:00	[-91.3, 17.4]	35	6/1/2008 3:00	[-89.5, 18.4]
al012019	Tropical Storm Andrea	5/20/2019 22:00	[-68.7, 28.8]	5/21/2019 21:00	[-68.3, 30.8]	35	5/21/2019 3:00	[-68.7, 29.5]
al022009	Tropical Storm Ana	8/11/2009 10:00	[-28.6, 14.4]	8/17/2009 21:00	[-68.0, 17.5]	35	8/16/2009 6:00	[-52.5, 14.5]
al032010	Tropical Storm Bonnie	7/22/2010 15:00	[-75.0, 21.9]	7/24/2010 21:00	[-87.6, 28.5]	35	7/23/2010 9:00	[-78.6, 24.1]
al042019	Tropical Storm Chantal	8/21/2019 3:00	[-56.2, 40.2]	8/24/2019 3:00	[-40.9, 35.6]	35	8/21/2019 15:00	[-51.6, 40.2]
al052013	Tropical Storm Erin	8/15/2013 3:00	[-23.5, 14.0]	8/18/2013 21:00	[-39.8, 20.4]	35	8/16/2013 9:00	[-30.5, 16.3]
al062019	Tropical Storm Erin	8/26/2019 21:00	[-72.5, 31.7]	8/29/2019 9:00	[-71.6, 36.1]	35	8/28/2019 9:00	[-72.4, 32.5]
al082015	Tropical Storm Henri	9/9/2015 4:30	[-61.5, 30.8]	9/11/2015 21:00	[-58.5, 40.0]	35	9/11/2015 3:00	[-60.7, 34.8]
al092010	Tropical Storm Gaston	9/1/2010 15:00	[-35.8, 12.4]	9/2/2010 21:00	[-39.5, 13.5]	35	9/2/2010 3:00	[-37.7, 13.4]
al092014	Tropical Storm Hanna	10/22/2014 3:00	[-92.9, 19.4]	10/28/2014 3:00	[-84.5, 14.5]	35	10/27/2014 18:00	[-83.5, 14.9]
al102012	Tropical Storm Joyce	8/22/2012 15:00	[-36.3, 12.4]	8/24/2012 15:00	[-46.2, 17.8]	35	8/23/2012 21:00	[-42.5, 15.9]

al112016	Tropical Storm Julia	9/14/2016 3:00	[-81.6, 30.3]	9/19/2016 3:00	[-78.4, 32.2]	35	9/14/2016 21:00	[-80.5, 32.1]
al112019	Tropical Storm Imelda	9/17/2019 17:00	[-95.4, 28.7]	9/18/2019 3:00	[-95.5, 29.8]	35	9/17/2019 21:00	[-95.3, 29.3]
al142008	Tropical Storm Nana	10/12/2008 21:00	[-37.9, 16.4]	10/14/2008 9:00	[-43.3, 18.4]	35	10/13/2008 3:00	[-38.8, 16.6]
al162010	Tropical Storm Nicole	9/28/2010 15:00	[-82.5, 20.6]	9/29/2010 21:00	[-80.0, 24.5]	35	9/29/2010 18:00	[-80.6, 23.5]
al012009	Tropical Depression One	5/28/2009 15:00	[-71.0, 37.3]	5/29/2009 21:00	[-62.3, 40.3]	30	5/29/2009 3:00	[-67.8, 38.1]
al022010	Tropical Depression Two	7/8/2010 3:00	[-93.9, 23.9]	7/8/2010 21:00	[-98.4, 26.2]	30	7/8/2010 12:00	[-96.2, 25.7]
al022014	Tropical Depression Two	7/21/2014 21:00	[-43.8, 11.6]	7/23/2014 15:00	[-56.0, 14.0]	30	7/22/2014 21:00	[-49.6, 12.9]
al032019	Tropical Depression Three	7/22/2019 21:00	[-78.6, 25.6]	7/23/2019 15:00	[-80.0, 29.0]	30	7/23/2019 15:00	[-80.0, 29.0]
al052010	Tropical Depression Five	8/10/2010 23:30	[-84.1, 26.0]	8/11/2010 21:00	[-87.6, 28.3]	30	8/11/2010 6:00	[-84.5, 26.3]
al082009	Tropical Depression Eight	9/25/2009 21:00	[-31.6, 16.4]	9/26/2009 21:00	[-35.7, 18.9]	30	9/26/2009 9:00	[-33.8, 17.6]
al082013	Tropical Depression Eight	9/6/2013 18:30	[-97.8, 22.3]	9/7/2013 9:00	[-99.3, 21.4]	30	9/6/2013 21:00	[-98.2, 22.2]
al082016	Tropical Depression Eight	8/28/2016 15:00	[-70.0, 31.5]	9/1/2016 9:00	[-69.2, 38.2]	30	8/30/2016 3:00	[-74.1, 33.8]
al092015	Tropical Depression Nine	9/16/2015 15:00	[-43.1, 15.0]	9/19/2015 21:00	[-49.9, 18.8]	30	9/17/2015 15:00	[-45.2, 16.1]
al102011	Tropical Depression Ten	8/25/2011 9:00	[-30.4, 12.4]	8/27/2011 3:00	[-34.0, 16.0]	30	8/26/2011 3:00	[-33.1, 14.1]
al112018	Tropical Depression Eleven	9/22/2018 3:00	[-53.4, 13.1]	9/23/2018 15:00	[-56.0, 14.5]	30	9/22/2018 9:00	[-53.5, 13.0]
al152019	Tropical Depression Fifteen	10/14/2019 21:00	[-20.2, 13.2]	10/16/2019 9:00	[-24.1, 17.3]	30	10/15/2019 15:00	[-21.6, 15.6]

al162008	Tropical Depression Sixteen	10/14/2008 15:00	[-83.0, 15.6]	10/16/2008 3:00	[-85.9, 15.3]	30	10/16/2008 0:00	[-85.6, 15.3]
al042017	Tropical Depression Four	7/6/2017 3:00	[-38.4, 12.8]	7/7/2017 21:00	[-52.5, 16.5]	25	7/6/2017 21:00	[-44.9, 13.1]

Table 2. Excess Twitter activity during storm. Outcome of Twitter data after subtraction of baseline activity levels. Baseline is determined as visualized in Figure 3.

Code	Name	Peak Tweet Date	Peak Tweet Count	Baseline Tweet Level	Total Excess Tweets
al052019	Hurricane Dorian	2019-09-01	58276	1649	998729
al132019	Hurricane Lorenzo	2019-09-21	6917	1124	79825
al122019	Tropical Storm Karen	2019-09-22	8279	2552	318994

Table 3. General Linear Model p-values. Output p-values for General Linear Models that determined optimal coefficients for Proximity, Intensity and their Interaction, as explicative variables of excess twitter activity

Location	Storm	P> z for Intensity	P> z for Proximity	P> z for Interaction
Puerto Rico	Dorian	0.07619226	0.03435301	0.05470535
Puerto Rico	Karen	0.84771792	0.90918496	0.9538549
Puerto Rico	Lorenzo	0.3558961853	-	-
Bahamas	Dorian	0.20105585	0.01878344	0.05815791
Bahamas	Karen	0.92925035	0.82394846	0.9465272
Bahamas	Lorenzo	0.3558961853	-	-