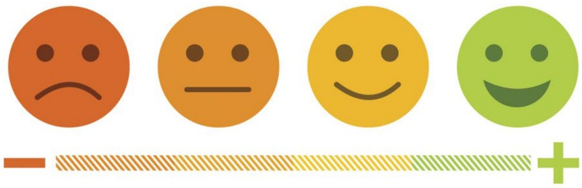

Emotional response to climate hazards on Twitter

MSc Earth Surface & Water – Master Thesis – GEO4-1520

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'He who has a why to live for

can bear almost any how'

Friedrich Nietzsche

Voor Opa, dr. Ido (Eddy) Bossema, die mij de liefde voor de wereld, en met name de natuur, op een wetenschappelijke manier ontdekken toonde.

Abstract

As the consequences of climate change are increasingly becoming more and more harmful for humans and other living beings, a change towards a sustainable society becomes more urgent. How the public thinks about topics regarding climate change, may be visible in social media. In this study Twitter data have been analysed to gain information about public response to climate hazards by using artificial intelligence techniques. An increasing body of research has suggested that the processing of information, decision-making and action-taking, and behaviour with regards to climate change, hazards and risks are largely determined by emotions. Identifying emotions, such as fear, anger, joy and surprise in our communication about topics can enhance our understanding and predicting ability of individual and societal visions, reactions, and indirectly behaviour and actions. This opens up the possibility to study the relation between climate hazards and emotional expressions, responses and effects. Understanding tweet activity and its associated emotions before, during and after climate hazards can have significant implications for interventions towards preparedness, safety, regulations and recovery during future climate hazards. In addition to global response, information about tweet activity and emotional response in different regions can add to these implications and interventions. Twitter is chosen as social network forum due to its global usage, the current purpose of Twitter with regards to sharing opinions and expressions, the coverage of a very wide range of topics and the fact that the analysis of a large amount of data is facilitated for scientific purposes.

The main question of this thesis is as follows: *How does the public respond (emotionally) to climate hazards on Twitter?* The underlying questions that guide the research and analysis are:

1) How does tweet activity vary before, during and after a climate hazard?
2) How do tweet emotion patterns vary before, during and after a climate hazard?
3) How do climate hazard related tweet activity and emotion patterns vary per location?

First a literature study was conducted that discusses climate change and natural hazards, psychology of emotions and behaviour and its link to climate change and the expression and recognition of emotions in linguistics. This is followed by an outline of previous research regarding climate hazards, social media and emotions.

Concepts from literature regarding emotions and emotion recognition were integrated to collect and analyse Tweet datasets from Twitter for three different climate hazards. Tweets were collected before, during and after these climate hazards. Tweet datasets were collected by selection on specific words, start and end date and locations. This was followed by the extraction of emotions from the tweet texts in these datasets. The resulting tweet and emotion data were analysed to identify patterns regarding tweet activity and emotional response. Three climate hazards were selected:

1) Temperature rise on Antarctica and the global emotional response in March 2022.
2) Tornado outbreak in South West USA and the national (American) response in December 2021.
3) Hurricane Ida in the state Louisiana and the national (American) response in August 2021.

All three events were short-lasting events that lasted between 1-3 days to be able to analyse the tweet and emotion trend before, during and after the event on a 4-week timescale. Tweets regarding the temperature rise on Antarctica were collected on a global level to analyse global response.

Tweets regarding the tornado outbreak and Hurricane Ida were collected within the United States to analyse the tweet activity and emotional response on a national scale and also regional scale by analysing tweet activity and emotion response for states in the West US, Southeast US and Northeast US.

The results show different time series of tweet activity and emotion distributions for the three climate hazards and opens up the possibility to compare tweet activity and emotion distributions before, during and after these hazards.

Tweet activity around climate hazards follow the anticipatory, core and aftermath phases as the framework of Murthy & Gross (2017) proposed. Tweet activity peak during the core event and show a gradual decrease during the recovery phase. The anticipatory phase shows a gradual rapid increase when the climate hazard is a predictable event. During sudden, unpredicted climate hazards, tweet usage increases very rapidly within 24 hours to peak during the core event Also, the emotion distribution shows an increase in negative reactions of 10-15% at the moment when a climate hazard takes place. The emotion distributions follow a similar trend as tweet activity during the anticipatory and core phase from the proposed framework. The aftermath is unclear due to distortion of second events and is questioned to last longer than tweet activity as specific induced emotions may be longer amongst the public.

The emotion anger is substantially larger for the hurricane and tornado cases in comparison with the Antarctica case, which can be explained by the visible impacts during the hurricane and tornado hazards and the association of hurricanes and tornadoes to climate hazards. The tornado event shows substantially more fearful reactions than the hurricane event that contains a high level of the emotion fear. It is suggested that this difference in fear and anger proportions lies in the predictability or controllability of the event. Further, the proportion of positive reactions is overall for all three cases major and requires more research. The regions where a climate hazard occur show the largest tweet activity as was expected. However, the emotion distributions are quite similar for all regions and the region where an event occurs does not show an increase in negative emotions as the hypothesis suggested.

The found tweet activity and emotional response patterns in this thesis can be useful for governments and organisations to communicate more effectively with the public by aiming for better preparation and recovery of climate hazards and also enhancing positive attitude towards climate change topics.

Preface & acknowledgement

Lectori Salutem, Beste Lezer,

Voor u ligt mijn masterthesis: *'Emotional response to climate hazards on Twitter'*. Hoogstwaarschijnlijk markeert en bekroont deze thesis, die tot heden beschouwd kan worden als mijn opus magnum, het einde van mijn universitaire studietijd waarbij ik een bachelor Aardwetenschappen, 0,8 master Energy Science en een master Earth Surface and Water voltooide.

Onze planeet is in groot gevaar. Op 4-jarige leeftijd begon dit besef te dagen, nadat ik in de Efteling een WNF 3D film zag waarbij Oerang Oetangs uit de boom gezaagd werden. Een beeld dat voor altijd op mijn netvlies gegrift zal blijven staan en wat de allereerste wortel voedde van behoefte om me in te zetten voor een duurzame planeet. Deze behoefte samen met mijn mateloze fascinatie voor de Aarde resulteerde in één van mijn beste beslissingen ooit. Namelijk om in 2014 de collegebanken van de Universiteit Utrecht te betreden als kersverse student Aardwetenschappen.

Het onderwerp van deze masterthesis bracht mij in de gelegenheid om de zeer interessante onderwerpen klimaatverandering, artificial intelligence, dynamiek van de maatschappij, wetenschapsfilosofie, neuro- en gedragswetenschappen en de kunst van goed, gevat en helder schrijven uit te pluizen en te combineren. Al deze informatie gaf mij een belangrijke kompasrichting om mijn off-road pad met de thematiek klimaatveiligheid, duurzaamheid en de harmonie tussen aarde en mens verder uit te zoeken én te bewandelen. Daarnaast kreeg mijn abstract denken een nieuwe dimensie en leerde ik ontzettend veel over energie en tijdsbalans, de menselijke methodes van het universum verklaren en de daarbij behorende beperkingen, en inspireerde Python mij hoe ik mijn gedachten en gevoelspatronen kan structureren.

Ik hoop dat u, als lezer, meekrijgt dat aandacht besteden aan onze cognitieve patronen, die onze houding en gedrag ten opzichte van klimaatverandering bepalen, cruciaal is om onze planeet te transformeren tot een duurzaam geheel. Daarnaast hoop ik dat dit werk hoopvolle emoties bij u teweegbrengt (Wees gerust, voel geen druk om deze hoop te laten blijken in Tweets. Dat ga ik niet analyseren). Want hoop is de benzine voor krachtige en energieke actie. De geschiedenis herhaalt zich en toonde ons keer op keer dat onze mind het op dat moment aanwezige wereldprobleem kon oplossen. Ik hoop dat deze thesis u laat inzien dat mede door de ontwikkeling van artificial intelligence ook onze huidige klimaatprobleem te overwinnen is. En laten we zorgen dat artificial intelligence een verlengde blijft van onze brein, zodat straks in een duurzame toekomst, artificial intelligence niet ons volgende wereldprobleem wordt.

Tot slot wil ik nog wat woorden van dankbaarheid besteden aan een aantal personen. Ik voel momenteel veel dankbaarheid, en daarom zou ik dankbaarheid zeker toevoegen mocht ik ooit de behoefte hebben om net zoals Robert Plutchik mijn eigen emotie-classificatiesysteem te creëren. Ik realiseer me dat niet alleen het vangen van emoties úit woorden ontzettend lastig kan zijn, zoals ik ervoer tijdens mijn onderzoek. Ook het vangen van emoties ín woorden lijkt zo nu en dan onmogelijk. Toch ga ik een poging wagen. Maar het is goed om te realiseren dat het woord dank hier veel meer dimensies kent dan de 4 letters die het begrip op papier weerspiegelen.

Allereerst wil ik mijn ouders bedanken voor hun onvoorwaardelijke liefde en steun. Zonder hen was ik nooit de persoon geworden die ik nu ben. Zeker op dit moment in mijn leven ben ik heel dankbaar dat mijn moeder me als kind alle ruimte gaf om de wereld op mijn manier te ontdekken en dat mijn vader afgelopen twee jaar altijd bereid was om mee te denken en me te adviseren.

Daarnaast ben ik mijn begeleider Maarten Kleinhans voor eeuwig dankbaar voor de waardering die hij toonde voor de persoon die ik echt ben. Dat vergeet ik nooit en is iets wat ik meeneem ongeacht welke paden ik bewandel en welke bergen ik beklim. Daarnaast ben ik hem heel dankbaar voor het meedenken en de vrijheid die hij me gaf om een afstudeeronderwerp, voor zowel mijn bachelor scriptie als master scriptie (!), te kiezen die mij lag en die ik interessant en uitdagend vond.

Ik wil Erik van Sebille graag heel erg bedanken voor zijn openheid en enthousiasme om mee te denken over een interessant afstudeerproject en de wil om dit te begeleiden. Daarnaast wil ik hem bedanken voor zijn rationele blik op de wereld, wat mijn perspectief verrijkte, en ook zijn communicatie en reactiesnelheid wat mij veel rust gaf.

Daarnaast wil ik Yaël Duindam bedanken. Wij ontmoetten elkaar in 2015 tijdens de Honours reis naar Georgië en nu, 7 jaar later, ontwikkelden wij een vriendschap waar ik nooit van had durven dromen. Ik wil haar bedanken voor alle inspiratie en levenswijsheid die ze mij gaf afgelopen jaren, en ook alle steun en kracht die ze mij gaf afgelopen half jaar.

Ook wil ik kort Diggy Dex, Sía en Nils van der Poel bedanken die mij met hun inspirerende woorden in de vorm van muziek en interviews kracht gaven op moeilijke momenten. Daarnaast verdient de chocolatier van Tony Chocolonely een vermelding.

Tot slot zijn een aantal mensen op de universiteit die afgelopen 8 jaar een ontzettend belangrijke rol hebben gespeeld, die absoluut een vermelding verdienen. Dank aan Elisabeth Addink voor alle steun en wijsheid die ze mij meegaf in het Honours programma. Dank aan Philip Minderhoud voor de levenswijsheid die hij uitstraalt en zijn levensinsteek die mij inspireert. Dank aan Paul Meijer voor het enthousiasme dat hij uitstraalde tijdens het vak systeem Aarde 1 en zijn perfecte collegestem en presenteer houding (zijn hoorcolleges waren één van de weinigen waar ik vrijwillig heen ging). Ook wil ik Evert Nieuwlaar bedanken vanuit Energy Science, die mij ondersteunde in mijn toelating tot een dubbele master en mij inspireerde met zijn scheikundige blik op koken en kooktechnieken. Verder dank aan Almar de Ronde voor zijn nooit oordelende open oor en het vertrouwen dat hij me gaf mijn eigen pad te kiezen. Ook dank aan Marcel van der Perk voor zijn altijd zeer snelle reacties als master coördinator en zijn opgenomen hoorcolleges die je op eigen snelheid kon kijken waardoor de fysieke hoorcolleges werden gebruikt voor verdieping van kennis in de vorm van vragen en discussies. Tot slot dank aan Wilma Wessels, voor de mogelijkheid om voor een Honours component een creatief practicum voor het vak Tijd en Causaliteit in elkaar te zetten over de evolutie van het paard en de zebra. Dit was één van de leukste opdrachten die ik deed voor mijn studie en het gaf me veel inzichten. Ik zal deze mensen stuk voor stuk op gepaste wijze bedanken. Namelijk door op een willekeurig moment met een goede fles wijn op hun kantoordeur aan te kloppen.

Finis et principium est.

Ik wens u veel (hoopvol) leesplezier,

Marieke Jacobs

Utrecht, 16 juli 2022

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1. Introduction

1.1. Context and societal relevance

Climate change and exploitation of the earth have devastating consequences that become clearer every day. The dynamics of the planet, such as weather patterns, ocean currents and temperature levels have been affected worldwide. As these consequences are increasingly becoming more and more harmful for humans and other living beings, the urgency to change towards a sustainable society grows (Crist et al., 2017; IPCC, 2022; Su et al., 2021). The transition towards a sustainable society involves contributions of society in its entirety and of the individuals (Grisogono, 2020). Identifying and understanding societal and individual perspectives on climate change and its consequences is important, as this information gives insight in how individuals and entire societies can be motivated to be engaged in sustainable development.

A common way to gain such information is by analysing social media platforms with artificial intelligence techniques. The use of social media, as a communication and information tool rapidly expands with an increasing influence in our daily lives (Sharma & Sharma, 2020). In 2021, 4.48 billion people were actively using social media and networks, which is a result of a steady increase of 13.13% over the past 6 years (Marechal et al., 2019; Statista, 2022). Social networks, such as Twitter, Instagram, Facebook and TikTok enhance communication amongst individuals and connect people universally (Kaur et al., 2020). Using social networks is a way to express oneself by sharing his or her perspectives, thoughts and mental state on different issues (Sailunaz & Alhajj, 2019). Therefore social media can be an important tool in measuring and analysing societal patterns and dynamics (Kaur et al., 2020). Twitter, worldwide used by 400 million people, is primarily used to share opinions and daily activities and feelings (Pathak et al., 2017). With the current negotiations of Elon Musk to buy Twitter with the purpose of turning it into a more open platform, the use of Twitter as debating platform might even increase (Duffield, 2022).

A large part of personal sharing on Twitter and other social media platforms, as well as in other forms of communication, exists of the expression of emotions. An emotion is a multidimensional concept that reflects the personality, vision and perspective of an individual and is directly expressed in the behaviour of humans (Sailunaz & Alhajj, 2019). Identifying emotions, such as fear, anger, joy and surprise in our communication and reactions about topics can enhance our understanding and predicting ability of individual and societal visions, reactions to events, and indirectly our behaviour and actions (Lair et al., 2020; Odou & Schill, 2020). In this thesis, I analyse the emotional response on Twitter around specific hazards that are climate change-related.

1.2. Problem definition and research aim

Several studies have been conducted on identifying emotions on social networks in relation to major events, such as elections or the covid pandemic, in order to identify behaviour and perspectives of individuals (Campos et al., 2021; Kaur et al., 2020; Loureiro & Alló, 2020; Willson et al., 2021). One study examined the dynamics of emotions during the covid pandemic, measured over a timeseries of consecutive days, and found a correlation between the trend of negative emotions on Twitter and mortality and infection rates (Kaur et al., 2020). Regarding natural hazards, a study investigated usage patterns on social media before, during and after natural hazards with a focus on the number of tweets and specifically used words in Tweets (Niles et al., 2019). This was based on a suggested framework of tweet usage around events consisting of an anticipatory trend, a core event and an aftermath (Murthy & Gross, 2017). The results show that the usage of Twitter gradually increases during the anticipatory phase, peak during the event itself, and gradually decreases during the recovery phase (Figure 1). It was also found that during the anticipatory phase the frequency of Tweets related to the event is larger for predicted natural hazards than for unpredicted natural hazards.

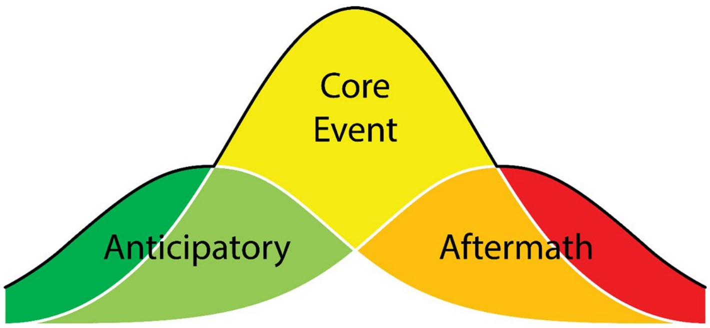


Figure 1: The framework suggested by Murthy & Gross (2017) that shows the timeline of Twitter response for a natural hazard with a pre-phase (anticipatory), central phase (core event), and recovery phase (aftermath) (Niles et al., 2019).

An experimental investigation on how the interaction between emotion and thinking styles affects judgements about natural hazards found that the interaction between emotion and thinking style affected risk assessment and to what extent an individual was prepared for a climate hazard (Lair et al., 2020). Thus emotions identification can be a proxy for the way that people approach climate hazards and their preparedness for hazards.

In addition to these studies, the research field regarding Twitter use and emotion expression around climate hazards is growing (section 2.5). However, the emotional expressions, responses and effects that are induced on Twitter by climate hazards is largely unknown (Loureiro & Alló, 2020; Niles et al., 2019; Willson et al., 2021). A significant gap remains within understanding the emotional response of individuals before, during and after climate hazards. Understanding tweet patterns and its associated emotions can have important implications for creating interventions in the preparedness, safety, regulations and recovery of future climate hazards (Niles et al., 2019). That is because the processing of information, decision-making and action-taking, and behaviour with regards to climate change, hazards and risks are largely determined by emotions rather than factual information (Brosch & Steg, 2021; du Bray et al., 2018). Identifying these tweet and emotion patterns can thus be essential in for example disaster communication and the type of disaster information that is spread, consequently affecting decisions and actions of individuals. Positive communication styles can, for example, trigger positive feelings that can accelerate action-taking towards interventions on both individual and societal level (Brosch, 2021) (Section 2.2).

From a broader climate change perspective, getting a clear understanding of the emotional response on Twitter to climate change-related events can be crucial information to identify attitudes and perspectives on climate change (Velez & Moros, 2021). Understanding these societal attitudes regarding climate change can help to improve expressions, behaviour, attitude and response in order to tackle the current global climate issues (Odou & Schill, 2020). For example, emotional response patterns can be essential for governments and organisations to communicate more effectively with the public by aiming for a more prepared individual approach to natural hazards during the event itself and also in the preparation and recovery phase. Emotional response patterns can also be used in communication to enhance the mental health of people regarding climate change to support positive action-based behaviour and thinking styles and minimize climate anxiety, and even lead to a more action-based approach to climate change in general.

Although this information about emotional response in relation to climate hazards is thus crucial, a significant knowledge gap remains within the understanding of tweet activity and emotion response before, during and after natural hazards. Therefore, the following research question guides this thesis:

How does the public respond (emotionally) to climate hazards on Twitter?

The main questions that guide the research and analysis are:

1) How does tweet activity vary before, during and after a climate hazard?
2) How do tweet emotion patterns vary before, during and after a climate hazard?
3) How do climate hazard related tweet activity and emotion patterns vary per location?

1.3. Research approach

First a literature study was conducted. Following a brief overview of natural hazards associated to climate change (Section 2.1), the psychology of emotions and behaviour is described and its relation to climate change is conceptually developed (Section 2.2.). In order to quantify this relation, the analysis of emotion expression in linguistics by artificial intelligence techniques is reviewed (Section 2.3). Also, previous research regarding climate hazards, social media and emotions is described (Section 2.4.).

Following the literature study, a code was developed to collect Tweet datasets from Twitter by selecting specific words, time intervals and locations (Section 3.1). Twitter is chosen as social network forum due to its global usage, the current purpose of Twitter with regards to sharing opinions and expressions, the coverage of a very wide range of topics and the fact that the analysis of a large amount of data is facilitated for scientific purposes (Statista, 2022). Tweets have been collected before, during and after selected climate hazards. Three climate hazards were selected for the analysis: 1) Temperature rise on Antarctica and the global emotional response in March 2022, 2) Tornado outbreak in South West USA and the national (American) response in December 2021, 3) Hurricane Ida in the state Louisiana and the national (American) response in August 2021. All three events were short-lasting events that lasted between 1-3 days to be able to analyse the tweet and emotion trend on a 4 week time scale. This 4 week timescale was set from 2 weeks before to 2 weeks after the event to analyse tweet and emotion response before, during and after the event. Tweets regarding the temperature rise on Antarctica were collected on a global level to analyse global response. Tweets regarding the tornado outbreak and Hurricane Ida were collected within the United States to analyse the tweet activity and emotional response on a national scale and also regional scale by selecting tweets per state.

After collecting tweets on a 4 week timescale for the three mentioned climate hazards, emotions were extracted from the text of the collected tweets. The resulting data was analysed and visualised as time series of emotion distributions for the three climate hazards for comparison of tweet and emotion response before, during and after disaster events. Also local differences have been analysed and visualized (Section 4). The results are compared with the discussed literature and prior research (Section 5). This section also discusses the contribution of this study to the growing body of work, that explores emotions of the public on climate hazards in general and on social media with regards to climate change.

2. Literature

2.1. The bigger scope: climate change

Nowadays, it becomes more acknowledged that ecological balance and a sustainable society are essential for human life, as environmental degradation is occurring at global scale. The consequences are visible everywhere and climate hazards in a large variety of forms are occurring with a higher frequency (IPCC, 2022). Restoring human connection with the planet and the environment is an important solution to mitigate climate consequences, stabilize the planet, and develop a sustainable society, that is in balance with its environment (Folke et al., 2011; Rands et al., 2010). Actively promoting environmental awareness, behaviour and actions and setting targets are crucial for the development of a sustainable civilization (Campos et al., 2021; Charnley et al., 2017).

One of the major pillars in the broadest context of sustainability are The Sustainable Development Goals, also known as SDGs. The SDGs were introduced by the United Nations in 2015 with the purpose to globally protect the planet, end poverty and strive for global peace (Figure 2) (UN, 2015). Whereas analysis of emotions to enhance sustainability can be performed within all SDG topics, sustainability is within this thesis downscaled and defined to protection of the planet and decreasing anthropogenic activities that induce climate hazards.

Although climate hazards are mainly driven by greenhouse gas emissions which cause global warming, other human exploiting activities can induce new climate hazards or even accelerate occurring climate hazards. Common exploiting activities are deforestation, pollution of water, air and soil, extended water use, etc (Tsatsaris et al., 2021). Climate hazards threaten human health, economic stability and the well-fare and safety of natural and built environments. The main events include heat waves, wildfires, heavy precipitation events, flooding, intense hurricanes, tornados, landslides, soil degradation, and soil degradation. These occur in different areas of the world and the type of hazards mainly depends on the type of climate and exploitation activities of the region (Lenton et al., 2019).

In recent decades, the world experienced a rising number of all types of climate hazards (Figure 3) (Birkmann et al., 2022; Emel ÖNAL et al., 2021). As a result of the continuous anthropogenic emissions and exploitation of the planet, the frequency and intensity of climate hazards are expected to increase (Garschagen et al., 2021). A variety of risk assessments have been performed regarding the spatial variability of climate hazard risks and also regarding the types of risks. For example, the International Military Council for Climate Security (IMCCS) identified and assessed the risks of phenomena that endanger global security. The main outcomes of the report show that on a 2021-2041 timescale, the highest assessed risks threatening global security were driven by climate change-related natural hazards and all shift to a catastrophic level on a 20 year timescale (Figure 4). The most pressing climate security phenomena are all weather related and the major risks forecasted for 2041 are exposure to extreme heat and precipitation. In addition Birkmann et al. (2022) examined the global spread of vulnerability to climate hazards and concluded that the mortality rate for flood, drought and storm-related climate hazards was 15 times higher for countries that were ranked as highly vulnerable compared to low vulnerable countries.

The associated impacts of climate hazards are expected to rise further as a result of both the increasing population and ageing of infrastructure of human settlements (Aghakouchak et al., 2020). Some of these impacts will result into an increasing number of climate refugees, increased food shortages and risk of war. Another potential danger is the co-occurrence and cascade of natural hazards, also known as the compound effect. Droughts, heat waves, wildfires, and floods often result from interactions between various physical processes that in isolation might not be considered extreme but when combined result in significant impacts. These types of events are referred to as compound events (Zscheischler et al. 2018). For example, higher temperatures can increase the frequency of heat waves and alter the global water cycle, which induces heavy precipitation events (Aghakouchak et al., 2020). In this study, only single events are taken into account.

From annual climate security report of the IMCCS and the annual risk assessment report of the National Oceanic and Atmospheric Administration (NOAA), results especially showed a high climate hazard occurrence in the United States the last decades (Figure 7). The United States has a large variety of climate zones, resulting into the USA frequently subjected to a large variety of climate hazards (Figure 5&6) (Iglesias et al., 2021). In 2020 and 2021 this became clear as the US has been subjected to respectively 22 and 20 climate hazards in total. The visibility of the harmful impacts of climate change and hazards and thus severity become more clear and climate change consciousness increase amongst individuals, especially those who are exposed to this severity in real life or on social media (Bail et al., 2018; Yang et al., n.d.). The total costs of climate change damage has been estimated for 2020 and 2021 to be respectively 95 and 148 billion dollars and 262 and 724 deaths (NOAA, 2022). At the end of the century, climate change is in the US expected to cause an increase of 1.2% of Gross Domestic Product per 1 Celsius rise (Hsiang et al., 2017). Also, research show that 57% of the US built environment is located into areas with a high hazard risk (Iglesias et al., 2021).

Figure 2: Overview of all 17 Sustainable Development Goals (SDGs) that have been proposed in 2015 by the United Nations and thoroughly outlined in the SDG Report. (UN, 2015)

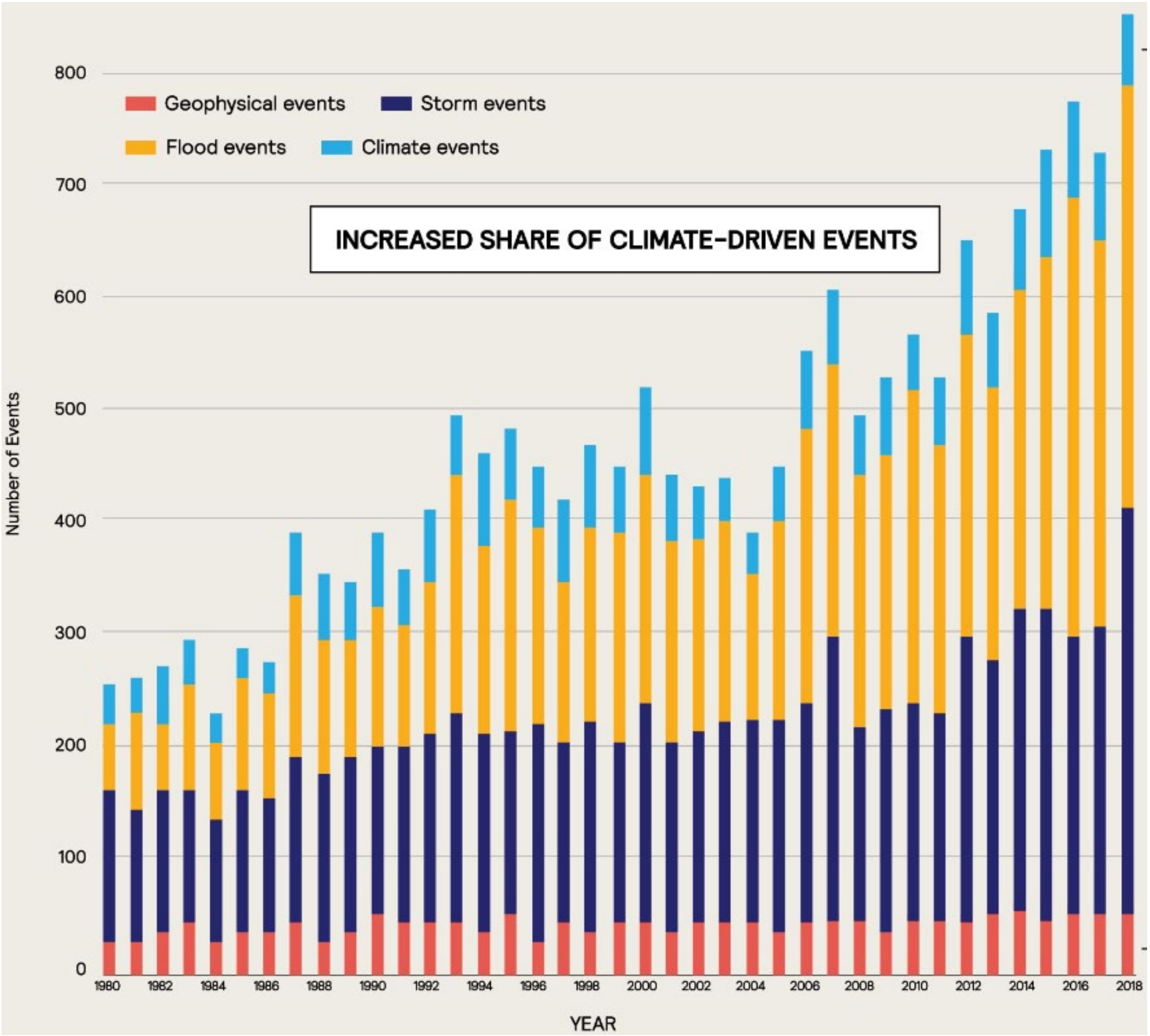


Figure 3: A graph that shows the amount of disasters that have taken place at a global level. In the last century, the amount of climate hazards have increased enormously. Hydrological and meteorelogical climate hazards shows the highest increase. Biological events include epidcemics, insect infesations, climatological events include droughts, wildfires, glacial lake outbursts, hydrological events include flooding, landslides, meteorological include storms, extreme temperature and extreme fog events, and geophysical include earthquakes, mass movements, volcanic activities, tsunamis and extreme rockfalls. (Accounted events have caused at least one fatality and/or produced normalised losses > US$ 100k, 300k, 1m, or 3m (depending on the assigned World Bank income gorup of the affected country) (Munich RE, 2018).

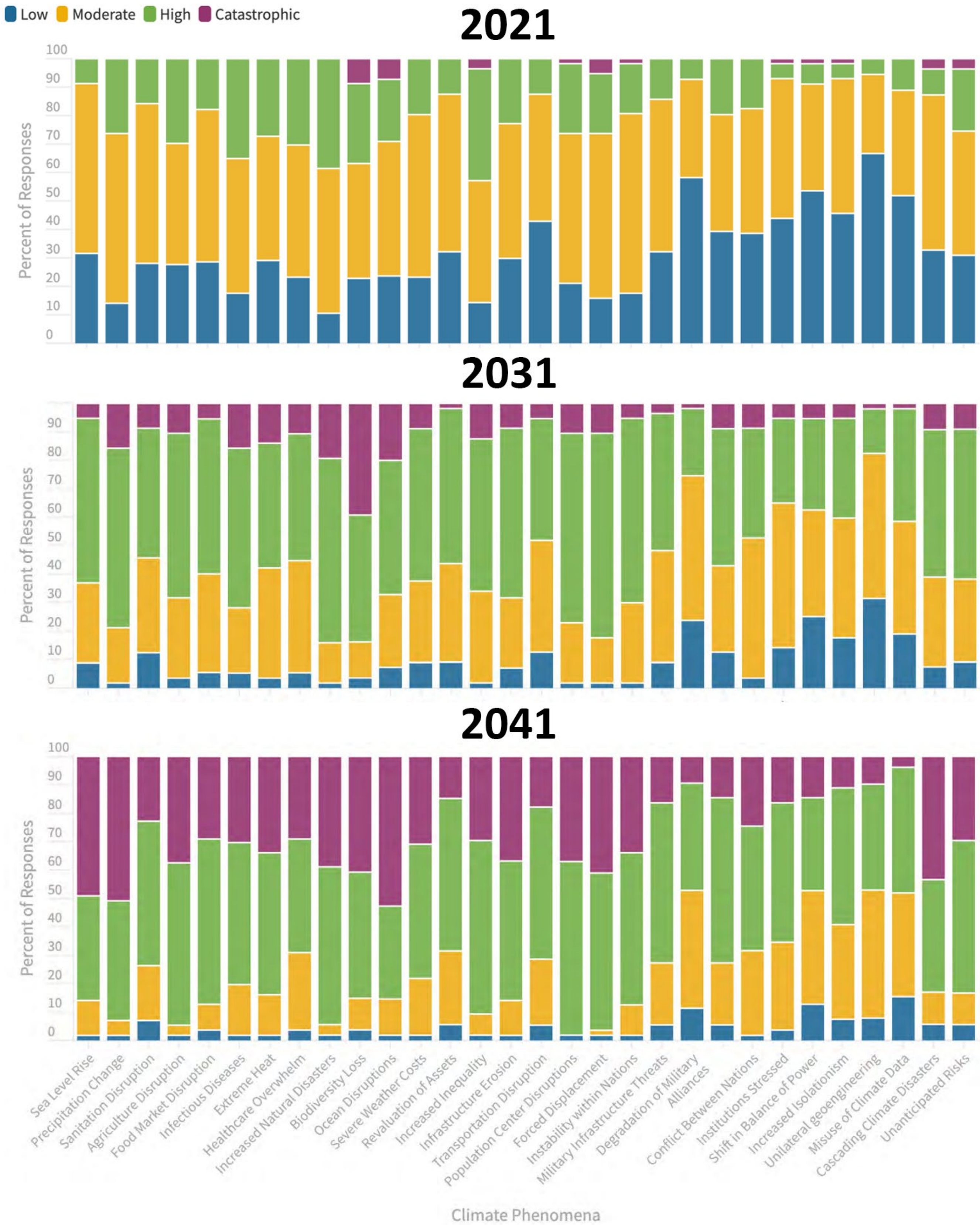
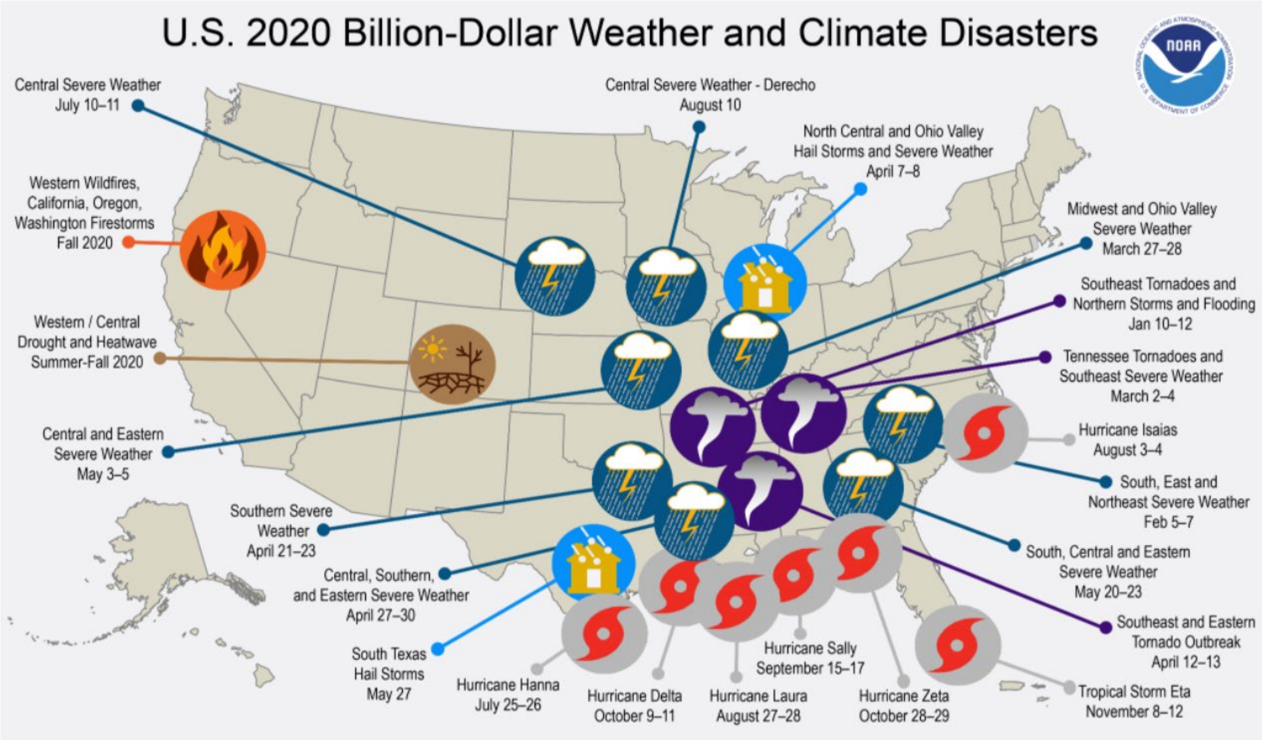


Figure 4: Risks for climate security phenomena for the year 2021, 2031 and 2041, showing an increase of risk level over time. These phenomena include the categories Ecosystem Security, Health Security, National Security, and Water Security (IMCCS, 2021)



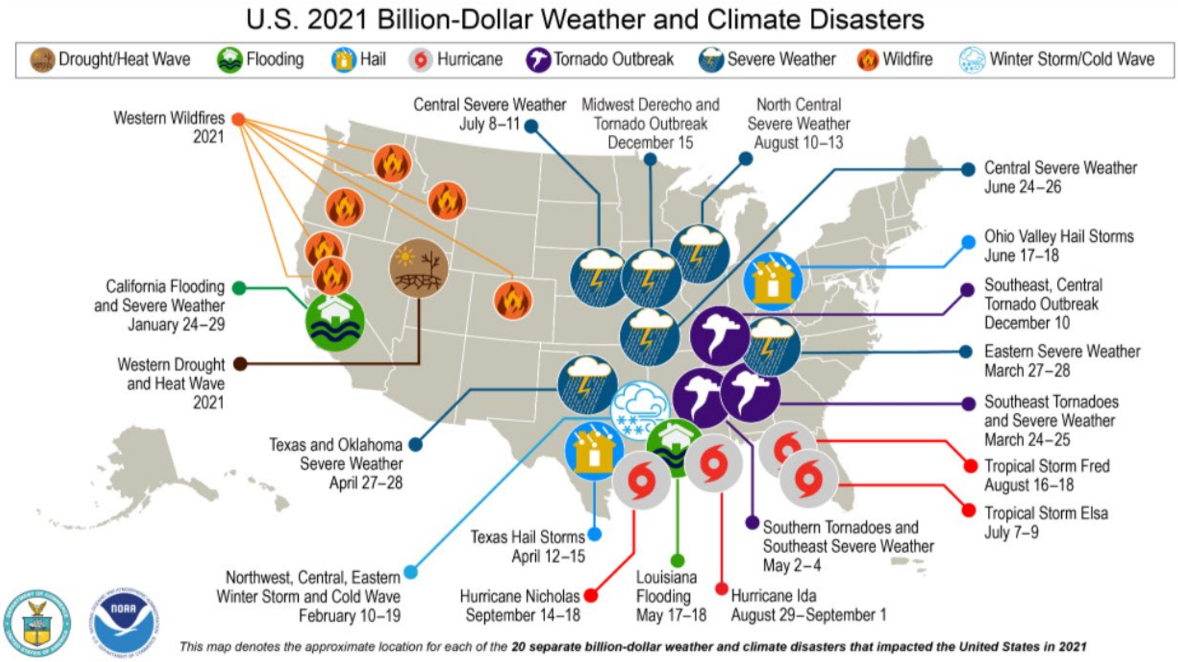


Figure 5: These maps from NOAA show an overview of all climate hazards that occurred in the US in respectively 2020 and 2021. It is visible that wildfire events mainly take place in the western part of the US, severe weather events and tornadoes mainly affect the north eastern part, and hurricanes mainly affect the southeast coast. (NOAA, 2022)

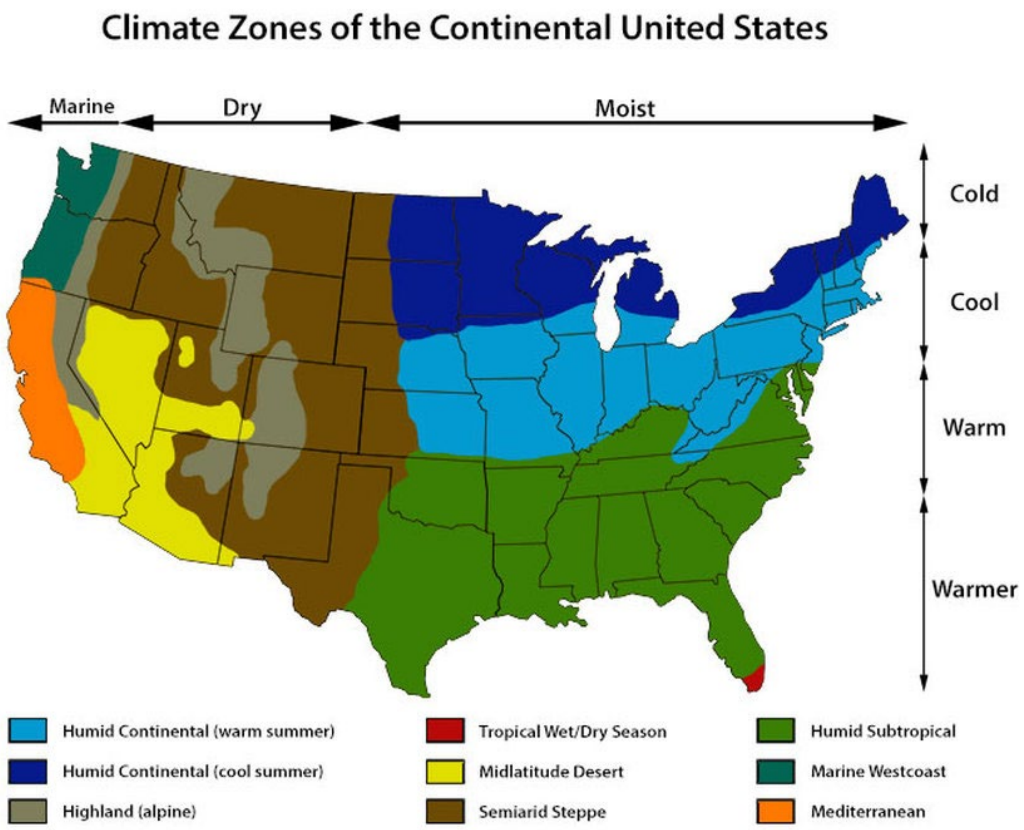


Figure 6: A map of the subdivision of different climate zones in the US. The main division seen here is a dry climate in the western part, a humid and subtropical climate in the southeast part and a continental climate in the northeast (edited from IECC (2012)).

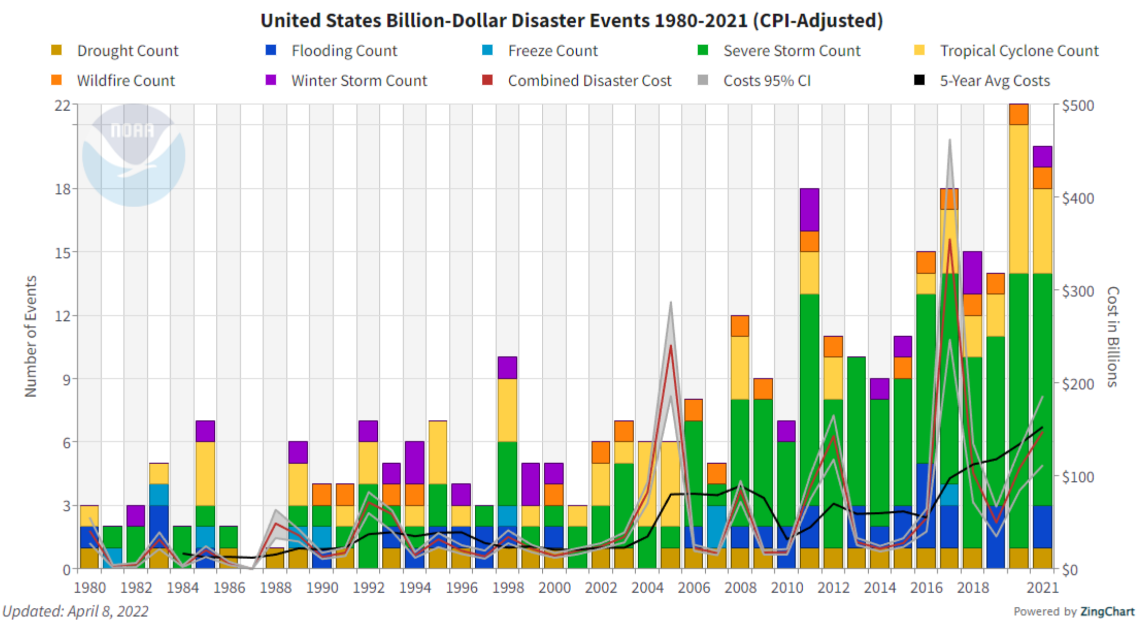


Figure 7: Number of events and the total damagae costs per year from 1980 to 2019 for different climate hazards. From the graph an increase in amount of hazards can be observed, where mainly flooding events and severe storms increase. The damage costs also increases over the years. (NOAA, 2022)

2.2. Psychology of behaviour and emotions

The term emotion is a difficult concept. As the importance of emotions for human behaviour (regarding climate change) becomes clearer, this section describes basic knowledge about emotions and their occurrence, the connection between emotions and behaviour, and the link between emotions, behaviour and climate change.

2.2.1. Basic emotions and behaviour

An emotion is considered a multidimensional characteristic that reflects personality and feelings and is expressed in communication and behaviour (Clayton & Karazsia, 2020; Marechal et al., 2019). The most widely accepted definition of an emotion is described as being a response that is a result of an interaction between physiological actions, cognitive processes, subjective feelings, and the resulting behavioural outcome on a perceived situation by an individual (APA, 2021). People express emotions as a response of their feelings and reactions on external stimuli, such as other persons and events (Sailunaz & Alhajj, 2019). Various communication methods can be used to transfer emotions to other individuals. Various common methods of expressing emotions are using linguistics, phonetics, and facial expressions. Linguistics is the study of language, phonetics is the classification of speech sounds and semantics is the study of word meanings. These three can be expressed both through speech, with semantics, intonation and body language and physical facial expressions, and through text, with semantics, punctuation and emoticons (Campos et al., 2021). In this study, emotion expression through semantics, or the meaning of words, will be taken into account.

In addition to the general term emotion, different emotional states can be distinguished. A variety of models have been established which characterize and distinguish different emotional states (Cowen & Keltner, 2017; Cruz-Villalobos & Barret, n.d.). According to the Farlex Medical Dictionary, an emotional state is defined as 'A mental state that arises spontaneously rather than through conscious effort and is often accompanied by physiological changes', or 'A strong feeling, aroused mental state, or intense state of drive or unrest directed toward a definite object or event, or a memory of such object or event and evidenced in both behaviour and in psychologic changes, with accompanying autonomic nervous system manifestations.' (Farlex Medical Dictionary, 2022). A complication is the subjectivity of emotions and expressions thereof. Where one person will experience fear, and expresses this with heavy emotion expressions, another person will experience anger with subtle expressions. Consequently, where one would use a specific word, intonation or facial expression, another would not. Therefore, it is essential to understand the individual semantic space of the emotional experiences of an individual (Keltner & Lerner, 2010). Semantic spaces is defined as domain of natural language with aim to create representations of natural language with the purpose of capturing meaning (Odou & Schill, 2020). However, some more general emotion and expression patterns do exist and are commonly used by many individuals. These general patterns are used as fundaments in most emotional models (Cowen & Keltner, 2017).

One of the most widely used emotion model is the Ekman model (Ekman, 1999; Tracy & Randles, 2011). This model distinguishes 6 basic emotions, namely fear, anger, sadness, disgust, surprise and joy. The emotion model of Plutchik (1994), used in this study, is based on the Ekman model and added the emotions trust and anticipation. Fear, anger, sadness and disgust are in general seen as negative emotions, whereas joy, anticipation and trust as positive. Surprise is a rather neutral emotion that can have positive as well as negative intentions.

2.2.2. Link between emotion and behaviour

Nowadays, it becomes clearer that emotion and behaviour are strongly interconnected. The occurrence of emotions is an immediate intrinsic experience with the result that emotion has a strong impact on conscious and unconscious processes in the human mind. The solid intertwinement between cognitive processes and emotional experiences lead to a behavioural outcome. Cognition evokes emotion and as emotion determines how information is selected and interpreted, emotion thus affects cognition (Brosch & Steg, 2021).

The appraisal of relevance of a certain issue determines the specific emotions someone experiences. These experienced emotions evoke actions by activating so-called motivational action tendencies and unconscious and conscious assessment of the situation (Figure 8). The process of appraisal can be managed with both reasoning and associative-based mechanisms. Reasoning-based appraisal, or attentional prioritization, is a gradual, more active and effortful process in which someone can assess the situation consciously. Associative appraisal, or situational interpretation, is based on previous experiences and occurs largely unconsciously and passively (Brosch & Steg, 2021). After and during this coping and assessment process, emotions influence cognitions and judgements, such as specific climate change perceptions and beliefs, and they trigger motivational tendencies (Brosch, 2021). A motivation tendency is the tendency to nearly automatically act with sudden behaviour when experiencing a specific emotion. For example, fear can automatically lead to defensive behaviour and attitude such as fight, flight, or freeze, sadness can lead to the tendency to change one's circumstances, and guilt can lead to the tendency to repair a situation. Some motivation tendencies are quite common and are felt by people universally, whereas others are variable per individual (Frijda et al., 1989). The experienced emotions and associated behaviour is encoded in the memory and result into the development of anticipated emotions, that again affects experienced emotions. (Taufik et al., 2016).

Thus, emotional reactions that an individual experiences or expects to experience after executing a specific behaviour is a crucial driver for future behaviour and action. The role emotion plays in thoughts and actions of individuals shows the importance of mapping emotions with regards to understanding, mapping, predicting and influencing (sustainable) behaviour (Gross, 2013).

The main division that can be made is whether a perceived emotion is pleasant or unpleasant. This experienced positive or negative affect will lead to a negative or positive anticipated affect that will determine whether a specific behaviour will be shown or avoided. In general, the human mind strives for an increase in positive experiences and feelings and an avoidance of negative experiences and feelings (Brosch & Steg, 2021).

This effect of anticipated emotions have also a large impact on climate related topics, as positive anticipated feelings can results into vicious positive feedback cycles that enhance climate favoured behaviour.

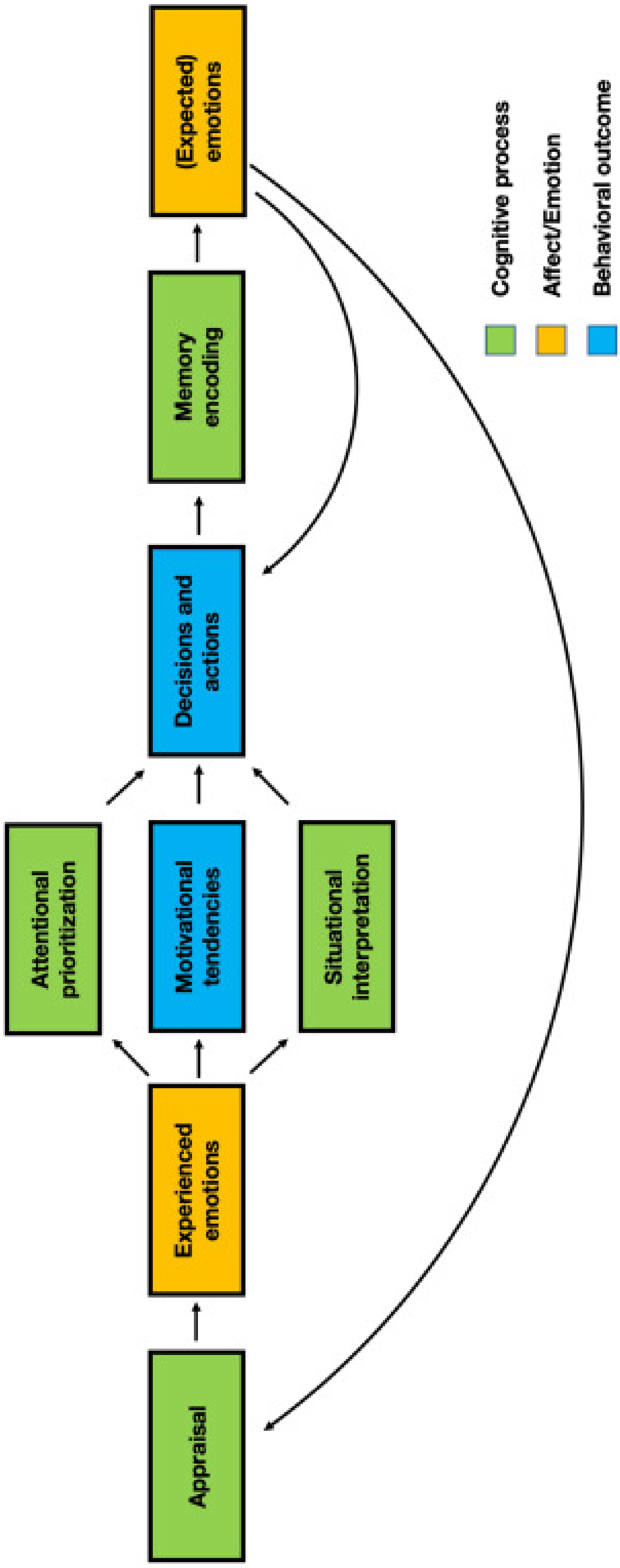


Figure 8: This figure shows a schematic overview of the relation and interaction between experienced emotions, expected emotions and decision making (Brosch & Steg, 2021).

2.2.3. Emotions and behaviour with regards to climate change

Nowadays, the understanding of behaviour and emotions with regards to climate change is still developing (Ejelöv et al., 2018). Whereas prior research mainly focused solely on cognitive factors, such as risk perceptions, values, social norms, beliefs, attitudes and cognitive biases, nowadays more research is focussed on emotional factors (Clayton et al., 2015; Hahnel et al., n.d.) (Brosch & Steg, 2021; du Bray et al., 2018).

One study found that anticipated positive feelings better predicted the intention of people to make pro-sustainable decisions and actions than the giving of (rational) information about the beneficial consequences of sustainable actions (Odou & Schill, 2020) (Figure 9). This emotion-action-anticipated emotion mechanism is very strong, due to the intrinsically rewarding sensation someone experiences. Thus, sustainable campaigns that (positively) resonate with people's feelings and emotions can be a better way to encourage sustainable behaviour (Taufik et al., 2016). Other studies have examined the effectiveness of fear-based and hope-based sustainable campaigns (Poels & Dewitte, 2019).

When fear is the dominant emotion in campaigns regarding a certain (sustainable or pro-environmental) topic with the intention to activate people, these campaigns tend to be unsuccessful (Witte and Allen 2000). The reason is that the dominant action tendency of fear in general is flight and avoidance. However, when campaigns lead to hopeful emotions, people seem to be more sensitive and open to information and other perspectives (Keltner and Haidt 2003). They experience less time pressure, have more patience, are more tended to help people, and prefer experiences to objects (Rudd, Vohs, and Aaker 2012) (Poels & Dewitte, 2019).

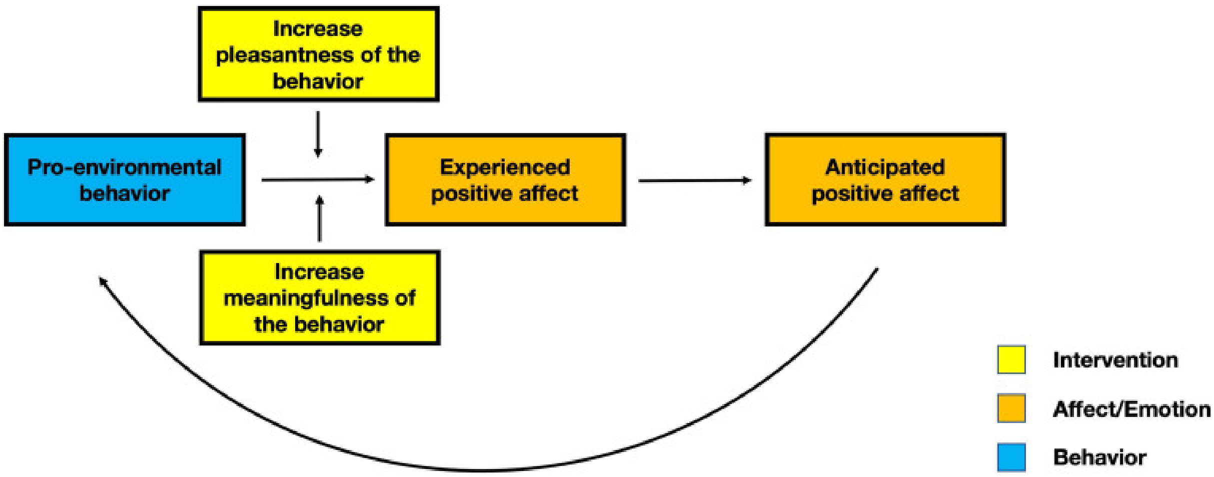


Figure 9: In this view, the feedback mechanism regarding positive anticipated emotions is shown. Anticipated positive emotions will increase the pleasantness and meaningfulness of the behaviour which results into an new experience positive affect (Brosch & Steg, 2021).

Thus, many studies agree on the large role emotions and feelings play with regards to sustainable issues. Striving for positive feelings will create positive anticipated behaviour, inducing a positive feedback loop that enhances sustainable behaviour and actions. This feedback mechanism is crucial for developing long term sustainability (Brosch, 2021; Taufik et al., 2016). As climate hazards are direct, visible and confronting consequences of climate change, understanding emotional patterns of humans regarding climate hazards can lead to better understanding, regulation and behaviour shifts towards a sustainable society (Lair et al., 2020).

Another important aspect in the relation between feeling and behaviour, is the group-based emotion. Studies have revealed that in addition to the personal relevance and importance of climate-related issues, individual and public attitudes about climate policies and climate change are not only shaped by social identities, norms, and other sociocultural factors, but also collective emotions play an important role (Harth, 2021 +bron). This effect of collective emotion can drive major shift in behaviour on individual and group scale (Du Bray et al., 2019).

A major platform of emotion communication and expression is social media. Participation in the public debate increased extensively with the rise of social media and global availability of information on the internet in the form of articles, scientific studies, blogs, videos, vlogs, etc. Social media is the main medium to communicate with others all around the globe. These platforms are important information sources that contribute to the debate on (sustainable) issues as individuals with different norms, values, cultures and perspectives share their opinion and concerns (Loureiro & Alló, 2020). In addition, governments, leaders and large companies also address updates, crises, announcements trough social media platforms. Regarding debates and public opinions the main social media platform is Twitter (Trilling, 2015). Due to participation of all sorts of people, institutions and organisations that express opinions, feelings and daily activities, social media can be seen as a mirror of the real society, that can identify emotions, opinions, events, disasters, spread of (dis)information and news amongst the public all around the world (Nazar & Pieters, 2021). One of the major ways to identify and analyse these social media developments is by the use of artificial intelligence.

2.3. Artificial intelligence

2.3.1. State of the art

While technology, social networks and psychological science are currently expanding, emotion and sentiment analysis have become a new field of research. Artificial intelligence is used to automatically recognize emotions from communication media. Emotions are expressed by audio, video, visuals, emojis, and most commonly by text (Campos et al., 2021). Although supervised and unsupervised learning, and also deep learning, which are able the model human language, are progressing rapidly, these machine learning techniques have limitations as a result of the difficulty of emotion recognition from text (Zhou et al., 2020).

The main difficulty lies within the expressing emotions in linguistics. People express their emotional states within a certain semantic space, including a large variety of semantic terms that is connected to a large variety of emotional states varying per individual (Cowen & Keltner, 2017). Tools are mostly built based on a commonly grounded semantic space by for example crowdsourcing. However, no fixed rules exist.

In addition, language itself in the form of linguistics is very complex, as humans express themselves in infinite ways both verbally (speech) and written (text). Communication occurs via a large variety of languages and dialects, which all have different terms, idioms, abbreviations, accents, and grammar and syntax rules. Additionally, as language is continuously under development, new words are constantly added and words from different languages are borrowed (Zhou et al., 2020). To eliminate this issue, in this research only English language have been taken into account.

2.3.2. Natural Language Processing (NLP)

While supervised and unsupervised learning, and specifically deep learning, are now widely used for modelling human language, there's also a need for syntactic and semantic understanding and domain expertise that are not necessarily present in these machine learning approaches. NLP is important because it helps resolve ambiguity in language and adds useful numeric structure to the data for many downstream applications, such as speech recognition or text analytics (Ahmad, 2017).

Natural Language Processing (NLP) is a technique within artificial intelligence in which technology and machines are used to automatically understand, interpret and manipulate human language. NLP aims to solve the complex issues that faces linguistics, by taking into account ambiguity in language and creating numerical structures for language data. NLP brings together many disciplines, such as computer science, linguistics and psychology, and aims to connect human communication can computer understanding. This technology is rapidly evolving as a result of the increase of big data availability and powerful computing methods and algorithms (Kumar & Panda, 2020).

Analysing people's emotions, feelings, perspectives and attitudes towards a specific entity, event, issue or product, is defined as sentiment analysis. Sentiments can be divided in different spectra, such as positive, neutral, and negative, or in more detailed emotions, such as happiness, sadness or fear (Al-Halah et al., 2020). Another division can be based on the degree of action people are tended to take on basis of a specific feeling, emotion or attitude (Cosmides & Tooby, 2000; Poels & Dewitte, 2019).

As a result of the complexity of emotions, psychology, and linguistics of humans, detecting emotions from text has still a lot of challenges to identify and face. Some major challenges include the expression of multiple emotions in a single piece of text, the implicit use of emotions in text, and sarcasm that for real human beings can sometimes already be difficult to recognize (Sailunaz & Alhajj, 2019).

In this study, lexicon based learning is used to detect emotions. Lexicon based learning is an algorithm that assigns an emotion score to single words. When this algorithm is used to screen a text, this text will be assigned a specific emotion score, based on the mentioned words (Section 3.1).

2.4. Existing research on emotions, climate hazards and Twitter

This section discusses literature regarding emotions on Twitter, climate hazards on Twitter, and emotions regarding natural hazards to show similarities with this study.

Existing studies regarding emotional response on Twitter have significant outcomes. One study of emotion and sentiment analysis on a Twitter dataset showed that replies on an original tweet contain similar emotions and sentiments and agree with the content (Sailunaz & Alhajj, 2019). Another study monitored the dynamics of emotions over a specific time interval regarding COVID-19. The results show that the emotion sadness is prominent emotion during the measured period. Another main result was the correlation between emotional characteristics of Twitter users and the infection and mortality rates (Kaur et al., 2020). In addition, Pathak et al. (2017) proposed a mechanism to analyse emotion dynamics over time and location regarding climate change topics during the Climate Conference in Paris in 2015. Another study that assessed emotions related to climate change topics was performed by (Loureiro & Alló, 2020). They analysed Tweets related to climate change for the UK and Spain for the first 6 months of 2019. The results show geographic variability in emotions, as messages in the U.K. showed less negative emotions than Spain. Regarding specific emotions, Spain shows a clear majority in fearful reactions, emotions in the UK are more moderate.

Studies of Twitter behaviour related to natural hazards are rare. One study monitored social media dynamics during multiple flood events. The results show that tweet activity correlate with temporal variations in hazard monitoring data (Shoyama et al., 2021). Niles et al. (2019) showed that the relation between tweet volume and different keywords linked to hurricanes, tornados and flooding events followed a trend that distinguishes an anticipatory phase, core phase and aftermath phase (Figure 1). People used Twitter more frequently in preparation for a hurricane events, whereas around tornado and flooding events Twitter was more frequently used during the event itself and during the recovery phase (Niles et al., 2019).

Some experimental psychology studies on emotions and natural hazards exist. Insinga et al. (2022) surveyed populated coastal regions of Oregon on emotions and grouped habitants on risk and knowledge. The study found that when knowledge and risk awareness increased, emotions and attitudes became more negative, especially when conditions became worse. A study has been conducted about attitudes towards tornados and earthquakes within Oklahoma. Findings suggest that an earthquake event evokes more fearful reactions than tornado events and the emotions patterns show slight demographic variations (Greer et al., 2022).

2.5. Hypotheses

Based on the previously discussed literature, knowledge gaps and societal relevance, the following working hypotheses are proposed.

- The amount of tweets that are related to a climate hazard will peak during the core event of the specific hazard and will gradually decrease in the days after the event, or the aftermath, following the framework proposed by Murthy and Gross (2017). When the climate hazard is anticipated, the amount of tweets will gradually increase the days before the core event during the anticipatory phase.
- The percentage of negative emotions in tweets that are related to a climate hazard are expected peak just after the climate hazard, following the same trend observed by Kaur et al. (2020). Also the negative emotion response is expected to follow a similar pattern with an anticipatory phase, core phase and aftermath phase.
- The overall emotional reactions is expected to show negative emotions, such as fear, sadness and anger for all tweets that are related to a climate hazard, such as shown in Loureiro & Alló (2020) and Kaur et al. (2020).
- In the region where the climate hazard occurs, the amount of tweets and the percentage of negative emotions in that specific region will be higher in comparison with other regions, as individuals in this region will see the impact or are subject to the climate hazard, provoking more reactions and also more intense emotions. This hypothesized outcome is in alignment with results from Loureiro & Alló (2020), that showed an increase in negative reactions regarding climate change in a country where climate change impacts are more visible.
- Climate disasters that have the most visible impact are expected to show the most fearful reactions, which was seen in the found relation between mortality rates and increase in negative emotions from Kaur et al. (2020) and also observed in the increased negative climate change reactions in Spain by Loureiro & Alló (2020).

3. Materials and methods

In this research, data was collected from Twitter in order to analyse tweet activity and emotional responses of Twitter users around climate hazards (Figure 10). First, tweets were collected for three climate hazards per 24 hours on a 4 week timescale. Tweets were collected on specifically chosen keywords and geographic location. Secondly, an analysis conducted to extract emotions from the text of the collected tweets with Natural Language Processing techniques. In this analysis, the text was first cleaned and pre-processed after which emotions were extracted from the cleaned text. This data is stored and visualized in order to identify tweet activity and emotion patterns (Figure 11). Tweets were collected before, during and after selected climate hazards. Three cases were selected:

1) Temperature rise on Antarctica and the global emotional response in March 2022
2) Tornado outbreak in South West USA and the national (American) response in December 2021
3) Hurricane Ida in the state Louisiana and the national (American) response in August 2021.

All three events were short-lasting events that lasted between 1-3 days to be able to analyse the tweet and emotion trend before, during and after the event on a 4-week timescale. Tweets regarding the temperature rise on Antarctica were collected on a global level to analyse global response. Tweets regarding the tornado outbreak and Hurricane Ida were collected within the United States to analyse the tweet activity and emotional response on a national scale and also regional scale by selecting tweets per state (Figure 12). The keywords that have been chosen are 'Antarctica', 'Tornado' and 'Hurricane'. The Antarctica case was also chosen to serve as a reference, as the word 'antarctica' is not specifically connected to a climate hazard.

Twitter has been chosen as social media platform with the following reasons. As mentioned before, Twitter is globally used to express opinions on a great variety of issues and can thus provide a real view of the public sentiment and perspectives. Also, Twitter is used among professionals, students, ordinary people and organizations of all ages, races, cultures and genders. Therefore Twitter can function as a reflection of society. Also, as tweets have a limited amount of 280 characters, tweets can easily be analysed and compared. By using Twitter data, data can be accessed of people who otherwise are difficult to reach with surveys or experiments.

Section 3.1. describes the collection and analysis methods, section 3.2 explains why and which parameters have been chosen for the specific study , and section 3.3. discusses the limitations of the model.

3.1. Tool description

3.1.1. Data collection

Data was collected and analysed in Python 3.9.7. Tweets were collected with the Twitter Search API, which is a tool that enables licensed people to stream tweets that contain by the user selected keywords, dates, usernames and locations. To access this, permission for a scientific Twitter developer account was asked and granted. The Twitter Search API was accessed with the Python library Tweepy, that can with the use of a query search selectively. The Twitter Search API is a tool that provides access to the full Twitter data archive. With Tweepy the Search API can be accessed (*Tweepy*, 2022). Tweets were selected on specific keywords used in tweet text, username, whether to include retweets, and a specific time interval by adding a start date and end date. All collected datasets were stored in Pandas DataFrames. In addition to tweet text, other data that were collected from the tweets are username, user location, user description, userID, tweet date and time, follower count of user, like count of tweet, retweets count of tweet, and reply count of tweet (see figure 11 for simplified version)

3.1.2. Emotion analysis

After completing the data collection process, the text from the tweets was pre-processed to only analyse words. This was done by cleaning the text from emojis, images, videos, URLS, numbers, capital letters, and punctuation. Then, emotions were detected from the text with NRC lexicon (*NRC Emotion Lexicon*, n.d.). NRC lexicon is a tool that assigns emotion scores to a given text or set of words. In this package, a large list of English words are per word associated with a specific emotion distribution from 0 (not associated) to 1 (associated). The emotions are based on the Plutchik emotion model and thus include anger, fear, sadness, disgust, surprise, anticipation, trust and joy. The model also is able to assign a negative and positive sentiment. As in this study only emotion patterns are taken into account, these sentiments have been filtered out. The associations per word are based on crowdsourcing. The tool is able to produce an emotion score on a text, by identifying and combining individual words and their emotional score. The model is solely able to recognize English text. It must be mentioned that NRC lexicon associated the chosen keywords ‘hurricane’ and ‘tornado’ with the emotion fear. Therefore, the words ‘hurricane’ and ‘tornado’ were removed during the text cleaning phase and not included in the emotion analysis.

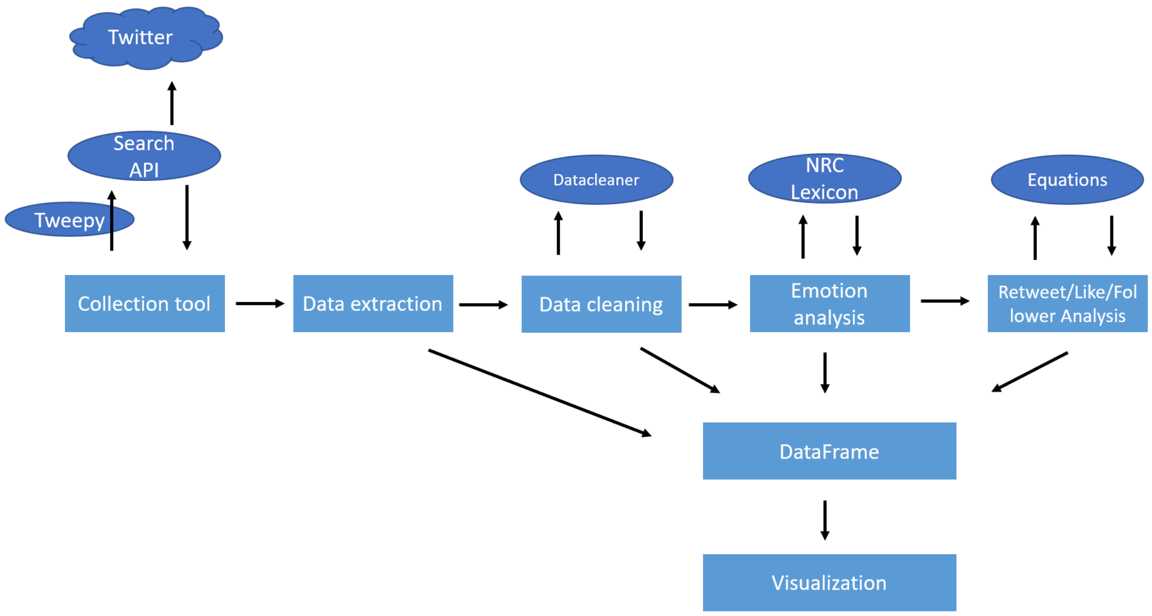


Figure 10: Flow diagram of the data study.

A

Author_id	Username	Author_followers	Author_Tweets	Author_description	Author_location	Tekst	Created_at	Geo	Retweets	Replies	Likes
539012343	ElleTeam Blonde	2207	18741	from Silicon Valley to our Midwest to NYC #progressivevalues	New York	Antarctica. We are so doomed!	2022-03-19 23:59:42+00:00	'place_id': '94965b2c45386f87	2	1	5

B

Clean_up_text	Fear	Sadness	Anger	Disgust	Surprise	Anticipation	Trust	joy
antarctica we are so doomed	0.33	0.00	0.33	0.33	0.00	0.00	0.00	0.00

Figure 11: Example of the resulting dataframes. Part A shows all data that was collected per tweet. Part B shows the result after cleaning the text and performing an emotional analysis. Data was collected and stored in a dataframe per 24 hours. The length of each dataframe depends the amount of tweets that were found with the specific keyword.

3.1.3. Emotional reach via followers, likes and retweets

In addition to emotional analysis of the original tweets, emotion of the original tweets and the data regarding retweets, likes and number of followers of the user of the specific tweets were used to calculate how the correspondence and reach were on a certain tweet. In other words, it was analysed how much a tweet with a certain emotion score was retweeted, liked and seen by followers (note that followers are not the same as viewers as tweets can be viewed by more people). This was defined as the potential reach, that has a different meaning and implication for follower, retweet and like correspondence.

Follower reach represents to what extent certain emotions are seen by followers of the user. Although follower count is not a perfect reflection of visibility and influence of the user, it is used as a proxy to estimate the reach. The emotion score that represents follower reach for emotion x is calculated as the sum of the amount of followers by the original emotion score per tweet i divided by the total number of tweets:

$$Follower\ ES\ (x)(i) = \frac{\sum_{i=0}^{m} Follower\ CT\ (i)\ \cdot\ ES\ (x)\ (i)}{m}$$

With:

$Follower\ ES = the\ emotion\ score\ that\ represents\ the\ reach\ via\ followers\ (\%)$
$Follower\ CT = \ the\ count\ or\ the\ amount\ of\ followers\ per\ user$
$ES = \ the\ original\ emotion\ score\ (\ \%)$
$x = \ the\ specific\ emotion\ (fear, anger, sadness, disgust, surprise, anticipation, trust\ or\ joy)$
$i = \ the\ number\ of\ tweet\ in\ the\ dataframe\ (that\ has\ the\ size\ 0\ to\ m)$
$m = \ the\ total\ number\ of\ tweets\ in\ the\ dataframe$
$(total\ amount\ of\ tweets\ per\ selected\ time\ interval\ (in\ this\ case\ 24\ hours)$

Like reach represents to what extent certain emotions in tweets are liked. The like of a tweet implies agreement or recognition to a certain extent. The emotion score that represents reach via likes for emotion x is calculated as the sum of the amount of likes by the original emotion score per tweet i divided by the total number of tweets:

$$Like\ ES\ (x)(i) = \frac{\sum_{i=0}^{m} Like\ CT\ (i)\ \cdot\ ES\ (x)\ (i)}{m}$$

With:

$Like\ ES = the\ emotion\ score\ that\ represents\ the\ reach\ via\ likes\ (\%)$
$Like\ CT = \ the\ count\ or\ the\ amount\ of\ likes\ per\ tweet$

Retweet reach represents to what extent people share tweets on their timeline. The action of retweeting a tweet goes beyond liking a tweet, as by retweeting one shares the specific tweet on his timeline and thus becomes part of the spread of certain tweet content. The emotion score that represents reach via retweets for emotion x is calculated as the sum of the amount of retweets by the original emotion score per tweet i divided by the total number of tweets:

$$Retweet\ ES\ (x)(i) = \frac{\sum_{i=0}^{m} Retweet\ CT\ (i)\ \cdot\ ES\ (x)\ (i)}{m}$$

With:

$Retweet\ ES = the\ emotion\ score\ that\ represents\ the\ reach\ via\ retweets$ (%)
$Retweet\ CT =\ the\ count\ or\ the\ amount\ of\ retweets\ per\ tweet$

3.1.4. Geographic variability

A regional emotion analysis was performed for case 2 as well as case 3, in order to analyse the spatial variability of emotional response and investigate how a hazard affected the severity of emotions in the directly hit regions compared to other not directly hit regions. As the tool can select tweets on state, the US has been divided into 3 parts. The subdivision of states per part are based on the climate zones (Figure 6) and type of disasters that occurred in different regions in 2020 and 2021 (Figure 5) and are shown in Figure 12.

For the regional cases additional figures have been created to show the severity of emotions and the amount of tweets per region. No retweets, likes and followers have been taken into account in the geographic analysis as only the count of retweets, likes and followers of the original tweet is identified. The location of the retweet, likes and followers count are unknown and not specifically bound to the same region.

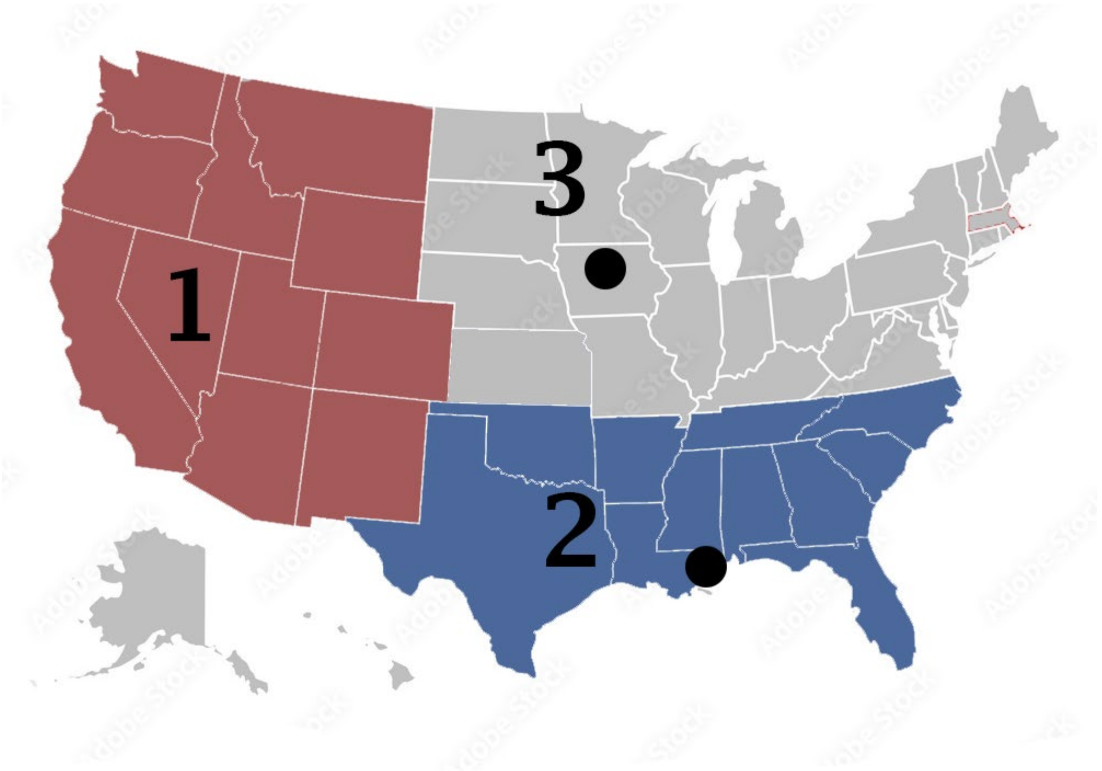


Figure 12: This map shows the state distribution that has been used to analyse geographic variability in tweets and emotion patterns. This distribution is based on variability of climate zones and the type of natural hazards that occurred in 2020 and 2021.

3.2. Research approach

The datasets of tweets were collected per climate hazard by selection on a specific keyword, a timeframe with start and end date, the geographic scale. All retweets were excluded in order to only take into account the original tweets (only the amount of retweets per original tweet was stored in the dataset). For every case a keyword was chosen that was commonly used during the specific hazard. The timeframe was set as 2 weeks before and 2 weeks after the actual event in order to investigate the development of tweets regarding the hazard before and after the event. Datasets were collected with a timeframe of 24 hours. All three cases were chosen to be short-lasting, finite events that lasted 1-3 days in 2021 or 2022. The final datasets contain respectively 73921 extracted tweets (Figure 13).

Global: Case 1: Antarctica Temperature rise

Last march, sudden extreme temperature rises were recorded in eastern parts of Antarctica near Vostok. This ´climate hazard´ was selected as first case to study the global emotional response. The main reason for this is that this hazard does not have direct impact at that same moment on anyone (expect the small amount of people being present in these places) and are as far away for every person. This was done to filter out an eventual distorted view of people who might feel the impact and show more severe emotions. The first temperature anomaly was observed on March 15th 2022 . The timeframes was set from 2 weeks before to 2 weeks after the actual event. The chosen keyword was 'Antarctica'.

US: Case 2: Tornado outbreak & Case 3: Hurricane Ida

Case 2 and 3 consisted of climate hazards were occurred in the US and this had the following reasons. As the tool is only able to analyse English texts and English is the native language in the US, tweets regarding the hazards are better found and can all be analysed, resulting into a better result and a better reflection of society. As the US has a great variety of different climates and there is a clear difference in the type of hazards that occur in different areas. However, as the US is one country and has national news channels, all Americans are in principal informed and aware of the hazard and are thus able to spread and show expressions on Twitter. Additionally, a large part of the American society uses twitter, namely 76,9 million or 23,3% of the American population, and thus contribute to the reflection of society. Also, all climate hazards including specific data such as date, location and the estimated damage costs are mapped and published by the National Center for Environmental Information within the National Oceanic and Atmospheric Administration (NOAA).

The tornado and Hurricane Ida were chosen to analyse, as the amount of collected tweet data in the selected timeframes was sufficient to analyse. They both occurred in different parts of the US, the tornado in Kentucky and Tennessee in the Mideast, and Hurricane Ida in Louisiana at the Southeast coast. Also, the economic damage and mortality rates were high in comparison to other US hazards. The events occurred in a short period of time and were non-lasting. The timeframes for both cases were selected from 2 weeks before the actual event to 2 weeks after. The chosen keywords resulted into relatively 'tornado' for case 2 and 'hurricane' for case 3.

Case	Description	Location	Damage costs (Billion $)	Mortality rates	Keyword	Date	Start timeframe	End timeframe	Total amount of tweets
Case 1	Parts of eastern Antarctica have seen temperatures hover 70 degrees (40 Celsius) above normal for three days. The average high temperature in Vostok — at the center of the eastern ice sheet — is around minus-63 (minus-53 Celsius) in March. But on Friday, the temperature leaped to zero (minus-17.7 Celsius), the warmest it's been there during March since record keeping began 65 years ago. It broke the previous monthly record by 27 degrees (15 Celsius).	Vostok, Antarctica	N/A	N/A	Antarctica	16-3-2022	2-3-2022	30-3-2022	49,973
Case 2	Historic December tornado outbreak across several southeast and central states caused devastating damage across many towns and cities. This outbreak produced two long-tracked EF-4 tornadoes across Arkansas, Missouri, Tennessee and Kentucky. The longest tornado track was nearly 166 miles across Kentucky and a small portion of Tennessee. This was the longest-tracked tornado on record in Kentucky and was a U.S. record tornado track length for the month of December. There were over 800 total miles of tornado path length on December 10. The peak intensity from this outbreak was EF-4 rated wind speeds of 190 mph in Mayfield, Kentucky. This day was also the deadliest December tornado outbreak recorded in the United States surpassing the Vicksburg, Mississippi tornado of December 5, 1953, which caused 38 fatalities.	Arkansas, Missouri, Tennessee, Kentucky, US	$ 4.0	93	Tornado	10-12-2022	25-11-2022	23-12-2022	7,986
Case 3	Category 4 Hurricane Ida made landfall near Port Fourchon, Louisiana with maximum sustained winds of 150 mph (240km/h) and a minimum central pressure of 930 mb. Ida was one of three hurricanes in recorded history to make landfall in Louisiana with 150 mph winds, along with Hurricane Laura in 2020 and the 'Last Island' hurricane of 1856. Grand Isle, Louisiana took a direct hit with 100% of its homes damaged and nearly 40% were nearly-to-completely destroyed. There was heavy damage to the energy infrastructure across southern Louisiana causing widespread, long duration power outages to millions of people.	Louisiana, US	$ 76.5	96	Hurricane	29-8-2022	15-8-2022	12-9-2022	15,962

Figure 13: This scheme summarizes major information and the chosen parameters for each case. Event description from NOAA (2021).

3.3. Model limitations

Analysis of emotions from text has several limitations. Communication of emotions in linguistics is multidimensional and within linguistics one can express emotions in many different ways (Section 1.4). Here the analysis is based on the semantic meaning of single words, which means that emotions in the form of emoticons, exclamation marks, abbreviations, etc, are not taken into account. This also means that sarcasm cannot be interpreted from text, which is sometimes used to express emotions with emphasis.

NRC Lexicon is only able to analyse English text. This limitation is partly resolved by selecting natural hazards within the US, which is a large country with intense use of Twitter in English.

In this study, one keyword has been chosen per climate hazard, and thus some tweets about the hazard that do not contain this specific keyword are excluded. This is partly covered by choosing a word that was most related to the climate hazard and assumed to be most used.

Twitter enables users to put location off, and thus part of the tweets in a certain area are excluded as location and thus state is unknown (Chapter 4).

4. Results

4.1. Case 1: Antarctica

On March 16th 2022, different weather stations in the eastern part of Antarctica started to measure high temperatures that eventually became record-breaking. The temperature increase reached an average of -29 degrees Celsius, which is 40 °C higher than normal for that time of the year. The first tweet regarding this specific subject was sent by one of the scientists from the Concordia weather station on March 16th, which mentioned the abnormal increase of temperature and showed the temperature graph for the weather station. Two days later, on March 18, a major channel Capital Weather Gang sent a tweet into the world regarding the temperature rise. This was the first tweet that went viral with a retweet count exceeding 1300 (Figure 14).

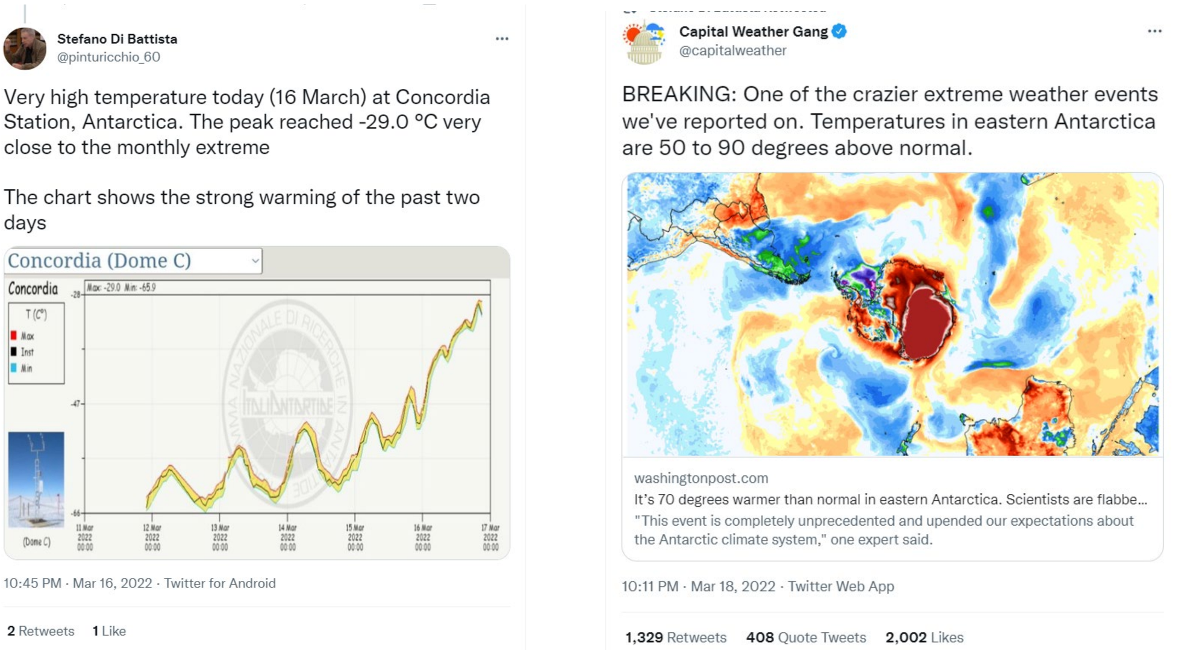


Figure 14: The left figure shows the original first tweet that was published by a scientist for the Concordia weather station about the temperature increase. The right figure shows the original tweet that went viral.

4.1.1. Antarctica: Tweet response

In figure 15, tweet activity variation during the climate hazard is clearly visible as three clear high and sharp peaks are notable, which respectively amount to 4700, 3500 and 3700 tweets. The black line on March 17th indicates the moment at which the first tweet regarding the temperature rise was published and the black line on March 18th refers to the date when the first tweet went viral. On March 19th, the amount of tweets rise rapidly and peak on March 20th, whereafter the amount of peak decreases more gradually in the consecutive 3 days. The peak that follows between March 24th and 27th, shows an rapid increase in 24 hours, followed by a decrease in 2 days. The first peak is the highest with 4700 tweets. The amount of tweets increase here rapidly as well and is followed by a rapid decrease in contrast to the other peaks, resulting into a small and high peak. Before the peaks occur, the word Antarctica is with a certain frequency used in tweets (around 900 per day globally).

The emotion response during the climate hazard change show changes when tweet activity peak. Around March 9th, the centre of the first peak, the emotion distributions shows a shift towards positive emotions where mainly joy increases with approximately 10% and fear and anger decrease with 10%. During the second peak on March 20th, a shift can be noticed towards an overall higher percentage of negative tweets, in which mainly fear increases with 10% and surprise with 5%. The positive emotions trust, anticipation and joy decrease equally. Around the third peak, no sudden changes in emotion distributions are observed. Negative emotions (fear, sadness, anger and disgust) comprise over the 4 week period around 35%, positive emotions (anticipation, trust and joy) for around 50%, and surprise (which can either positive or negative) counts for 5%.

Retweets and likes patterns follow quite similar patterns for case 1 (Figure 17). The main change is the 40% increase of negative emotions in likes and retweets during peak 2 immediately after the event went viral at March 18th. All negative emotions increase, with fear and sadness have the highest contribution. After the second peak, the results show a sudden decline in negative emotions, which is immediately followed by a 40% increase of negative emotions 2 days later on March 27 and 28. This increase consists equally of the emotions fear, sadness and anger.

No significant patterns have been observed in the first peak within retweets and likes. Regarding follower trend, users with many followers have a very high percentage of first positive emotions, followed two days later with a majority of the distribution exists of sad emotions. Four days after the actual news went viral, negative emotions peak to 70%. Also after the third peak, the consecutive 2 days after event, the contribution of negative emotions increase.

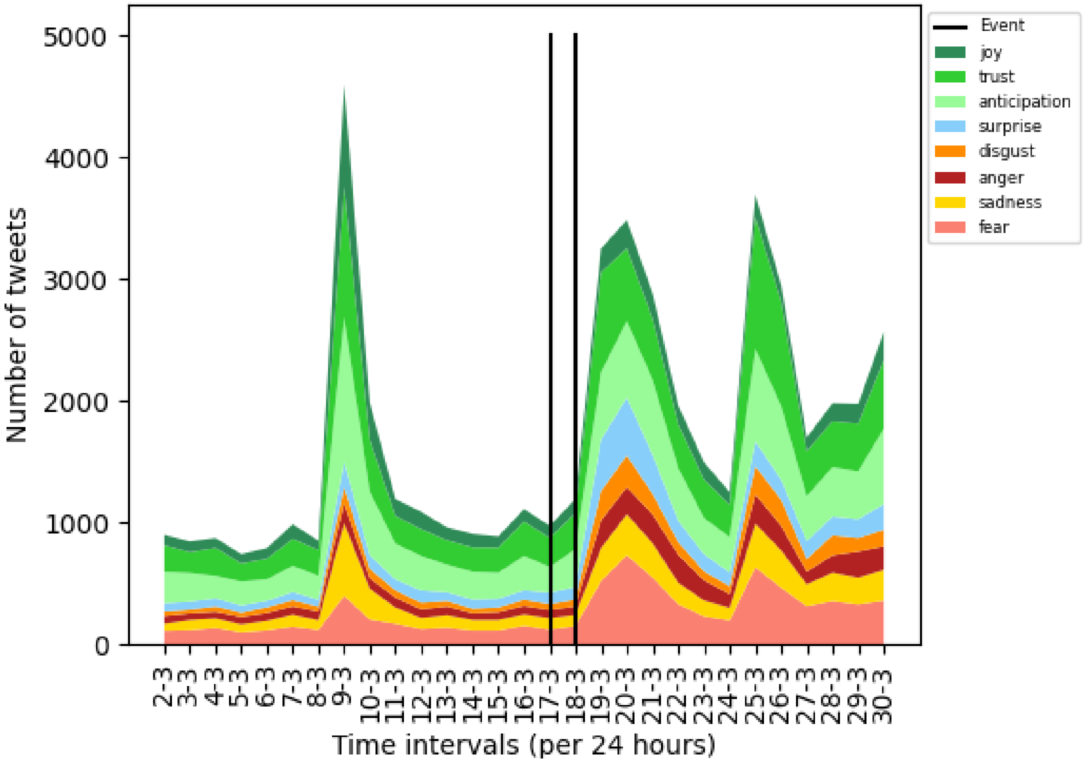


Figure 15: Absolute emotion distribution and tweet pattern for over a time-interval of a month for case 1: The temperature rise on Antarctica on 17-3-2022. The y-axis is showing the amount of tweets and the x-as shows the specific date. The black line on 17-3 indicates the date on which the first tweet about the temperature rise was sent and the black line on 18-3 indicates the date on which the first tweet went viral.

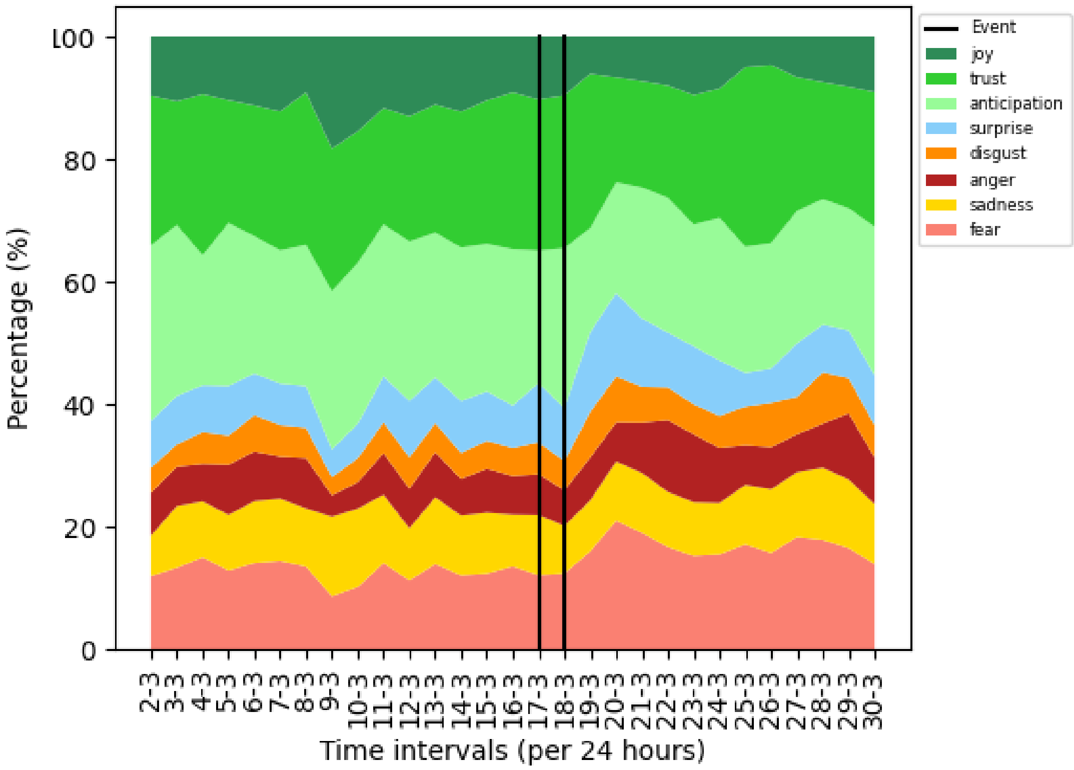


Figure 16: Normalized emotion distribution and tweet pattern for over a time-interval of a month for case 3: The temperature rise on Antarctica on 17-3-2022. The y-axis is showing the percentages per emotion and the x-as shows the specific date.

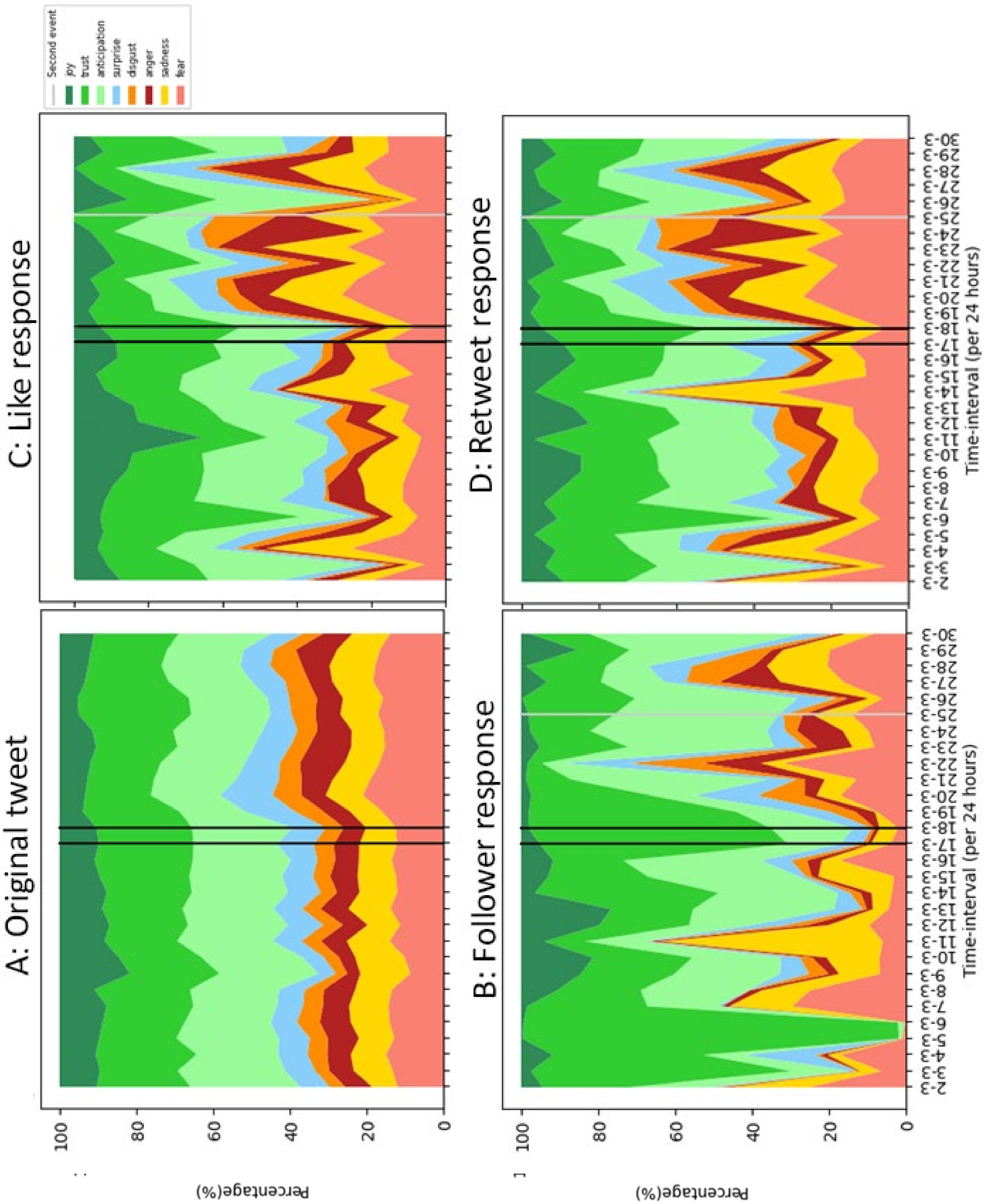


Figure 17: Absolute emotion distribution and tweet activity for a) the original tweet (on the top left), b) the follower response (left below), c) the like response (on the top right), and d) the retweet response (right below) over a time-interval of a month for case 1: The temperature rise on Antarctica on 17-3-2022. The y-axis is showing the percentage of tweets and the x-as shows the specific date. The grey line refers on 25-3 refers to the melt of the icecap.

2.2.2. Antarctica: Result interpretation

Three peaks, rather than one, are visible. Further investigation shows that on March 9th, an old ship that sank a century ago has been found in the waters of Antarctica. The equal trend in the peaking tweets that contain the word Antarctica and this news event highly suggests a correlation. An equal correlation has been found for the third peak, as on March 25th, a part of a large icecap located on the eastern part of Antarctica collapsed as a result of the increased temperatures the days before.

Some of the main results occur as expected. These include the strong correlation between the amount of tweets and specific news events about Antarctica. When a news event spread, the tweet usage increases. The exponential increase in tweet usage indicates that within 24 hours the response on these events is large and very sudden. The slight more gradual decrease after the spikes indicates that tweet usage recovers more gradually.

The second peak and the increase in negative emotions, implicates that the news about the temperature increase on Antarctica induces negative reactions in tweets. The increase in mainly fearful reactions may be caused by the unexpectedness of the event. The shift towards positive reactions in the first peak can be explained by the rather positive news about the ship, a cultural heritage, that was found.

However, other observations are less straightforward. No significant change occurs in the emotion distribution of the third peak. Fearful emotions do not increase, despite the fact that the breaking of an icecap is a climate event that seem to have the same level of severity as temperature rises. The small increase in negative emotions that does occur on March 28th might be a delayed reaction. However, this does not coincides with the third peak that occurs on March 25th. One explanation is that people may experience less fear when a second severe event occurs rapidly after the first one.

Another result that is questioned is the majority of positive emotions that generally occur around this event. One of the primary explanations for this is that the word Antarctica is not specifically related to a climate hazard, which means that tweets that include the word Antarctica do not necessarily relate the climate hazards on Antarctica. This assumption is confirmed when looking on tweet level, as some of the tweets mention Antarctica without referring to a climate hazard.

Furthermore, it is remarkable that the highest peak is caused by an event that is not climate related. However, this spike like peak is more momentary whereas the second and third peak are slightly smaller and broader, which means that response on these events lasts longer.

Regarding retweets and likes trends, the results mainly show that negative messages are largely retweeted and liked. Also, like and retweet trends show similar patterns. These observations indicate that messages with a negative loading are agreed on and spread and that this agreement and spreading occur at the same rate.

The relayed negative emotions spike in the follower graph indicate that users with a lot of followers, mainly influencers, respond approximately 2 to 4 days later, as negative emotions peak at that moment.

4.2. Case 2: December Tornado

On December 15, a tornado outbreak affected the Mideast part of the US. Minnesota and Wisconsin were victim to much damage. 57 hurricane-force wind reports were received by the National Weather Service (Figure 14).

4.2.1. December Tornado: Tweet response

The tweet activity during the Tornado event show some major changes. From figure 18 a major peak is observed at December 12th that exceeds 3000 tweets. The amount of tweets exponentially increase in the first 24 hours after the tornado hit. Between December 11th and 12th the amount of tweets declines exponentially to 750 tweets, followed by a gradual decrease from December 12th.onwards. A second peak is observed at December 15th that reaches a peak of 900 tweets in 24 hours. After this the tweets decrease rapidly in 2 days and then slowly extinguishes. At December 6th, the results show a small peak, increasing and declining both in 24 hours. Just before the main event, tweets increase very gently from December 9th to December 10th to 150 tweets. Except for the first small spike at December 6th, the amount of tweets containing the word tornado are very low.

The emotion response during the event contain many fluctuations and do not show any obvious sudden changes (Figure 19). The amount of fear and anticipation are overall highest and both comprise around 20% of the tweets. Sadness, anger, and disgust amount for another 20%, resulting into an overall contribution of negative emotions of around 50%.

The results of retweet, likes and follower response, displayed in figure 20, show a large variability in emotions and clear trends and patterns are absent. From figure 20b and 20c, it can be observed that retweet and like patterns show similar variabilities. The results first show a 20% increase of negative retweets and likes just after the main event on December 10th, where fear accounts for the largest part. Another 24 hours later, a sudden decrease in fearful reactions of 40% occurs, that is mainly replaced by the emotions joy and trust. 24-48 hours later, the emotion fear spikes again, before the tornado event in the Midwest occurs on December 15th. Another observation is the peak in trustful and joyful tweets respectively 3 and 4 days after both tornadoes, which are both followed by a sharp increase in fearful tweets. The follower pattern in figure 21 shows a slight increase in negative emotions after the main tornado event and the Midwest tornado outbreak in the first 28 hours, followed by a sharp and momentary increase in positive emotions. Note the white space in the retweet pattern on December 12th. No tornado tweets were retweeted at this date.

The major observation that can be seen from figure 21 is the clear peak that occurs in all areas after the tornado outbreak on December 10th. Within 24 hours all peaks reach a maximum and decrease rapidly within the next 24 hours to a specific level, that is higher than before the event occurs. The southeast area shows the absolute most tweets with 900, whereas the northeast area shows 190 and the western area around 50.

In the northeast, the main peak is shown during Midwest Tornado and reach around 300 tweets. During the same tornado event the amount of tweets in the southeast area increases to approximately 100 tweets, and also in the northeast a slight increase is shown. The southeast area shows a tweet increase around December 6th.

The emotion distribution patterns do not show patterns. However the overall negative emotions are high varying from 60 to 80%, where fear is the largest contributor amounting to circa 50%.

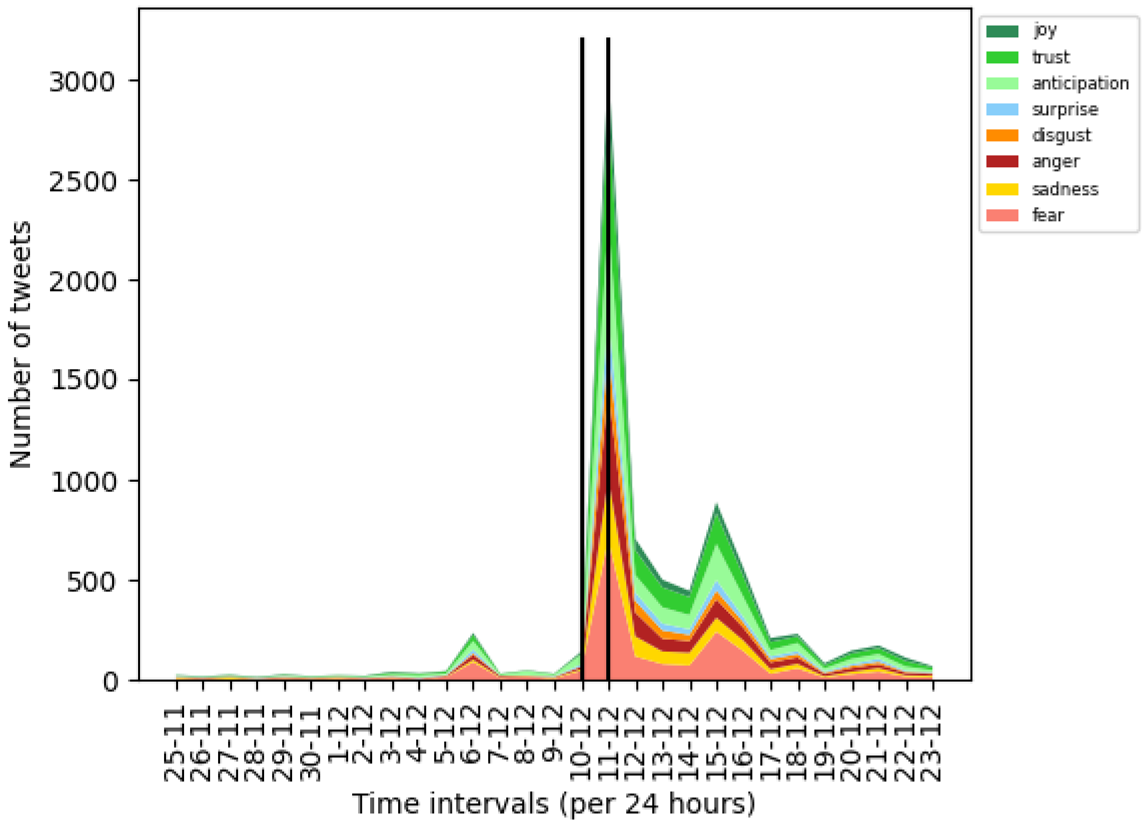


Figure 18: Absolute emotion distribution and tweet pattern for over a time-interval of a month for case 2: The Tornado that hit mid-west USA on 15-12-2021. The y-axis is showing the amount of tweets and the x-as shows the specific date.

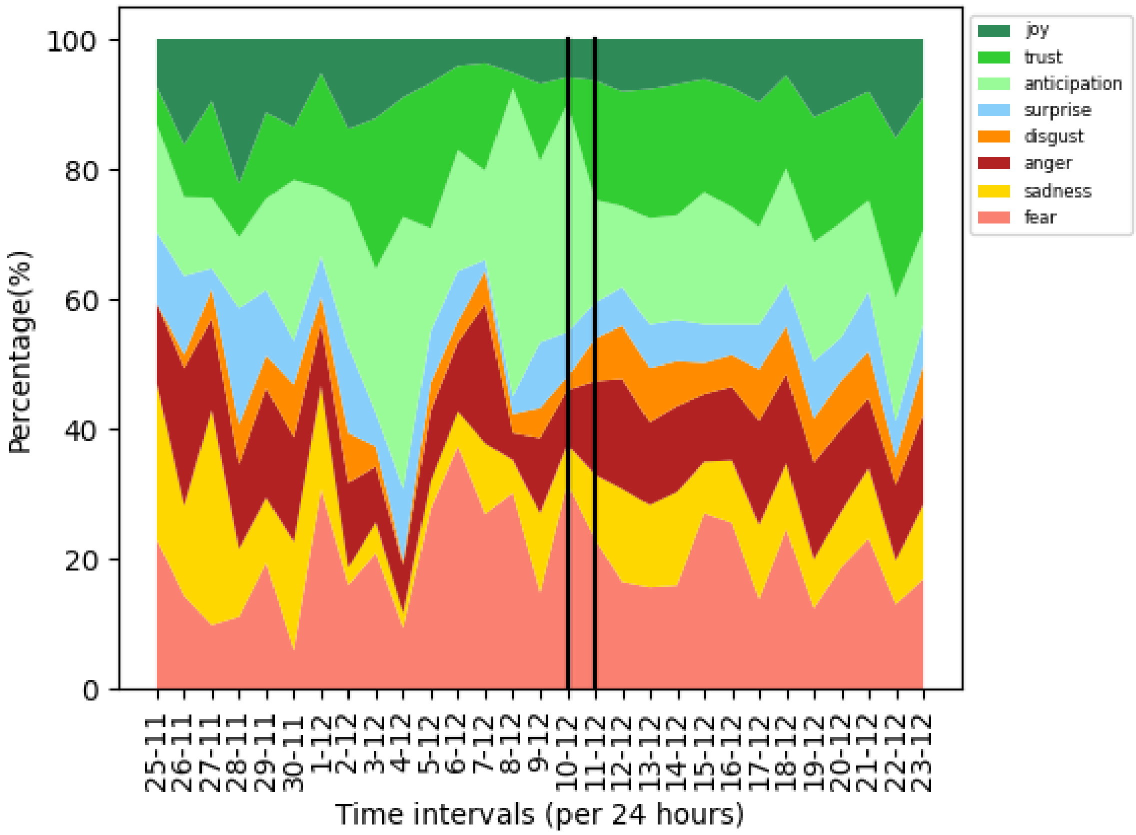


Figure 19: Normalized emotion distribution and tweet pattern for over a time-interval of a month for case 2: The Tornado that hit mid-west USA on 15-12-2021. The y-axis is showing the percentages per emotion and the x-as shows the specific date.

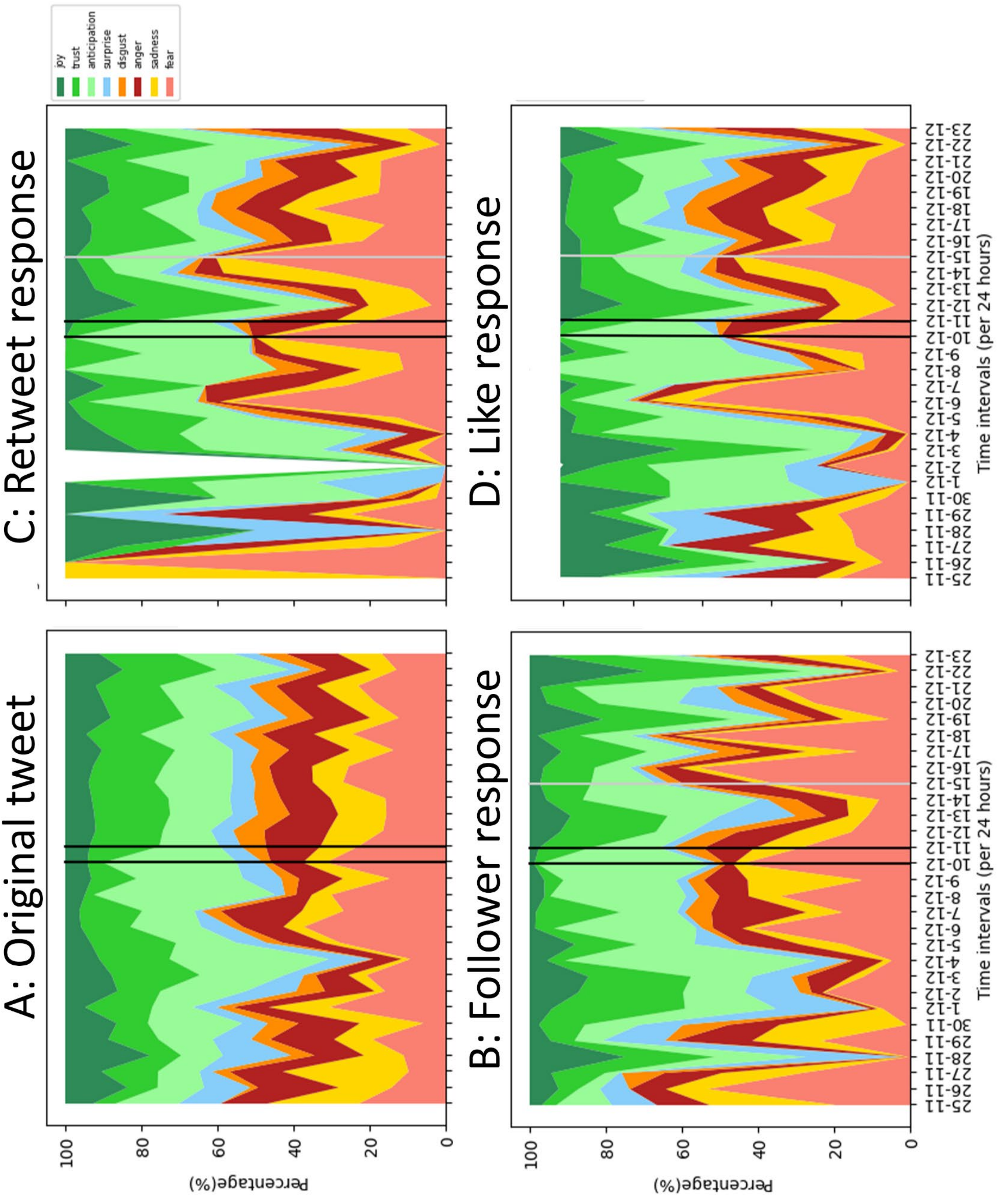


Figure 20: Absolute emotion distribution and tweet activity for a) the original tweet (on the top left), b) the follower response (left below), c) the like response (on the top right), and d) the retweet response (right below) over a time-interval of a month for case 2: Tornado Mideast US on 15-12-2021 The y-axis is showing the percentage of tweets and the x-as shows the specific date.

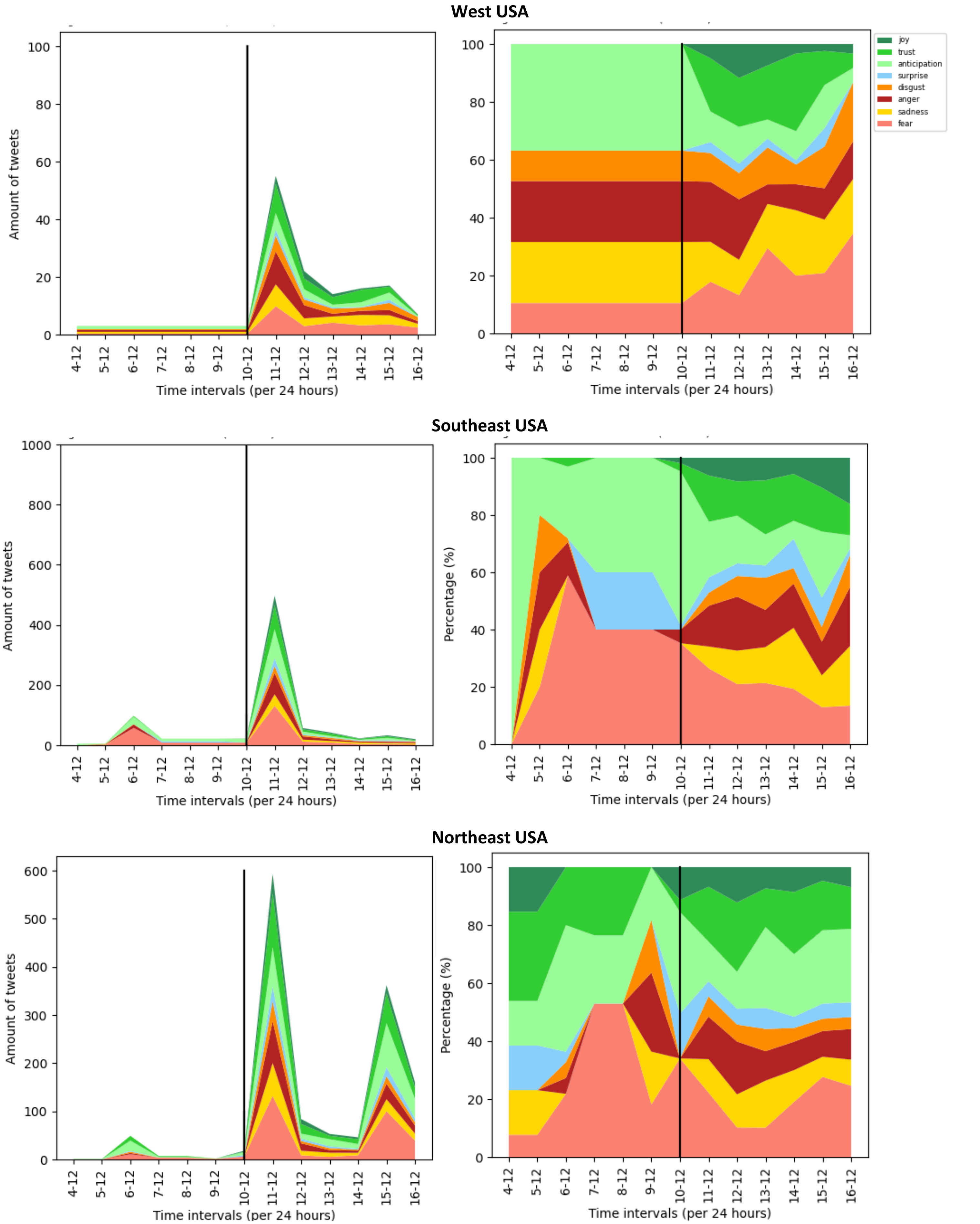


Figure 21: Tweet usage (left) and normalized emotion distribution (right) for area 1 (top), area 2 (centre), and area 3 (bottom) for the tornado case. Y-axis shows respectively the amount of tweets and the emotion in percentage and the x-axis shows the date.

4.2.2. December Tornado: Result interpretation

From the results three peaks on different scales can be observed. The highest peak on December 11th correlates to the selected tornado event. The peak on December 6th correlates with a small tornado event that occurred in Mid Tennessee. The peak at December 15th correlates tornado outbreak in the Midwest of the USA, as shown in 18.

Figure 18 shows expected tweet usage patterns, that correlates with the main Tornado event. The sudden peak that arises and the slightly more gradual decrease, are the same patterns that were observed in the Antarctica case. The smaller peaks correlate with the mentioned tornado events, and confirm that a smaller event also has a lower tweet response. The very low response before a tornado occurred show that the topic tornado is not a daily subject that occupy people on Twitter. No clear patterns can be observed within the emotion response as a result of the fluctuations in the emotion distribution.

The main trend within the retweet, like and follower response is the slight increase in negative emotions in the first 48 hours, followed by a sharp increase in positive, mainly anticipative emotions. The increase in anticipative emotions might be a result of an increase in retweets and likes regarding tweets of people who were affected or victim of the tornado outbreak, confirming people's safety.

The results per region show that in every region tweet responses are present regarding the tornado event. The highest peak in the southeast region corresponds with the main tornado outbreak that occurred on the boundary between the southeast and northeast and the highest peak in the northeast region corresponds with a tornado in this region, and thus indicates that the region where an event occurs shows the highest tweet response. The emotion distribution remains very constant, as seen in other trends before.

The small peak seen in the southeast on December 6th is related to the above mentioned small tornado event in Mid-Tennessee. The other areas show no tweet response regarding around this event.

4.3. Case 3: Hurricane Ida

On August 29th, Hurricane Ida hit the south-eastern coast of the US, near Louisiana. The hurricane was a deadly and destructive event and was ranked category 4 (Figure 13).

4.3.1. Hurricane Ida: Tweet response

Figure 22 shows overall three peaks, with the main peak reaching over 3000 tweets. It can be noticed that before this main peak, the amount of tweets that contain the word Hurricane gradually increases. This gradual increase starts from August 26, 3 days before the main event. The drop after the main peak is gradual and shows similar patterns as the other cases. However, the drop is interrupted with the evolution of a second smaller peak that spikes at September 2nd. After this peak, the tweet usage gradually decreases and seem to stabilize. This stabilized level is higher than the level before the events. Between August 19th and August 23th another peak is visible that reaches just over 1000 tweets. Again a gradual increase is shown and the peak occurs for 2 consecutive days, followed by a sudden decrease.

The emotion distribution, as shown in figure 23, shows a small increase in negative reactions two days before the event occurred. This increase of around 10% remains after the event. The negative emotions are around 40%, from which fear, sadness and anger show equal percentages of around 10-15%.

In addition to hurricane Ida that correlates with the highest peak in figure 22, the smaller peak at September 9th correlates with flash floods and tornadoes, that occurred on the same date, and were remnants of Hurricane Ida. The broader peak that starts at August 19th coincides with Hurricane Henry that occurred near and around New York City.

The patterns of responses in the form of retweets and likes show similar trends. The distribution positive and negative is overall equal. Most remarkable is the sudden increase in anticipated tweets that are liked and retweeted 48 hours after Hurricane Ida. The follower pattern shows a high variability in emotion distribution. No clear trends are observed.

The regional variability shows that Hurricane Ida was noticed in tweets in all regions. The southwest area, the region where Hurricane Ida occurred, shows the highest amount of tweets. The west and northeast area show a substantial lower amount of tweets with a maximum of 70 tweets. The northeast shows a slight increase at September 2nd, and this is also very slightly seen in the west and southeast area.

The emotion distribution shows a constant emotion response with some fluctuations that do not show consistency with the peaks. The overall distribution shows consistency in the different areas which comprises approximately 60% negative emotions, from which 35% are fearful emotions.

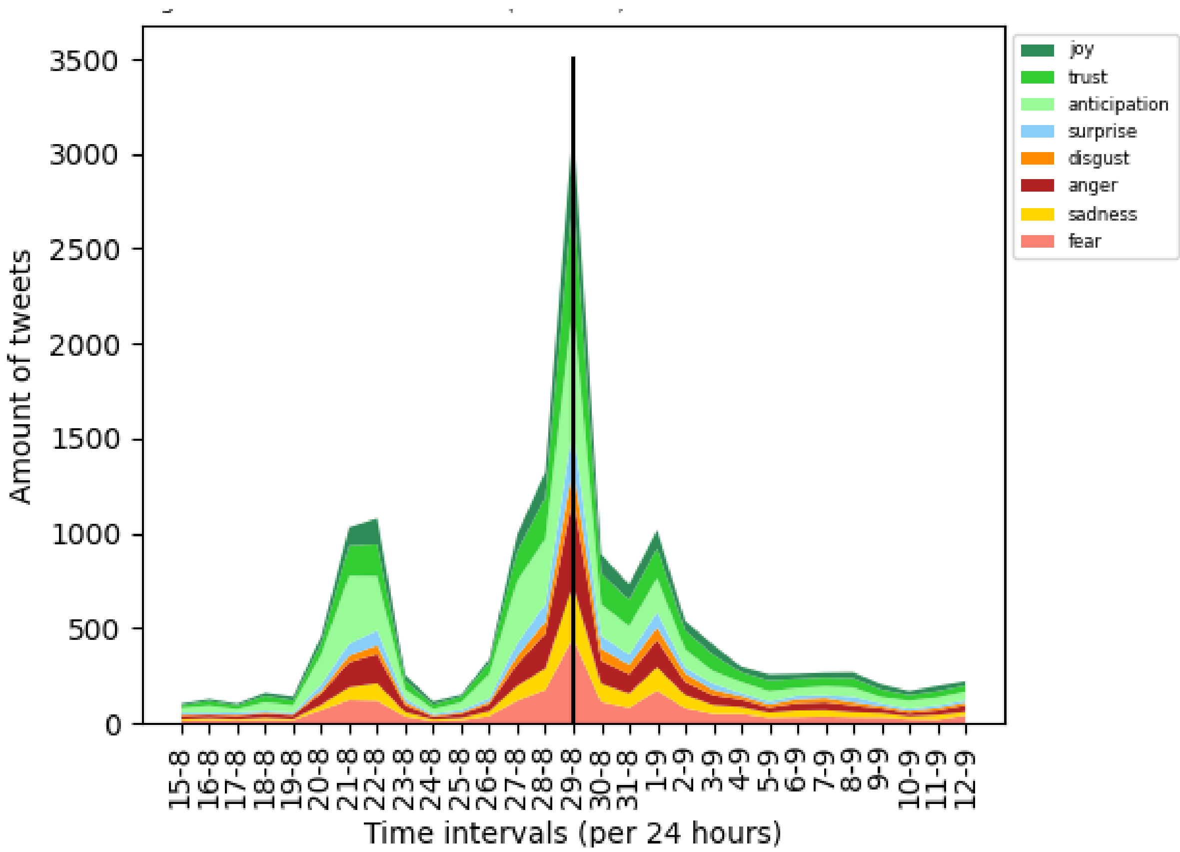


Figure 22: Absolute emotion distribution and tweet pattern for over a time-interval of a month for case 3: Hurricane Ida that hit the Southeast Coast of the USA on 29-8-2021. The y-axis is showing the amount of tweets and the x-as shows the specific date.

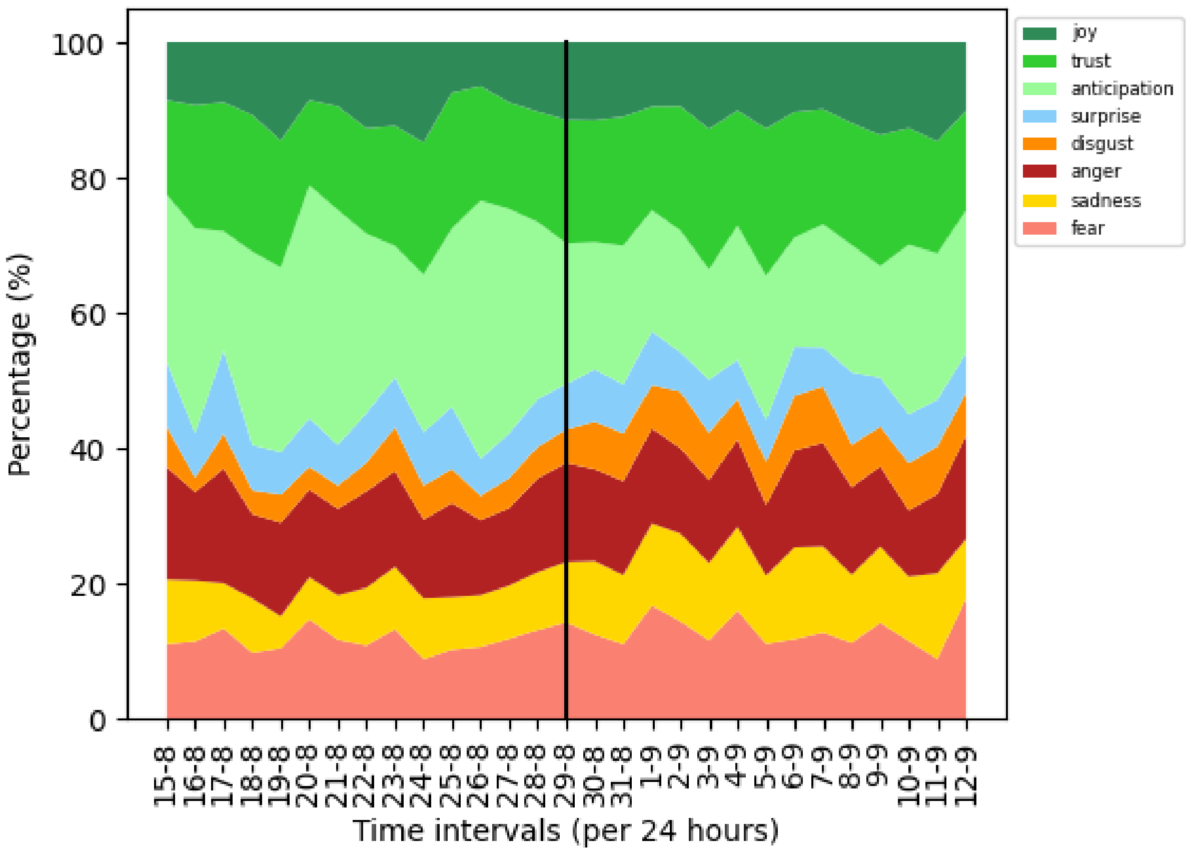


Figure 23: Normalized emotion distribution and tweet pattern for over a time-interval of a month for case 3: Hurricane Ida that hit the Southeast Coast of the USA on 29-8-2021. The y-axis is showing the percentages per emotion and the x-as shows the specific date.

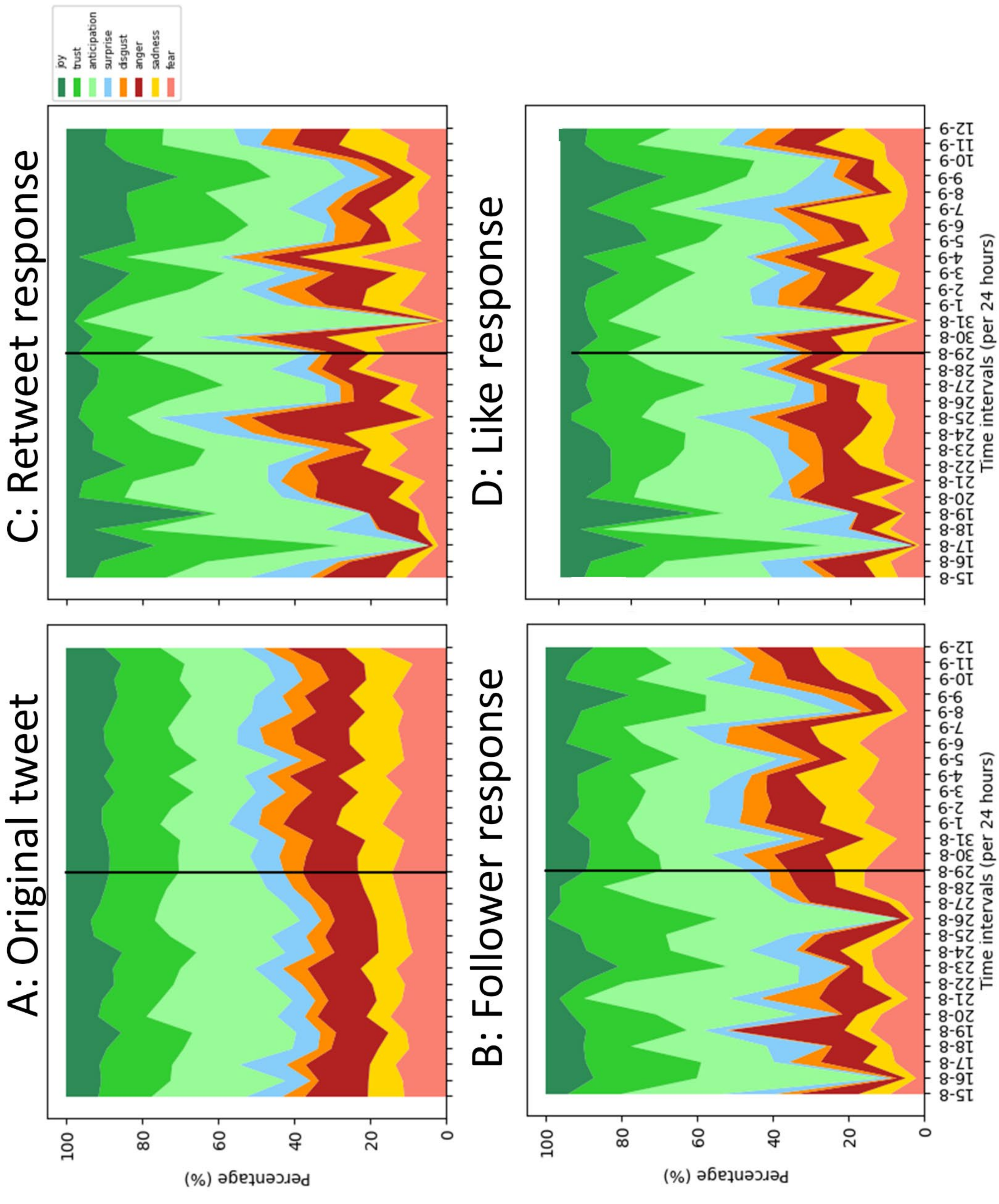


Figure 24: : Absolute emotion distribution and tweet activity for a) the original tweet (on the top left), b) the follower response (left below), c) the like response (on the top right), and d) the retweet response (right below) over a time-interval of a month for case 2: Hurricane Ida US on 29-08-2021 The y-axis is showing the percentage of tweets and the x-as shows the specific date.

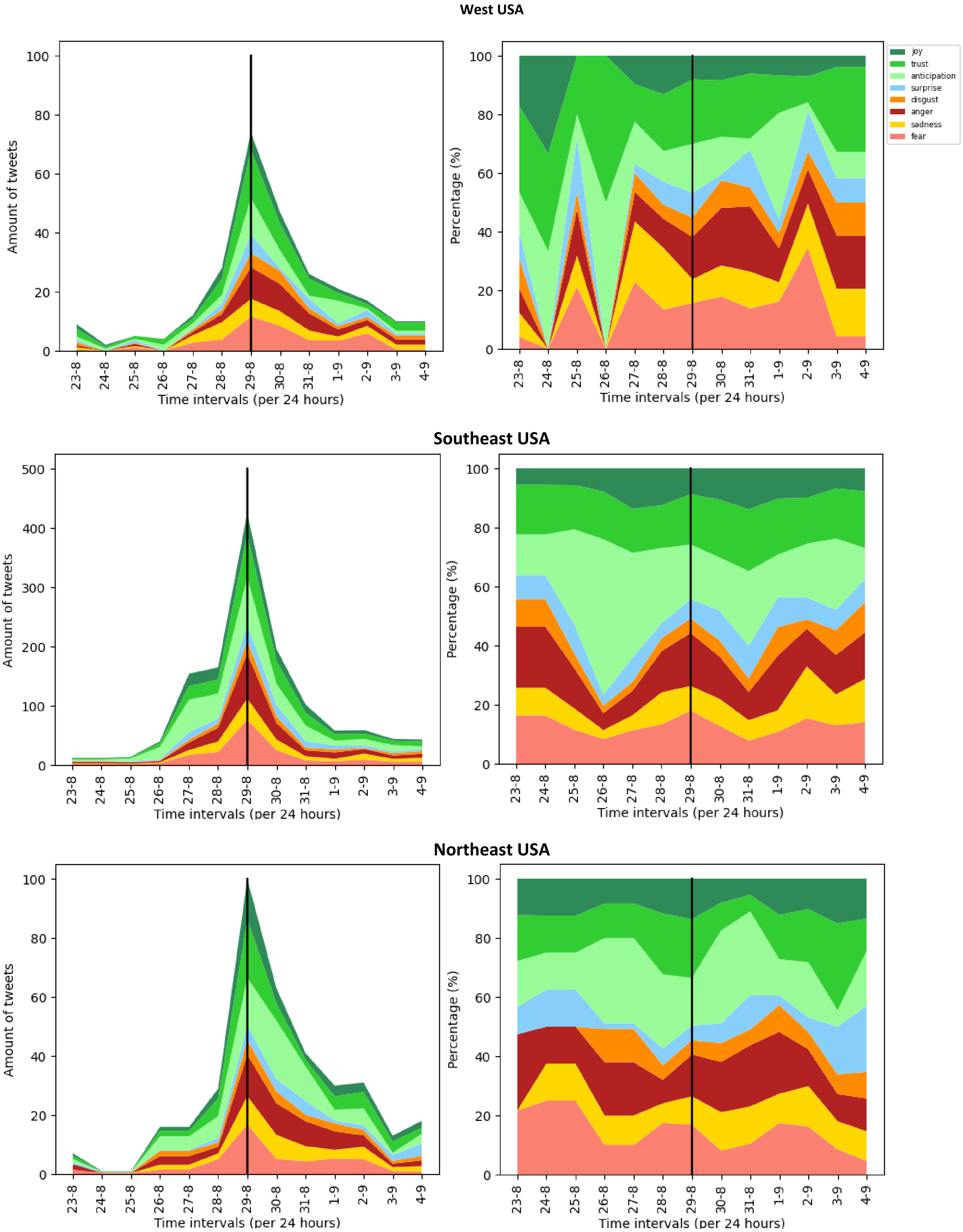


Figure 25: Tweet usage (left) and normalized emotion distribution (right) for area 1 (top), area 2 (centre), and area 3 (bottom). Y-axis shows respectively the amount of tweets and the emotion in percentage and the x-axis shows the date.

4.3.2. Hurricane Ida: Result interpretation

The tweet usage patterns correlate to events regarding hurricanes, as seen in previous cases. The main difference however, is seen in the gradual increase that leads up to the main peak. The gradual increase is suggested to be caused by the fact that hurricanes are predictable events. As they are already mentioned and warned for before the actual event, tweets can build up gradually instead of creating a sudden increase in 24 hours. Another significant observation is the elevated stabilized level in the aftermath in comparison with the basic level before for the hurricane events.

Regarding retweet, like and followers response the main trend of a spike in anticipation 48 hours after the event is similar to the tornado event and can be explained by the presence of tweets regarding rescues, as hopeful rescue tweets are plausible for hurricane events as well.

As the amount of tweets in southeast area, where Hurricane Ida occurred, is highest, the suggestion made for the tornado event is confirmed and the highest tweet response occurs in the region that is affected by the hazard. The emotional distribution remains, similar to previous cases, nearly consistent over time.

5. Discussion

5.1. Comparison between natural hazards

5.1.1. Tweet activity during natural hazards

In all three cases, the amount of tweets that mention a certain hazard are precisely peaking around the specific hazard, following the framework proposed by Murthy & Gross (2017). The amount of tweets peak during the core event and all show a gradual decrease during the aftermath phase, as was hypothesized. The higher frequency during disaster events was also observed by Stokes & Senkbeil (2017) who found a higher tweet frequency during tornado outbreaks. The anticipatory phase is mainly clearly observed for the Hurricane case, but is also seen to a much smaller extent in the Antarctica and Tornado case. An explanation for this is the unexpectedness of the Antarctica and Tornado hazards which were forecasted only a few hours before, whereas the Hurricane hazard was a predicted event. This implies that hazards that are predictable up to a week in advance result in earlier responses on Twitter and also a larger and longer anticipatory event. This coincides with the hypothesis and mentioned findings of Niles et al. (2019), whose results confirm that the more predictable an event, the larger the anticipatory phase is.

The absolute amount of tweets that is maximally reached for the Antarctica event is only 30% higher than the tornado and hurricane event, despite the Antarctica case containing a global tweet set. The total tweet amount of 3000, which only includes tweets from the US, is a high response in comparison with the global response in the Antarctica case that varies between 3300 and 4300. This may be caused by an arguable large Twitter response of US citizens in general. This large response in the US might be caused by the visible and severe impact that a hurricane and tornado event has, whereas the temperature rise on Antarctica does not result into direct visible damage.

The relationship between visibility of the damage and tweet response is strengthened by the observed emotion response, where the tornado and hurricane event contain respectively 7% and 4% more negative tweets. This relation is in alignment with the hypothesized trend that negative emotions would be larger when hazard damage was visible and harmful. These relationship was also observed by Clayton (2020) which mention a correlation between more anxious and sorrower reactions and Australian visible climate change effects, such as wildfires and droughts. Du Bray et al. (2019) also found a more negative response under both men and woman with regards to direct climate threats. In addition, the higher percentage of negative emotions can be explained by the fact that the words ‘hurricane’ and ‘tornado’ are per definition associated with a natural hazard and thus will be accompanied with more negative emotions in tweets. Antarctica is not perse related to a climate hazard and can cover tweet topics that are associated with more positive emotions as well. This also coincides with the base level of tweets regarding Antarctica before the actual events. This base level is already at a certain level, suggesting that Antarctica is frequently mentioned topic that is not only used during a natural hazard and thus involve non-climatic emotion responses as well. On the contrary, tweets mentioning tornado and hurricane before the anticipatory phase of the events are scarce, consolidating the specific association with natural hazards that is observable in the emotional response.

Another main observation is the equal amount of maximum tweets posted during the hurricane and tornado hazard, implying that both events were by the public assessed with the same degree of severity. This coincides with the mortality rates from both events, namely 93 within the Tornado event and 96 within the Hurricane event as shown in figure 13. This suggests that the degree of assessed severity of an event, which relates to the part of negative emotions, is in alignment with mortality rates. The assessed severity of an event does not coincide with the damage costs, as the damage costs of Hurricane Ida were 20 times higher than the Tornado outbreak and the part of negative emotions differ only 3%. The relationship between emotion response and mortality rates is consistent with Kaur et al. (2020) who found a correlation between mortality rates and tweets related to the Covid pandemic. Although the Covid pandemic is not of the same category as the natural hazards that were depicted in this study, it was also an event that caused damage and evoked responses similar to natural hazards.

Another significant observation is the peak that correlates to the shipwreck finding, which can be seen as a reference event. A non-climatic event, in this case a shipwreck finding, also follows the proposed framework of Murthy & Gross (2017). A rather remarkable development is that this non-climate event without resulting harmful impacts, leads to more response in the first 24 hours after the news, than a climate hazard, that is potentially dangerous. However, the climate hazard shows a smaller, but also a broader peak, implying that this climate related topic thus remains longer under discussion on Twitter than a non-climate related event, such as the finding of a shipwreck.

5.1.2. Emotion distribution during natural hazards

The hypothesis that indicated an increase of negative emotions direct after the event is confirmed by the Antarctica and Hurricane hazard with an increase of negative emotions of circa 15% in both cases. The short-lasting 10% increase of positive emotions during the shipwreck event, indicates that overall emotion patterns on Twitter are affected by both non-climate and climate related events. The shift towards negative or positive emotions depends on whether the event is perceived as negative or positive and shift with 10%-15%. Regarding the Tornado case, no conclusions can be drawn as the emotion pattern shows too many fluctuations. However, these fluctuations do not counteract with the observed patterns for the Antarctica and Hurricane cases.

It was hypothesised that negative emotions for a climate hazard would increase during core events and that a pattern would be visible that follows the anticipatory phase, core phase and aftermath in the same way as observed in the absolute tweet amounts. In the Hurricane emotion distribution, negative emotions increases at the same moment tweet activity increases, which indicates an anticipatory phase for the emotion response as well. However, no aftermath phase can be observed in all cases. The first plausible explanation is that an aftermath phase cannot be observed as a result of the unexpected other events that took place after the main event (i.e. the icecap melting, the second tornado on December 15th, and the flooding caused by the hurricane). Another explanation is that while tweet activity reduces relatively fast after the event, the emerged negative emotions are longer used in tweet expressions and thus the aftermath phase is longer than the selected two week timescale. This second assumption is in line with the proposed emotion perception and the vicious feedback cycle (in this case negative) that is caused by anticipated emotions (Figure 8&9) (Odou & Schill, 2020). Once an (in this case negative) emotion is induced, this emotion can be experienced for much longer due to this anticipated emotion feedback system.

Taking a closer look at the average emotion distribution and the 8 distinguished specific emotions, similarities and differences can be observed between the three cases over a 4 week time period (Figure 26) and also during the peak of the core event (Figure 27). The main observations of the emotion distribution of the peak in comparison with the 4 week time period is the increase in fear for the tornado and hurricane event and an increase in fear and surprise for the Antarctica case. This change for the Antarctica case is caused by filtering out the positive emotion increase that was a result of the shipwreck finding. The increase in anger in general shows that during the core phase of the hazard, angry emotions increase.

Zooming in on the 4 week emotion distribution, a rather unexpected result is the overall minority of negative emotions for all three cases, varying between 36 and 43%. Apparently for all climate hazards, the part of positive emotions is dominant. One speculation is that when people are confronted with harmful climate hazards, they are more tended to react with sarcasm. However, a reason grounded by results and prior research remains unclear and more research is necessary for clarification. To get a better understanding, this future research could focus on tweet level to see how identified positive and negative tweets are framed and how people, instead of machine learning, interpret them.

For all three cases the percentages of the emotions joy, surprise, disgust and sadness are very similar. The main differences can be observed for the emotions fear, anger, trust and anticipation.

Zooming in on specific emotions observed for the Antarctica event in comparison with the two national Hurricane and Tornado events, the main difference lies within the larger contribution of the emotions anger for the Hurricane and Tornado event, whereas the Antarctica event contains a substantial larger part of the emotion trust. This implies that anger is evoked when climate events have visible impacts.

Comparing the emotion anger between the Hurricane and Tornado case, the Hurricane event shows the highest percentage for the emotion anger. A plausible explanation for this increase in fear is that when a climate hazard occurs that was predicted, people have the time to evaluate the situation. Where fear and panic might be the first reactions during an unpredicted event, a part of fear could be replaced by anger. Du Bray et al. (2019) also found an increase in the emotion anger as a response on climate change effects, especially under male respondents. Other research found that the emotion fear is related to pessimistic risk perception, whereas anger is related to optimistic risk perception (Lerner et al., 2003; Lerner & Keltner, 2001). When an event is predicted, people could have time to estimate optimistic scenario outcomes.

This suggested relationship between fear and unpredicted events is confirmed by the tornado event. The Tornado event, that was unpredicted, shows a larger amount of fearful reactions and a smaller amount of the emotions trust and anticipation. Findings of Grillon et al. (2004) confirm this, as this study found that fear is one of the major reactions that is evoked when unpredicted (external) events occur. Also the overall negative emotion response is largest for the Tornado case in comparison with the other cases, implying that a sudden climate hazard that have visible impacts, such as a tornado, results into the highest negative emotion response. Fearful reactions not only increase during sudden events, but also during uncontrollable events (Polizzi et al., 2020). Thus uncontrollability and unpredictability could both induce fearful reactions. To get more insight in the relationship between fear and uncontrollable versus unpredictable events, more research is required.

5.1.3. Follower, like and retweet response

Regarding responses in retweets, likes and followers no significant overlapping trends were found. However, the similar like and retweet patterns are notable and this indicates that the same tweets are liked and retweeted. One main cause may be that some tweets are going viral and are massively liked and retweeted, as seen in the tweet regarding Antarctica from the Capital Weather Gang, seen in figure 13.

As suggested by Abdullah et al. (2017), retweets are a good proxy for information spreading and the identifying the real feeling of individuals, because it was experimentally confirmed that retweets reflect the ´retweeter´ feeling and interests. In addition, a retweet seemed to be a sign to truly have the willingness to alert other people regarding a certain topic. The results in this thesis show that, as likes and retweets show similar patterns, likes can also be used as a proxy for information spreading.

The main observation regarding follower emotion trends is the delayed negative reaction pattern for the Antarctica event, which indicate that users with a large amount of followers respond with a delay on natural hazards. However, no specific trends can be observed as this is not confirmed by the other cases and neither by other studies regarding this specific observation.

A returning result was the steady peak in anticipation that was seen in the aftermath of the retweet patterns and like patterns. As suggested, this might be a result of an increase in retweets and likes of tweets from people who were affected or victim of the tornado outbreak, confirming people's safety. This suggestion is solidified by Truong et al. (2017), that confirms that Twitter is used for both conversational and informational processes, as highlighted. To confirm this suggestion, it may be useful to analyse tweet response at individual tweet level in future research.

5.1.3. Geographic analysis

Tweet usage is largest in the region where the natural hazards occur and was in the occurring areas around 10 times higher for the tornado event and 5 times higher for the hurricane event . No significant difference in emotion response between regions was found. The amount of tweets that were tweeted in regions further away from the location of the natural hazard was smaller, but showed a similar emotion distribution. Only one study was found regarding geographic patterns of emotional response on climate change keywords in tweets. The results showed that tweets in the United Kingdom showed less negative reactions than tweets in Spain, which may be a result of Spain being more subjected to climate hazards, such as droughts and drinking water scarcity (Loureiro & Alló, 2020). However, the results in this study do not show this relation between geographic (negative) response and the severity of a nearby climate hazard. Further, it must be mentioned that users are enabled to turn off their location, which means that only part of the data was analysed. For the main peak in the tornado event 1200 out of the 3000 tweets had location information and for the hurricane event this was 550 out of the 3000. To understand geographic emotion response patterns on climate hazards, more research is required.

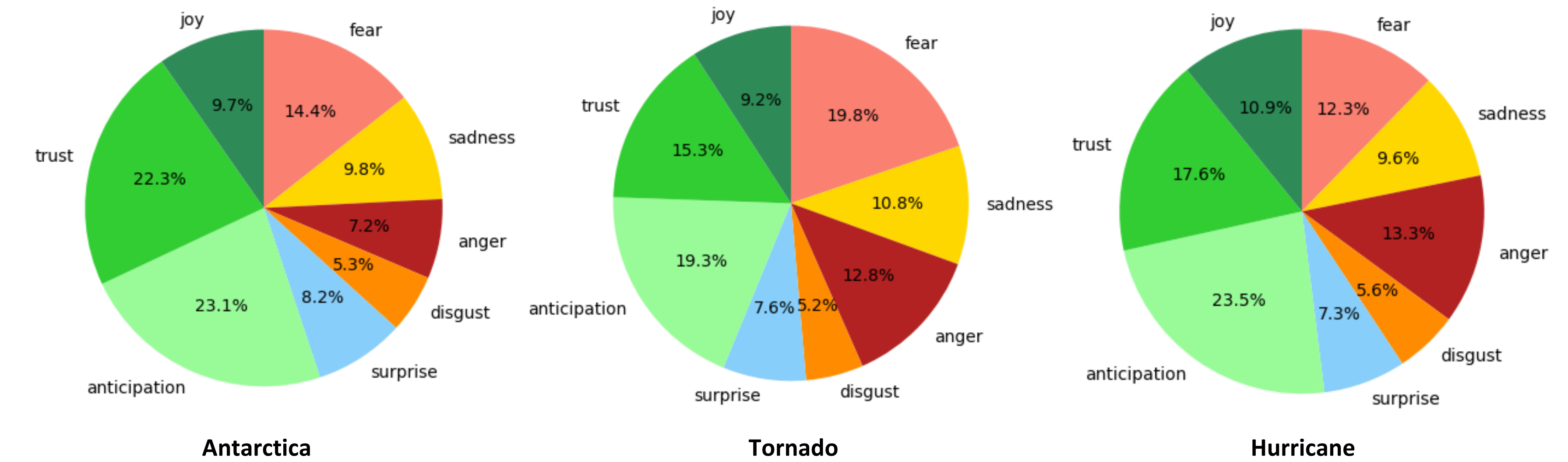


Figure 26: Circle diagrams of the emotion distribution with the eight specific emotions for all three cases over the 4 week time interval.

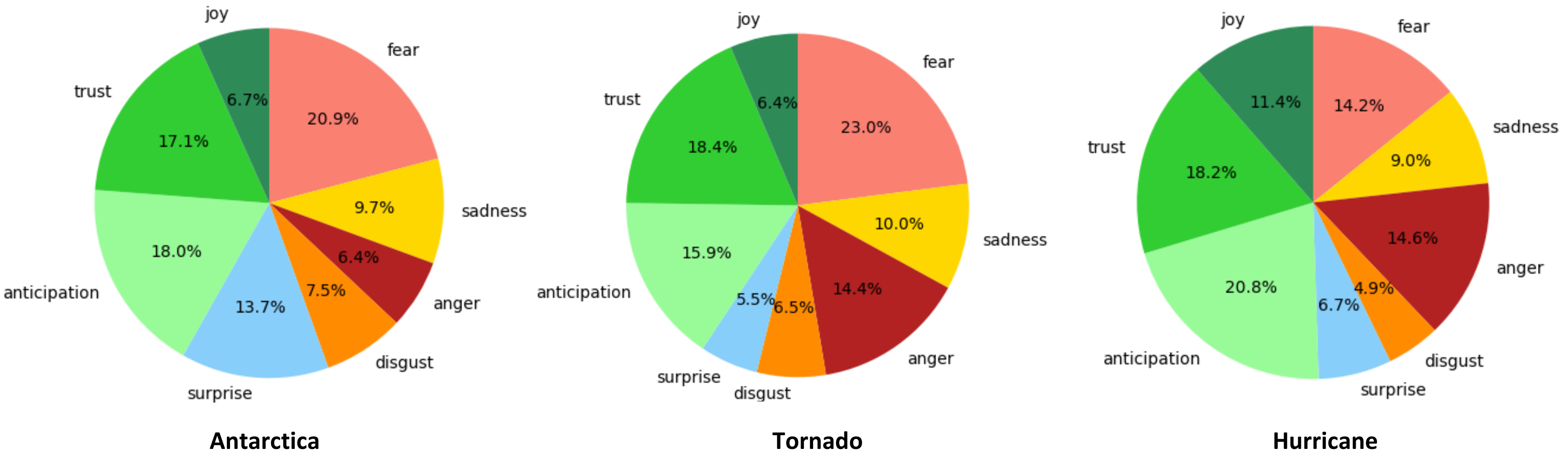


Figure 27: Circle diagrams of the emotion distribution with the eight specific emotions for all three cases during the peak phase.

5.2. Implications for Twitter usage in relation to climate change

As discussed in chapter 1, one of the main societal contributions of this thesis are the resulting emotional response patterns that can be crucial for governments and organisations to communicate more effectively with the public by aiming for better preparation and recovery of climate hazards and also enhancing positive attitude towards climate change topics.

Firstly, some general implications can be deducted from this study. During natural hazards that are highly predictable, such as hurricanes, Twitter can be used as an essential tool to share and spread crucial information about for example evacuation or action guidelines. For natural hazards, that occur unpredictable and sudden, such as tornadoes or floodings, Twitter can also be used as a communication tool to share for example emergency measures (Truong et al., 2014). In this case, the knowledge that tornado tweets will peak within 24 hours, can drive institutions to aim for effectively spreading useful information before the main peak is reached.

In addition to tweet activity, understanding emotional patterns and in what way social media is used before, during and after natural hazards can also be useful for recovery and communication efforts. Identification of emotions mostly seen on Twitter can lead to more effective communication methods that are adapted on these emotions and thus can result into a more effective approach towards climate hazards.

Also, identifying tweet usage and emotion patterns can help news channels, individual users, influential people, governments and social media designers to make better decisions about the sharing and spreading of information. As discussed earlier, emotions are powerful features that can impact people's behaviour. Thus an increase in hopeful tweets can have a large impact on peoples' anticipated emotions and actual behaviour and attitude. Sharing information and hopeful messages should thus be strived for by these mentioned groups.

Individual users can play a role in spreading useful and correct information and also in minimizing the spread of disinformation, as it is suggested that individuals play a significant role within disaster communication (Niles et al., 2019). Influential people also play a key role in communication, as spreading information through their network have a large amount of impact and the chance that a tweet goes viral is high. Influential people are as well often seen as key figures and can thus have a large impact on people's perceptions. In addition, governments and organizations can use Twitter to inform people on time and with correct information. As research suggests, disinformation mainly develops when news supply is low, while the demand is high (Shibutani, 1966). So organizations can play a major role in reducing the spread of disinformation by providing reliable information via official Twitter accounts. Also designers of social media can contribute to natural hazard monitoring by adapting Twitter applications. For example, a natural hazard mode can be created, or a risk rate or verification mode can be introduced, which in turn can be useful to let users make better decisions on Twitter about their tweet publishments.

Secondly, implications can be deducted from specific results as well. Zooming in on some specific results, several observed patterns in tweet activity and emotional response around climate hazards are useful for enhancing preparedness and recovery of natural hazards.

The suggested patterns of an increased response of the emotion anger during predicted climate hazards and an increased fearful response for unpredicted climate hazards can be essential information for communication method that is adequate for an angry or fearful public with an eye on enhancement of climate hazard attitude. In addition, the information of an earlier and larger response for predictable events can be used by organisations in the timing of certain to be communicated messages, such as communication of safety regulations. The knowledge about a high tweet frequency nearby the event can also be used in effective communication methods.

A separate implication needed to me mentioned is that the analysis performed in this study is a first approach to measure tweet activity and emotion pattern for natural hazards. However, this analysing method can, in addition to natural hazard monitoring, also be used to analyse tweet and emotion patterns for other climate and non-climate related topics.

5.3. Proposed future research

Several recommendations and suggestions for future research are proposed.

- Firstly, as mentioned in section 5.1. to explain the overall positive emotions that were observed in the responses of all three cases, it is proposed to analyse and interpret individual tweets and its emotions without NLP techniques to investigate how these positive and negative tweets are interpreted by real humans. In this way, sarcasm and emojis can for example be detected.
- Analysis of more natural hazards is proposed to get a more detailed and broader understanding of tweet activity and emotion response regarding climate hazards.
- More keywords can be analysed per natural hazard. This can be done in order to see what kind of words are used in tweets, when they are used and what emotions they contain. Analysing a word such as ‘food’, ‘safe’, or ‘hospital’ in combination with a natural hazard term can give insight in the severity of a natural hazard.
- In order to identify the relationship between severity and emotion response, emotion responses can be compared with other patterns that are related to severity, such as mortality rates, damage costs, refugee rates.
- Taking replies into account can give more insight. Although replies seem to mostly agree on a topic, it will result in more twitter data and thus gives more context and fundament to the analysis.
- Twitter is one forum to measure emotional response. It is proposed to use this analysis technique for other social media platforms to cover more digital responses.

6. Conclusions

The aim of this thesis is to get a general insight and qualitative understanding of how the public responds (emotionally) before, during and after climate hazards on Twitter. The main findings are:

- Tweet activity around climate hazards follow the anticipatory, core and aftermath phases as the framework of Murthy & Gross (2017) proposed. Tweet activity peak during the core event and show a gradual decrease during the recovery phase. The anticipatory phase shows a gradual rapid increase when the climate hazard is a predictable event. During sudden, unpredicted climate hazards, tweet usage increases very rapidly within 24 hours to peak during the core event.
- The emotion distribution shows an increase in negative reactions of 10-15% at the moment when a climate hazard takes place. The emotion distributions follow a similar trend as tweet activity during the anticipatory and core phase from the proposed framework. The aftermath is unclear due to distortion of second events and is questioned to last longer than tweet activity as specific induced emotions may be longer amongst the public.
- The maximum amount of tweets within the global Antarctica tweet set is only 30% higher than the US scaled hurricane and tornado tweet sets. This is suggested to be caused by an arguable large Twitter response of US citizens in general and the high visibility of the hurricane and tornado impacts.
- The emotion anger is substantially larger for the hurricane and tornado cases in comparison with the Antarctica case. This can be explained by the fact that hurricane and tornado hazards have visible impacts and also by the fact that the words 'hurricane' and 'tornado' are per definition related to climate hazards, which is not the case for the keyword 'antarctica'.
- The tornado event shows substantially more fearful reactions than the hurricane event that has contains a high level of the emotion fear. It is suggested that this difference in fear and anger proportions lies in the predictability or controllability of the event.
- Non climate related events, in this case a shipwreck finding, also follow the framework of Murthy and Gross (2017). The emotion response and tweet activity both follow the anticipatory, core and aftermath phases.
- The proportion of positive reactions is for all three cases in majority. More research is necessary to gain a better understanding of this phenomenon.
- The regions where a climate hazard occurs show the largest tweet activity as was expected. However, the emotion distributions are quite similar for all regions and the region where an event occurs does not show an increase in negative emotions as the hypothesis suggested.
- Like and retweet responses show similar patterns. Fearful like and retweet responses occur 1-2 days after the event. Follower patterns show delayed fearful responses 3-4 days after the event.

7. Literature

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Appendix I: Statement of originality

I declare that:

1. this is an original report, which is entirely my own work,
2. where I have made use of the ideas of other writers, I have acknowledged the source in all instances,
3. where I have used any diagram or visuals, I have acknowledged the source in all instances,
4. this report has not and will not be submitted elsewhere for academic assessment in any other academic course.

Student data:

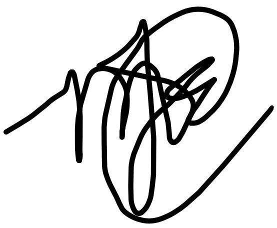
Name: Marieke Jacobs

Registration number: 4246918

Date:

16-7-2022

Signature:



Appendix II: Python code collection tool

```
# Python code created by Marieke Jacobs (4246918) at Utrecht University at
22-7-2022
# For MSc Project: 'Emotional response to climate hazards'
# In case of questions, point of contact or further explanation about
usage: mariekejacobs96@gmail.com

# -------------------------- IMPORT ------------------------------ #
####################################################################

import tweepy
import time
import pandas as pd
import re
from textblob import TextBlob
import matplotlib.pyplot as plt
from nrclex import NRCLex

import numpy as np




# -------------------------- DATA COLLECTION PART ( KEYWORD / TIME SEARCH )
------------------------------ #
###########################################################################
####################################
# Outcome is a dataframe, from which data like text/location etc can be
selected to do (emotional analyses on)

client =
tweepy.Client(bearer_token='AAAAAAAAAAAAAAAAAAAAAHvaYgEAAAAAVWwTcMh5iqr6eiB
eoQILPMUrIyk%3DorOKwmTMcK5SituxRJcfk60azzHFNtv4oJ1G2Aw1u7OcR8bifi',
wait_on_rate_limit=True)


#-------------------------PART 1: SEARCH TWEETS ----------------------------
----

#search on tweets and get all the extra information that is in the tweets,
do this per 500, as that is the maximum amount

climate_tweets = []
for response in tweepy.Paginator(client.search_all_tweets,
#response is a tijdelijke wegschrijving for elke loop #climate tweets is
gevuld met x*500 matrixen
                                 query ='tornado place_country:US -
is:retweet" ', # !!!! FILL IN KEYWORD, LOCATION AND WITHOUT RETWEETS
                                                                         #
KEYWORDS BY: ENTER SPECIFIC WORD
                                                                         #
LOCATION BY: info on: https://developer.twitter.com/en/docs/twitter-
api/tweets/search/integrate/build-a-query

# Example coordinate box: bounding_box:[westlong southlat eastlong
northlat]

# Example cirkle: point_radius:[longitude latitude radius] example:
```

```
point_radius:[2.355128 48.861118 16km] OR point_radius:[-41.287336
174.761070 20mi]

# Example country: place_country:US

                                  user_fields=['username', 'public_metrics',
'description', 'location'],
                                  tweet_fields=['created_at', 'geo',
'public_metrics', 'text'],
                                  expansions='author_id',
                                  start_time='2021-12-10T00:00:00Z', # !!!!
FILL IN PREFERABLE DATE
                                  end_time='2021-12-11T00:00:00Z',
                                  max_results=500):
    time.sleep(1)
    climate_tweets.append(response)

    result = []
    user_dict = {}

    # ------------------------PART 2: SEARCH AND ADD USER INFO ------------
--------------------
    # Loop through each response object and add username, followers, amount
of tweets, description and location
    for response in climate_tweets:
        # Take all of the users, and put them into a dictionary of
dictionaries with the info we want to keep
        for user in response.includes['users']:
            user_dict[user.id] = {'username': user.username,
                                  'followers':
user.public_metrics['followers_count'],
                                  'tweets':
user.public_metrics['tweet_count'],
                                  'description': user.description,
                                  'location': user.location
                                  }

# ------------------------PART 3: PUT ALL INFORMATION IN NEW DATAFRAME ----
----------------------------
            #put all the information out of climate_tweets matrix from step
1 and step 2 in a new organized dataframe

        for tweet in response.data:
            # For each tweet, find the author's information
            author_info = user_dict[tweet.author_id]
            # Put all of the information we want to keep in a single
dictionary for each tweet
            result.append({'author_id': tweet.author_id,
                           'username': author_info['username'],
                           'author_followers': author_info['followers'],
                           'author_tweets': author_info['tweets'],
                           'author_description':
author_info['description'],
                           'author_location': author_info['location'],
                           'text': tweet.text,
                           'created_at': tweet.created_at,
                           'geo': tweet.geo,
                           #'place_id': tweet.geo['place_id'],
                           #'coordinates': tweet.geo['coordinates'],

#'coordinates':tweet.geo['coordinates(['coordinates'])', Hoe gaat dit
```

```
werken? [coordinates] in [coordinates]? dus [coordinates[coordinates]]
                           'retweets':
tweet.public_metrics['retweet_count'],
                           'replies': tweet.public_metrics['reply_count'],
                           'likes': tweet.public_metrics['like_count'],
                           'quote_count':
tweet.public_metrics['quote_count']
                           })

    # Change this list of dictionaries into a dataframe
    df = pd.DataFrame(result) # !!!! RESULT IN IMPORTANT DATAFRAME

    #textdf= pd.DataFrame(df.text) # put on to make own new dataframe with
only text



# ------------------------- ANALISIS------------------------------ #
#####################################################################

# Currently only sentiment and polarity analysis including figures
(staafdiagram en cirkel kunnen ook nog) (see India Girl)

# Text clean, get rid of punctuation

def cleanuptext(txt):
    txt=re.sub(r'RT : ', '', txt)
    txt=re.sub(r"(@\[A-Za-z0-9]+)|([^0-9A-Za-z
\t])|(\w+:\/\/\S+)|^rt|http.+?", "", txt) #We tell our program to eliminate
the punctuation, URL, and @:
    return txt

df['cleanuptext']=df['text'].apply(cleanuptext) #add cleanuptextcolum to df


#  df.to_csv('academictest.csv') #save to excel file
# print(df.text) #just print text
#  df.text.to_csv('test.csv')  #save to text to excel file

#subjectivity function
def getTextSubjectivity(txt):
   return TextBlob(txt).sentiment.subjectivity

#polarity function
def getTextPolarity(txt):
   return TextBlob(txt).sentiment.polarity


# funtions to extra column in df
df['Subjectivity']=df['cleanuptext'].apply(getTextSubjectivity)
df['Polarity']=df['cleanuptext'].apply(getTextPolarity)


# identify neutral/positive/negative

def getTextAnalysis(a):
    if a<0:
        return "Negative"
    elif a==0:
        return "Neutral"
    else:
```

```
        return "Positive"

# neutral/positive/negative score to extra column in df
df['Score']=df['Polarity'].apply(getTextAnalysis)


# Making nice looking plot subjectivity vs polarity
for index, row in df.iterrows():
    if row['Score']=='Positive':
        plt.scatter(row['Polarity'],row['Subjectivity'], color='green')
    if row['Score']=='Negative':
        plt.scatter(row['Polarity'],row['Subjectivity'], color='red')
    if row['Score'] == 'Neutral':
        plt.scatter(row['Polarity'], row['Subjectivity'], color='blue')

plt.show()

#save by just copy pasting with mouse for now

# ----------------------- DETECT EMOTIONS ---------------------------------
-------
# NRC LEXICON
# From https://github.com/xiaoqingwan/NLP-Emotion-
Detection/blob/main/emotion_detection_nrclex.ipynb
# And used : python -m textblob.download_corpora (to make sure to make no
errors)

#detect emotions

#deze stap is nog beetje vaag en snap ik niet helemaal
#df['emotions'] = NRCLex(df['cleanuptext']).affect_frequencies
df['emotions'] = df['cleanuptext'].apply(lambda x:
NRCLex(x).affect_frequencies)
df = pd.concat([df.drop(['emotions'], axis = 1),
df['emotions'].apply(pd.Series)], axis = 1)


#plotmaking

df['anticipation'] = df['anticipation'].fillna(0)

# data = {"Emotions":["Fear", "Anger", "Anticipation", "Trust", "Surprise",
"Positive", "Negative", "Sadness", "Disgust", "Joy"],
#         "Percentage":[df['fear'].mean()*100, df['anger'].mean()*100,
df['anticipation'].mean()*100, df['trust'].mean()*100,
df['surprise'].mean()*100, df['positive'].mean()*100,
df['negative'].mean()*100, df['sadness'].mean()*100,
df['disgust'].mean()*100, df['joy'].mean()*100]
#         }
#
# dataFrame = pd.DataFrame(data=data)
#
# dataFrame.plot.bar(x="Emotions", y="Percentage", rot=70, title="Emotion
distribution")
#
# plt.show(block=True)
#
# datasecond = {"Emotions":["Fear", "Anger", "Anticipation", "Trust",
"Surprise", "Sadness", "Disgust", "Joy"],
#         "Percentage":[df['fear'].mean()*100, df['anger'].mean()*100,
df['anticipation'].mean()*100, df['trust'].mean()*100,
```

```
df['surprise'].mean()*100, df['sadness'].mean()*100,
df['disgust'].mean()*100, df['joy'].mean()*100]
#          }
# dataFramesecond = pd.DataFrame(data=datasecond)
#
# dataFramesecond.plot.bar(x="Emotions", y="Percentage", rot=70,
title="Emotion distribution")
#
# plt.show(block=True)

#Normalized emotions

#retweets
df['fear_normalized_retweet'] = df['fear'] * df['retweets']
df['anger_normalized_retweet'] = df['anger'] * df['retweets']
df['trust_normalized_retweet'] = df['trust'] * df['retweets']
df['surprise_normalized_retweet'] = df['surprise'] * df['retweets']
df['sadness_normalized_retweet'] = df['sadness'] * df['retweets']
df['disgust_normalized_retweet'] = df['disgust'] * df['retweets']
df['joy_normalized_retweet'] = df['joy'] * df['retweets']
df['anticipation_normalized_retweet'] = df['anticipation'] * df['retweets']

#likes
df['fear_normalized_likes'] = df['fear'] * df['likes']
df['anger_normalized_likes'] = df['anger'] * df['likes']
df['trust_normalized_likes'] = df['trust'] * df['likes']
df['surprise_normalized_likes'] = df['surprise'] * df['likes']
df['sadness_normalized_likes'] = df['sadness'] * df['likes']
df['disgust_normalized_likes'] = df['disgust'] * df['likes']
df['joy_normalized_likes'] = df['joy'] * df['likes']
df['anticipation_normalized_likes'] = df['anticipation'] * df['likes']

#followers
df['fear_normalized_followers'] = df['fear'] * df['author_followers']
df['anger_normalized_followers'] = df['anger'] * df['author_followers']
df['trust_normalized_followers'] = df['trust'] * df['author_followers']
df['surprise_normalized_followers'] = df['surprise'] *
df['author_followers']
df['sadness_normalized_followers'] = df['sadness'] * df['author_followers']
df['disgust_normalized_followers'] = df['disgust'] * df['author_followers']
df['joy_normalized_followers'] = df['joy'] * df['author_followers']
df['anticipation_normalized_followers'] = df['anticipation'] *
df['author_followers']


#averages table for graphs

#first panda dateframepje
#columns = ('fear_average', 'anger_average', 'antipication_average',
'trust_average', 'suprise_average', 'sadness_average', 'disgust_average',
'joy_average')


#emotions
fear_average = df['fear'].mean() / (df['fear'].mean() + df['anger'].mean()
+ df['anticipation'].mean() + df['trust'].mean() + df['surprise'].mean() +
df['sadness'].mean() + df['disgust'].mean() + df['joy'].mean())
anger_average = df['anger'].mean() / (df['fear'].mean() +
df['anger'].mean() + df['anticipation'].mean() + df['trust'].mean() +
df['surprise'].mean() + df['sadness'].mean() + df['disgust'].mean() +
df['joy'].mean())
```

```
anticipation_average = df['anticipation'].mean() / (df['fear'].mean() +
df['anger'].mean() + df['anticipation'].mean() + df['trust'].mean() +
df['surprise'].mean() + df['sadness'].mean() + df['disgust'].mean() +
df['joy'].mean())
trust_average = df['trust'].mean() / (df['fear'].mean() +
df['anger'].mean() + df['anticipation'].mean() + df['trust'].mean() +
df['surprise'].mean() + df['sadness'].mean() + df['disgust'].mean() +
df['joy'].mean())
surprise_average = df['surprise'].mean() / (df['fear'].mean() +
df['anger'].mean() + df['anticipation'].mean() + df['trust'].mean() +
df['surprise'].mean() + df['sadness'].mean() + df['disgust'].mean() +
df['joy'].mean())
sadness_average = df['sadness'].mean() / (df['fear'].mean() +
df['anger'].mean() + df['anticipation'].mean() + df['trust'].mean() +
df['surprise'].mean() + df['sadness'].mean() + df['disgust'].mean() +
df['joy'].mean())
disgust_average = df['disgust'].mean() / (df['fear'].mean() +
df['anger'].mean() + df['anticipation'].mean() + df['trust'].mean() +
df['surprise'].mean() + df['sadness'].mean() + df['disgust'].mean() +
df['joy'].mean())
joy_average = df['joy'].mean() / (df['fear'].mean() + df['anger'].mean() +
df['anticipation'].mean() + df['trust'].mean() + df['surprise'].mean() +
df['sadness'].mean() + df['disgust'].mean() + df['joy'].mean())

#normalized emotions retweet
fear_average_n_retweet = df['fear_normalized_retweet'].sum() /
(df['fear_normalized_retweet'].sum() + df['anger_normalized_retweet'].sum()
+ df['trust_normalized_retweet'].sum() +
df['surprise_normalized_retweet'].sum() +
df['sadness_normalized_retweet'].sum() +
df['disgust_normalized_retweet'].sum() + df['joy_normalized_retweet'].sum()
+ df['anticipation_normalized_retweet'].sum())
anger_average_n_retweet = df['anger_normalized_retweet'].sum() /
(df['fear_normalized_retweet'].sum() + df['anger_normalized_retweet'].sum()
+ df['trust_normalized_retweet'].sum() +
df['surprise_normalized_retweet'].sum() +
df['sadness_normalized_retweet'].sum() +
df['disgust_normalized_retweet'].sum() + df['joy_normalized_retweet'].sum()
+ df['anticipation_normalized_retweet'].sum())
trust_average_n_retweet = df['trust_normalized_retweet'].sum() /
(df['fear_normalized_retweet'].sum() + df['anger_normalized_retweet'].sum()
+ df['trust_normalized_retweet'].sum() +
df['surprise_normalized_retweet'].sum() +
df['sadness_normalized_retweet'].sum() +
df['disgust_normalized_retweet'].sum() + df['joy_normalized_retweet'].sum()
+ df['anticipation_normalized_retweet'].sum())
surprise_average_n_retweet = df['surprise_normalized_retweet'].sum() /
(df['fear_normalized_retweet'].sum() + df['anger_normalized_retweet'].sum()
+ df['trust_normalized_retweet'].sum() +
df['surprise_normalized_retweet'].sum() +
df['sadness_normalized_retweet'].sum() +
df['disgust_normalized_retweet'].sum() + df['joy_normalized_retweet'].sum()
+ df['anticipation_normalized_retweet'].sum())
sadness_average_n_retweet = df['sadness_normalized_retweet'].sum() /
(df['fear_normalized_retweet'].sum() + df['anger_normalized_retweet'].sum()
+ df['trust_normalized_retweet'].sum() +
df['surprise_normalized_retweet'].sum() +
df['sadness_normalized_retweet'].sum() +
df['disgust_normalized_retweet'].sum() + df['joy_normalized_retweet'].sum()
+ df['anticipation_normalized_retweet'].sum())
disgust_average_n_retweet = df['disgust_normalized_retweet'].sum() /
```

```
(df['fear_normalized_retweet'].sum() + df['anger_normalized_retweet'].sum()
+ df['trust_normalized_retweet'].sum() +
df['surprise_normalized_retweet'].sum() +
df['sadness_normalized_retweet'].sum() +
df['disgust_normalized_retweet'].sum() + df['joy_normalized_retweet'].sum()
+ df['anticipation_normalized_retweet'].sum())
joy_average_n_retweet = df['joy_normalized_retweet'].sum() /
(df['fear_normalized_retweet'].sum() + df['anger_normalized_retweet'].sum()
+ df['trust_normalized_retweet'].sum() +
df['surprise_normalized_retweet'].sum() +
df['sadness_normalized_retweet'].sum() +
df['disgust_normalized_retweet'].sum() + df['joy_normalized_retweet'].sum()
+ df['anticipation_normalized_retweet'].sum())
anticipation_average_n_retweet =
df['anticipation_normalized_retweet'].sum() /
(df['fear_normalized_retweet'].sum() + df['anger_normalized_retweet'].sum()
+ df['trust_normalized_retweet'].sum() +
df['surprise_normalized_retweet'].sum() +
df['sadness_normalized_retweet'].sum() +
df['disgust_normalized_retweet'].sum() + df['joy_normalized_retweet'].sum()
+ df['anticipation_normalized_retweet'].sum())

#normalized emotions likes
fear_average_n_likes = df['fear_normalized_likes'].sum() /
(df['fear_normalized_likes'].sum() + df['anger_normalized_likes'].sum() +
df['trust_normalized_likes'].sum() + df['surprise_normalized_likes'].sum()
+ df['sadness_normalized_likes'].sum() +
df['disgust_normalized_likes'].sum() + df['joy_normalized_likes'].sum() +
df['anticipation_normalized_likes'].sum())
anger_average_n_likes = df['anger_normalized_likes'].sum() /
(df['fear_normalized_likes'].sum() + df['anger_normalized_likes'].sum() +
df['trust_normalized_likes'].sum() + df['surprise_normalized_likes'].sum()
+ df['sadness_normalized_likes'].sum() +
df['disgust_normalized_likes'].sum() + df['joy_normalized_likes'].sum() +
df['anticipation_normalized_likes'].sum())
trust_average_n_likes = df['trust_normalized_likes'].sum() /
(df['fear_normalized_likes'].sum() + df['anger_normalized_likes'].sum() +
df['trust_normalized_likes'].sum() + df['surprise_normalized_likes'].sum()
+ df['sadness_normalized_likes'].sum() +
df['disgust_normalized_likes'].sum() + df['joy_normalized_likes'].sum() +
df['anticipation_normalized_likes'].sum())
surprise_average_n_likes = df['surprise_normalized_likes'].sum() /
(df['fear_normalized_likes'].sum() + df['anger_normalized_likes'].sum() +
df['trust_normalized_likes'].sum() + df['surprise_normalized_likes'].sum()
+ df['sadness_normalized_likes'].sum() +
df['disgust_normalized_likes'].sum() + df['joy_normalized_likes'].sum() +
df['anticipation_normalized_likes'].sum())
sadness_average_n_likes = df['sadness_normalized_likes'].sum() /
(df['fear_normalized_likes'].sum() + df['anger_normalized_likes'].sum() +
df['trust_normalized_likes'].sum() + df['surprise_normalized_likes'].sum()
+ df['sadness_normalized_likes'].sum() +
df['disgust_normalized_likes'].sum() + df['joy_normalized_likes'].sum() +
df['anticipation_normalized_likes'].sum())
disgust_average_n_likes = df['disgust_normalized_likes'].sum() /
(df['fear_normalized_likes'].sum() + df['anger_normalized_likes'].sum() +
df['trust_normalized_likes'].sum() + df['surprise_normalized_likes'].sum()
+ df['sadness_normalized_likes'].sum() +
df['disgust_normalized_likes'].sum() + df['joy_normalized_likes'].sum() +
df['anticipation_normalized_likes'].sum())
joy_average_n_likes = df['joy_normalized_likes'].sum() /
(df['fear_normalized_likes'].sum() + df['anger_normalized_likes'].sum() +
```

```
df['trust_normalized_likes'].sum() + df['surprise_normalized_likes'].sum()
+ df['sadness_normalized_likes'].sum() +
df['disgust_normalized_likes'].sum() + df['joy_normalized_likes'].sum() +
df['anticipation_normalized_likes'].sum())
anticipation_average_n_likes = df['anticipation_normalized_likes'].sum() /
(df['fear_normalized_likes'].sum() + df['anger_normalized_likes'].sum() +
df['trust_normalized_likes'].sum() + df['surprise_normalized_likes'].sum()
+ df['sadness_normalized_likes'].sum() +
df['disgust_normalized_likes'].sum() + df['joy_normalized_likes'].sum() +
df['anticipation_normalized_likes'].sum())

#normalized emotions followers
fear_average_n_followers = df['fear_normalized_followers'].sum() /
(df['fear_normalized_followers'].sum() +
df['anger_normalized_followers'].sum() +
df['trust_normalized_followers'].sum() +
df['surprise_normalized_followers'].sum() +
df['sadness_normalized_followers'].sum() +
df['disgust_normalized_followers'].sum() +
df['joy_normalized_followers'].sum() +
df['anticipation_normalized_followers'].sum())
anger_average_n_followers = df['anger_normalized_followers'].sum() /
(df['fear_normalized_followers'].sum() +
df['anger_normalized_followers'].sum() +
df['trust_normalized_followers'].sum() +
df['surprise_normalized_followers'].sum() +
df['sadness_normalized_followers'].sum() +
df['disgust_normalized_followers'].sum() +
df['joy_normalized_followers'].sum() +
df['anticipation_normalized_followers'].sum())
trust_average_n_followers = df['trust_normalized_followers'].sum() /
(df['fear_normalized_followers'].sum() +
df['anger_normalized_followers'].sum() +
df['trust_normalized_followers'].sum() +
df['surprise_normalized_followers'].sum() +
df['sadness_normalized_followers'].sum() +
df['disgust_normalized_followers'].sum() +
df['joy_normalized_followers'].sum() +
df['anticipation_normalized_followers'].sum())
surprise_average_n_followers = df['surprise_normalized_followers'].sum() /
(df['fear_normalized_followers'].sum() +
df['anger_normalized_followers'].sum() +
df['trust_normalized_followers'].sum() +
df['surprise_normalized_followers'].sum() +
df['sadness_normalized_followers'].sum() +
df['disgust_normalized_followers'].sum() +
df['joy_normalized_followers'].sum() +
df['anticipation_normalized_followers'].sum())
sadness_average_n_followers = df['sadness_normalized_followers'].sum() /
(df['fear_normalized_followers'].sum() +
df['anger_normalized_followers'].sum() +
df['trust_normalized_followers'].sum() +
df['surprise_normalized_followers'].sum() +
df['sadness_normalized_followers'].sum() +
df['disgust_normalized_followers'].sum() +
df['joy_normalized_followers'].sum() +
df['anticipation_normalized_followers'].sum())
disgust_average_n_followers = df['disgust_normalized_followers'].sum() /
(df['fear_normalized_followers'].sum() +
df['anger_normalized_followers'].sum() +
df['trust_normalized_followers'].sum() +
```

```
df['surprise_normalized_followers'].sum() +
df['sadness_normalized_followers'].sum() +
df['disgust_normalized_followers'].sum() +
df['joy_normalized_followers'].sum() +
df['anticipation_normalized_followers'].sum())
joy_average_n_followers = df['joy_normalized_followers'].sum() /
(df['fear_normalized_followers'].sum() +
df['anger_normalized_followers'].sum() +
df['trust_normalized_followers'].sum() +
df['surprise_normalized_followers'].sum() +
df['sadness_normalized_followers'].sum() +
df['disgust_normalized_followers'].sum() +
df['joy_normalized_followers'].sum() +
df['anticipation_normalized_followers'].sum())
anticipation_average_n_followers =
df['anticipation_normalized_followers'].sum() /
(df['fear_normalized_followers'].sum() +
df['anger_normalized_followers'].sum() +
df['trust_normalized_followers'].sum() +
df['surprise_normalized_followers'].sum() +
df['sadness_normalized_followers'].sum() +
df['disgust_normalized_followers'].sum() +
df['joy_normalized_followers'].sum() +
df['anticipation_normalized_followers'].sum())


# WAARDES WEGSCHRIJVEN EN OPSLAAN IN DATAFRAMES

EM = pd.DataFrame({
    "fear":[fear_average],
    "anger":[anger_average],
    "trust":[trust_average],
    "surprise":[surprise_average],
    "sadness":[sadness_average],
    "disgust":[disgust_average],
    "joy":[joy_average],
    "anticipation":[anticipation_average] },
    index=["t1a"] )

AB = EM * len(df)

NO = pd.DataFrame({
    "fear":[fear_average_n_retweet, fear_average_n_likes,
fear_average_n_followers],
    "anger":[anger_average_n_retweet, anger_average_n_likes,
anger_average_n_followers],
    "trust":[trust_average_n_retweet, trust_average_n_likes,
trust_average_n_followers],
    "surprise":[surprise_average_n_retweet, surprise_average_n_likes,
surprise_average_n_followers],
    "sadness":[sadness_average_n_retweet, sadness_average_n_likes,
sadness_average_n_followers],
    "disgust":[disgust_average_n_retweet, disgust_average_n_likes,
disgust_average_n_followers],
    "joy":[joy_average_n_retweet, joy_average_n_likes,
joy_average_n_followers],
    "anticipation":[anticipation_average_n_retweet,
anticipation_average_n_likes, anticipation_average_n_followers] },
    index=["t1b", "t1c", "t1d"] )

# SAVE FILES
```

```
df.to_csv('DA_9_Flooding_US_29-08-2022-30-08-2022.csv') #GIVE NAME BETWEEN
´....´

EM=EM*100
EM.to_csv('EM_9_US_Flooding.csv') #GIVE NAME BETWEEN ´....´

NO=NO*100
NO.to_csv('NO_9_US_Flooding.csv') #GIVE NAME BETWEEN ´....´

AB.to_csv('AB_9_US_Flooding.csv') #GIVE NAME BETWEEN ´....´
```

Appendix III: Python code visualisation

```
# Python code created by Marieke Jacobs (4246918) at Utrecht University at
22-7-2022
# For MSc Project: 'Emotional response to climate hazards'
# In case of questions or further explanation about usage, point of
contact: mariekejacobs96@gmail.com

import matplotlib.pyplot as plt

import pandas as pd
import numpy as np

#Read data files saved from DefCollector
#Collected per 24 hours in DefCollector, where -14  was the first collected
interval (in this case 14 days before the actual  climate hazard)
# WW means worldwide, Antarctica was keyword here.

EM_2 = pd.read_csv('EM_2_WW_Antarctica.csv', index_col=0).T

ABL_m14 = pd.read_csv('AB_-14_WW_Antarctica.csv', index_col=0).T
ABL_m13 = pd.read_csv('AB_-13_WW_Antarctica.csv', index_col=0).T
ABL_m12 = pd.read_csv('AB_-12_WW_Antarctica.csv', index_col=0).T
ABL_m11 = pd.read_csv('AB_-11_WW_Antarctica.csv', index_col=0).T
ABL_m10 = pd.read_csv('AB_-10_WW_Antarctica.csv', index_col=0).T
ABL_m9 = pd.read_csv('AB_-9_WW_Antarctica.csv', index_col=0).T
ABL_m8 = pd.read_csv('AB_-8_WW_Antarctica.csv', index_col=0).T
ABL_m7 = pd.read_csv('AB_-7_WW_Antarctica.csv', index_col=0).T
ABL_m6 = pd.read_csv('AB_-6_WW_Antarctica.csv', index_col=0).T
ABL_m5 = pd.read_csv('AB_-5_WW_Antarctica.csv', index_col=0).T
ABL_m4 = pd.read_csv('AB_-4_WW_Antarctica.csv', index_col=0).T
ABL_m3 = pd.read_csv('AB_-3_WW_Antarctica.csv', index_col=0).T
ABL_m2 = pd.read_csv('AB_-2_WW_Antarctica.csv', index_col=0).T
ABL_m1 = pd.read_csv('AB_-1_WW_Antarctica.csv', index_col=0).T
ABL_0 = pd.read_csv('AB_0_WW_Antarctica.csv', index_col=0).T
ABL_1 = pd.read_csv('AB_1_WW_Antarctica.csv', index_col=0).T
ABL_2 = pd.read_csv('AB_2_WW_Antarctica.csv', index_col=0).T
ABL_3 = pd.read_csv('AB_3_WW_Antarctica.csv', index_col=0).T
ABL_4 = pd.read_csv('AB_4_WW_Antarctica.csv', index_col=0).T
ABL_5 = pd.read_csv('AB_5_WW_Antarctica.csv', index_col=0).T
ABL_6 = pd.read_csv('AB_6_WW_Antarctica.csv', index_col=0).T
ABL_7 = pd.read_csv('AB_7_WW_Antarctica.csv', index_col=0).T
ABL_8 = pd.read_csv('AB_8_WW_Antarctica.csv', index_col=0).T
ABL_9 = pd.read_csv('AB_9_WW_Antarctica.csv', index_col=0).T
ABL_10 = pd.read_csv('AB_10_WW_Antarctica.csv', index_col=0).T
ABL_11 = pd.read_csv('AB_11_WW_Antarctica.csv', index_col=0).T
ABL_12 = pd.read_csv('AB_12_WW_Antarctica.csv', index_col=0).T
ABL_13 = pd.read_csv('AB_13_WW_Antarctica.csv', index_col=0).T
ABL_14 = pd.read_csv('AB_14_WW_Antarctica.csv', index_col=0).T


ABL_m14['2-3']=ABL_m14
ABL_m14['3-3']=ABL_m13
ABL_m14['4-3']=ABL_m12
ABL_m14['5-3']=ABL_m11
ABL_m14['6-3']=ABL_m10
ABL_m14['7-3']=ABL_m9
ABL_m14['8-3']=ABL_m8
ABL_m14['9-3']=ABL_m7
```

```
ABL_m14['10-3']=ABL_m6
ABL_m14['11-3']=ABL_m5
ABL_m14['12-3']=ABL_m4
ABL_m14['13-3']=ABL_m3
ABL_m14['14-3']=ABL_m2
ABL_m14['15-3']=ABL_m1
ABL_m14['16-3']=ABL_0
ABL_m14['17-3']=ABL_1
ABL_m14['18-3']=ABL_2
ABL_m14['19-3']=ABL_3
ABL_m14['20-3']=ABL_4
ABL_m14['21-3']=ABL_5
ABL_m14['22-3']=ABL_6
ABL_m14['23-3']=ABL_7
ABL_m14['24-3']=ABL_8
ABL_m14['25-3']=ABL_9
ABL_m14['26-3']=ABL_10
ABL_m14['27-3']=ABL_11
ABL_m14['28-3']=ABL_12
ABL_m14['29-3']=ABL_13
ABL_m14['30-3']=ABL_14


del ABL_m14['t1a']
ABL_m14=ABL_m14.T

#Normalized emotions

EML_m14 = pd.read_csv('EM_-14_WW_Antarctica.csv', index_col=0).T
EML_m13 = pd.read_csv('EM_-13_WW_Antarctica.csv', index_col=0).T
EML_m12 = pd.read_csv('EM_-12_WW_Antarctica.csv', index_col=0).T
EML_m11 = pd.read_csv('EM_-11_WW_Antarctica.csv', index_col=0).T
EML_m10 = pd.read_csv('EM_-10_WW_Antarctica.csv', index_col=0).T
EML_m9 = pd.read_csv('EM_-9_WW_Antarctica.csv', index_col=0).T
EML_m8 = pd.read_csv('EM_-8_WW_Antarctica.csv', index_col=0).T
EML_m7 = pd.read_csv('EM_-7_WW_Antarctica.csv', index_col=0).T
EML_m6 = pd.read_csv('EM_-6_WW_Antarctica.csv', index_col=0).T
EML_m5 = pd.read_csv('EM_-5_WW_Antarctica.csv', index_col=0).T
EML_m4 = pd.read_csv('EM_-4_WW_Antarctica.csv', index_col=0).T
EML_m3 = pd.read_csv('EM_-3_WW_Antarctica.csv', index_col=0).T
EML_m2 = pd.read_csv('EM_-2_WW_Antarctica.csv', index_col=0).T
EML_m1 = pd.read_csv('EM_-1_WW_Antarctica.csv', index_col=0).T
EML_0 = pd.read_csv('EM_0_WW_Antarctica.csv', index_col=0).T
EML_1 = pd.read_csv('EM_1_WW_Antarctica.csv', index_col=0).T
EML_2 = pd.read_csv('EM_2_WW_Antarctica.csv', index_col=0).T
EML_3 = pd.read_csv('EM_3_WW_Antarctica.csv', index_col=0).T
EML_4 = pd.read_csv('EM_4_WW_Antarctica.csv', index_col=0).T
EML_5 = pd.read_csv('EM_5_WW_Antarctica.csv', index_col=0).T
EML_6 = pd.read_csv('EM_6_WW_Antarctica.csv', index_col=0).T
EML_7 = pd.read_csv('EM_7_WW_Antarctica.csv', index_col=0).T
EML_8 = pd.read_csv('EM_8_WW_Antarctica.csv', index_col=0).T
EML_9 = pd.read_csv('EM_9_WW_Antarctica.csv', index_col=0).T
EML_10 = pd.read_csv('EM_10_WW_Antarctica.csv', index_col=0).T
EML_11 = pd.read_csv('EM_11_WW_Antarctica.csv', index_col=0).T
EML_12 = pd.read_csv('EM_12_WW_Antarctica.csv', index_col=0).T
EML_13 = pd.read_csv('EM_13_WW_Antarctica.csv', index_col=0).T
EML_14 = pd.read_csv('EM_14_WW_Antarctica.csv', index_col=0).T


EML_m14['2-3']=EML_m14
EML_m14['3-3']=EML_m13
```

```
EML_m14['4-3']=EML_m12
EML_m14['5-3']=EML_m11
EML_m14['6-3']=EML_m10
EML_m14['7-3']=EML_m9
EML_m14['8-3']=EML_m8
EML_m14['9-3']=EML_m7
EML_m14['10-3']=EML_m6
EML_m14['11-3']=EML_m5
EML_m14['12-3']=EML_m4
EML_m14['13-3']=EML_m3
EML_m14['14-3']=EML_m2
EML_m14['15-3']=EML_m1
EML_m14['16-3']=EML_0
EML_m14['17-3']=EML_1
EML_m14['18-3']=EML_2
EML_m14['19-3']=EML_3
EML_m14['20-3']=EML_4
EML_m14['21-3']=EML_5
EML_m14['22-3']=EML_6
EML_m14['23-3']=EML_7
EML_m14['24-3']=EML_8
EML_m14['25-3']=EML_9
EML_m14['26-3']=EML_10
EML_m14['27-3']=EML_11
EML_m14['28-3']=EML_12
EML_m14['29-3']=EML_13
EML_m14['30-3']=EML_14

del EML_m14['t1a']
EML_m14=EML_m14.T


NOL_m14 = pd.read_csv('NO_-14_WW_Antarctica.csv', index_col=0).T
NOL_m13 = pd.read_csv('NO_-13_WW_Antarctica.csv', index_col=0).T
NOL_m12 = pd.read_csv('NO_-12_WW_Antarctica.csv', index_col=0).T
NOL_m11 = pd.read_csv('NO_-11_WW_Antarctica.csv', index_col=0).T
NOL_m10 = pd.read_csv('NO_-10_WW_Antarctica.csv', index_col=0).T
NOL_m9 = pd.read_csv('NO_-9_WW_Antarctica.csv', index_col=0).T
NOL_m8 = pd.read_csv('NO_-8_WW_Antarctica.csv', index_col=0).T
NOL_m7 = pd.read_csv('NO_-7_WW_Antarctica.csv', index_col=0).T
NOL_m6 = pd.read_csv('NO_-6_WW_Antarctica.csv', index_col=0).T
NOL_m5 = pd.read_csv('NO_-5_WW_Antarctica.csv', index_col=0).T
NOL_m4 = pd.read_csv('NO_-4_WW_Antarctica.csv', index_col=0).T
NOL_m3 = pd.read_csv('NO_-3_WW_Antarctica.csv', index_col=0).T
NOL_m2 = pd.read_csv('NO_-2_WW_Antarctica.csv', index_col=0).T
NOL_m1 = pd.read_csv('NO_-1_WW_Antarctica.csv', index_col=0).T
NOL_0 = pd.read_csv('NO_0_WW_Antarctica.csv', index_col=0).T
NOL_1 = pd.read_csv('NO_1_WW_Antarctica.csv', index_col=0).T
NOL_2 = pd.read_csv('NO_2_WW_Antarctica.csv', index_col=0).T
NOL_3 = pd.read_csv('NO_3_WW_Antarctica.csv', index_col=0).T
NOL_4 = pd.read_csv('NO_4_WW_Antarctica.csv', index_col=0).T
NOL_5 = pd.read_csv('NO_5_WW_Antarctica.csv', index_col=0).T
NOL_6 = pd.read_csv('NO_6_WW_Antarctica.csv', index_col=0).T
NOL_7 = pd.read_csv('NO_7_WW_Antarctica.csv', index_col=0).T
NOL_8 = pd.read_csv('NO_8_WW_Antarctica.csv', index_col=0).T
NOL_9 = pd.read_csv('NO_9_WW_Antarctica.csv', index_col=0).T
NOL_10 = pd.read_csv('NO_10_WW_Antarctica.csv', index_col=0).T
NOL_11 = pd.read_csv('NO_11_WW_Antarctica.csv', index_col=0).T
NOL_12 = pd.read_csv('NO_12_WW_Antarctica.csv', index_col=0).T
NOL_13 = pd.read_csv('NO_13_WW_Antarctica.csv', index_col=0).T
NOL_14 = pd.read_csv('NO_14_WW_Antarctica.csv', index_col=0).T
```

```
FORMAT1=ABL_m14.T


NOL_m14['2-3 Tweet'] = FORMAT1['2-3'].T
NOL_m14['2-3 Retweets'] = NOL_m14['t1b']
NOL_m14['2-3 Likes'] = NOL_m14['t1c']
NOL_m14['2-3 Followers'] = NOL_m14['t1d']

NOL_m14['3-3 Tweet'] = FORMAT1['3-3'].T
NOL_m14['3-3 Retweets'] = NOL_m13['t1b']
NOL_m14['3-3 Likes'] = NOL_m13['t1c']
NOL_m14['3-3 Followers'] = NOL_m13['t1d']

NOL_m14['4-3 Tweet'] = FORMAT1['4-3'].T
NOL_m14['4-3 Retweets'] = NOL_m12['t1b']
NOL_m14['4-3 Likes'] = NOL_m12['t1c']
NOL_m14['4-3 Followers'] = NOL_m12['t1d']

NOL_m14['5-3 Tweet'] = FORMAT1['5-3'].T
NOL_m14['5-3 Retweets'] = NOL_m11['t1b']
NOL_m14['5-3 Likes'] = NOL_m11['t1c']
NOL_m14['5-3 Followers'] = NOL_m11['t1d']

NOL_m14['6-3 Tweet'] = FORMAT1['6-3'].T
NOL_m14['6-3 Retweets'] = NOL_m10['t1b']
NOL_m14['6-3 Likes'] = NOL_m10['t1c']
NOL_m14['6-3 Followers'] = NOL_m10['t1d']

NOL_m14['7-3 Tweet'] = FORMAT1['7-3'].T
NOL_m14['7-3 Retweets'] = NOL_m9['t1b']
NOL_m14['7-3 Likes'] = NOL_m9['t1c']
NOL_m14['7-3 Followers'] = NOL_m9['t1d']

NOL_m14['8-3 Tweet'] = FORMAT1['8-3'].T
NOL_m14['8-3 Retweets'] = NOL_m8['t1b']
NOL_m14['8-3 Likes'] = NOL_m8['t1c']
NOL_m14['8-3 Followers'] = NOL_m8['t1d']

NOL_m14['9-3 Tweet'] = FORMAT1['9-3'].T
NOL_m14['9-3 Retweets'] = NOL_m7['t1b']
NOL_m14['9-3 Likes'] = NOL_m7['t1c']
NOL_m14['9-3 Followers'] = NOL_m7['t1d']

NOL_m14['10-3 Tweet'] = FORMAT1['10-3'].T
NOL_m14['10-3 Retweets'] = NOL_m6['t1b']
NOL_m14['10-3 Likes'] = NOL_m6['t1c']
NOL_m14['10-3 Followers'] = NOL_m6['t1d']

NOL_m14['11-3 Tweet'] = FORMAT1['11-3'].T
NOL_m14['11-3 Retweets'] = NOL_m5['t1b']
NOL_m14['11-3 Likes'] = NOL_m5['t1c']
NOL_m14['11-3 Followers'] = NOL_m5['t1d']

NOL_m14['12-3 Tweet'] = FORMAT1['12-3'].T
NOL_m14['12-3 Retweets'] = NOL_m4['t1b']
NOL_m14['12-3 Likes'] = NOL_m4['t1c']
NOL_m14['12-3 Followers'] = NOL_m4['t1d']

NOL_m14['13-3 Tweet'] = FORMAT1['13-3'].T
NOL_m14['13-3 Retweets'] = NOL_m3['t1b']
```

```
NOL_m14['13-3 Likes'] = NOL_m3['t1c']
NOL_m14['13-3 Followers'] = NOL_m3['t1d']

NOL_m14['14-3 Tweet'] = FORMAT1['14-3'].T
NOL_m14['14-3 Retweets'] = NOL_m2['t1b']
NOL_m14['14-3 Likes'] = NOL_m2['t1c']
NOL_m14['14-3 Followers'] = NOL_m2['t1d']

NOL_m14['15-3 Tweet'] = FORMAT1['15-3'].T
NOL_m14['15-3 Retweets'] = NOL_m1['t1b']
NOL_m14['15-3 Likes'] = NOL_m1['t1c']
NOL_m14['15-3 Followers'] = NOL_m1['t1d']

NOL_m14['16-3 Tweet'] = FORMAT1['16-3'].T
NOL_m14['16-3 Retweets'] = NOL_0['t1b']
NOL_m14['16-3 Likes'] = NOL_0['t1c']
NOL_m14['16-3 Followers'] = NOL_0['t1d']

NOL_m14['17-3 Tweet'] = FORMAT1['17-3'].T
NOL_m14['17-3 Retweets'] = NOL_1['t1b']
NOL_m14['17-3 Likes'] = NOL_1['t1c']
NOL_m14['17-3 Followers'] = NOL_1['t1d']

NOL_m14['18-3 Tweet'] = FORMAT1['18-3']
NOL_m14['18-3 Retweets'] = NOL_2['t1b']
NOL_m14['18-3 Likes'] = NOL_2['t1c']
NOL_m14['18-3 Followers'] = NOL_2['t1d']

NOL_m14['19-3 Tweet'] = FORMAT1['19-3']
NOL_m14['19-3 Retweets'] = NOL_3['t1b']
NOL_m14['19-3 Likes'] = NOL_3['t1c']
NOL_m14['19-3 Followers'] = NOL_3['t1d']

NOL_m14['20-3 Tweet'] = FORMAT1['20-3']
NOL_m14['20-3 Retweets'] = NOL_4['t1b']
NOL_m14['20-3 Likes'] = NOL_4['t1c']
NOL_m14['20-3 Followers'] = NOL_4['t1d']

NOL_m14['21-3 Tweet'] = FORMAT1['21-3']
NOL_m14['21-3 Retweets'] = NOL_5['t1b']
NOL_m14['21-3 Likes'] = NOL_5['t1c']
NOL_m14['21-3 Followers'] = NOL_5['t1d']

NOL_m14['22-3 Tweet'] = FORMAT1['22-3']
NOL_m14['22-3 Retweets'] = NOL_6['t1b']
NOL_m14['22-3 Likes'] = NOL_6['t1c']
NOL_m14['22-3 Followers'] = NOL_6['t1d']

NOL_m14['23-3 Tweet'] = FORMAT1['23-3']
NOL_m14['23-3 Retweets'] = NOL_7['t1b']
NOL_m14['23-3 Likes'] = NOL_7['t1c']
NOL_m14['23-3 Followers'] = NOL_7['t1d']

NOL_m14['24-3 Tweet'] = FORMAT1['24-3']
NOL_m14['24-3 Retweets'] = NOL_8['t1b']
NOL_m14['24-3 Likes'] = NOL_8['t1c']
NOL_m14['24-3 Followers'] = NOL_8['t1d']

NOL_m14['25-3 Tweet'] = FORMAT1['25-3']
NOL_m14['25-3 Retweets'] = NOL_9['t1b']
NOL_m14['25-3 Likes'] = NOL_9['t1c']
```

```
NOL_m14['25-3 Followers'] = NOL_9['t1d']

NOL_m14['26-3 Tweet'] = FORMAT1['26-3']
NOL_m14['26-3 Retweets'] = NOL_10['t1b']
NOL_m14['26-3 Likes'] = NOL_10['t1c']
NOL_m14['26-3 Followers'] = NOL_10['t1d']

NOL_m14['27-3 Tweet'] = FORMAT1['27-3']
NOL_m14['27-3 Retweets'] = NOL_11['t1b']
NOL_m14['27-3 Likes'] = NOL_11['t1c']
NOL_m14['27-3 Followers'] = NOL_11['t1d']

NOL_m14['28-3 Tweet'] = FORMAT1['28-3']
NOL_m14['28-3 Retweets'] = NOL_12['t1b']
NOL_m14['28-3 Likes'] = NOL_12['t1c']
NOL_m14['28-3 Followers'] = NOL_12['t1d']

NOL_m14['29-3 Tweet'] = FORMAT1['29-3']
NOL_m14['29-3 Retweets'] = NOL_13['t1b']
NOL_m14['29-3 Likes'] = NOL_13['t1c']
NOL_m14['29-3 Followers'] = NOL_13['t1d']

NOL_m14['30-3 Tweet'] = FORMAT1['30-3']
NOL_m14['30-3 Retweets'] = NOL_14['t1b']
NOL_m14['30-3 Likes'] = NOL_14['t1c']
NOL_m14['30-3 Followers'] = NOL_14['t1d']

del NOL_m14['t1b']
del NOL_m14['t1c']
del NOL_m14['t1d']


REL=EM_2.copy()
del REL['t1a']


REL['2-3']=NOL_m14['2-3 Retweets']
REL['3-3']=NOL_m14['3-3 Retweets']
REL['4-3']=NOL_m14['4-3 Retweets']
REL['5-3']=NOL_m14['5-3 Retweets']
REL['6-3']=NOL_m14['6-3 Retweets']
REL['7-3']=NOL_m14['7-3 Retweets']
REL['8-3']=NOL_m14['8-3 Retweets']
REL['9-3']=NOL_m14['9-3 Retweets']
REL['10-3']=NOL_m14['10-3 Retweets']
REL['11-3']=NOL_m14['11-3 Retweets']
REL['12-3']=NOL_m14['12-3 Retweets']
REL['13-3']=NOL_m14['13-3 Retweets']
REL['14-3']=NOL_m14['14-3 Retweets']
REL['15-3']=NOL_m14['15-3 Retweets']
REL['16-3']=NOL_m14['16-3 Retweets']
REL['17-3']=NOL_m14['17-3 Retweets']
REL['18-3']=NOL_m14['18-3 Retweets']
REL['19-3']=NOL_m14['19-3 Retweets']
REL['20-3']=NOL_m14['20-3 Retweets']
REL['21-3']=NOL_m14['21-3 Retweets']
REL['22-3']=NOL_m14['22-3 Retweets']
REL['23-3']=NOL_m14['23-3 Retweets']
REL['24-3']=NOL_m14['24-3 Retweets']
REL['25-3']=NOL_m14['25-3 Retweets']
REL['26-3']=NOL_m14['26-3 Retweets']
```

```
REL['27-3']=NOL_m14['27-3 Retweets']
REL['28-3']=NOL_m14['28-3 Retweets']
REL['29-3']=NOL_m14['29-3 Retweets']
REL['30-3']=NOL_m14['30-3 Retweets']

RELT=REL.T

LIL=EM_2.copy()
del LIL['t1a']


LIL['2-3']=NOL_m14['2-3 Likes']
LIL['3-3']=NOL_m14['3-3 Likes']
LIL['4-3']=NOL_m14['4-3 Likes']
LIL['5-3']=NOL_m14['5-3 Likes']
LIL['6-3']=NOL_m14['6-3 Likes']
LIL['7-3']=NOL_m14['7-3 Likes']
LIL['8-3']=NOL_m14['8-3 Likes']
LIL['9-3']=NOL_m14['9-3 Likes']
LIL['10-3']=NOL_m14['10-3 Likes']
LIL['11-3']=NOL_m14['11-3 Likes']
LIL['12-3']=NOL_m14['12-3 Likes']
LIL['13-3']=NOL_m14['13-3 Likes']
LIL['14-3']=NOL_m14['14-3 Likes']
LIL['15-3']=NOL_m14['15-3 Likes']
LIL['16-3']=NOL_m14['16-3 Likes']
LIL['17-3']=NOL_m14['17-3 Likes']
LIL['18-3']=NOL_m14['18-3 Likes']
LIL['19-3']=NOL_m14['19-3 Likes']
LIL['20-3']=NOL_m14['20-3 Likes']
LIL['21-3']=NOL_m14['21-3 Likes']
LIL['22-3']=NOL_m14['22-3 Likes']
LIL['23-3']=NOL_m14['23-3 Likes']
LIL['24-3']=NOL_m14['24-3 Likes']
LIL['25-3']=NOL_m14['25-3 Likes']
LIL['26-3']=NOL_m14['26-3 Likes']
LIL['27-3']=NOL_m14['27-3 Likes']
LIL['28-3']=NOL_m14['28-3 Likes']
LIL['29-3']=NOL_m14['29-3 Likes']
LIL['30-3']=NOL_m14['30-3 Likes']

LILT=LIL.T


FOL=EM_2.copy()
del FOL['t1a']

FOL['2-3']=NOL_m14['2-3 Followers']
FOL['3-3']=NOL_m14['3-3 Followers']
FOL['4-3']=NOL_m14['4-3 Followers']
FOL['5-3']=NOL_m14['5-3 Followers']
FOL['6-3']=NOL_m14['6-3 Followers']
FOL['7-3']=NOL_m14['7-3 Followers']
FOL['8-3']=NOL_m14['8-3 Followers']
FOL['9-3']=NOL_m14['9-3 Followers']
FOL['10-3']=NOL_m14['10-3 Followers']
FOL['11-3']=NOL_m14['11-3 Followers']
FOL['12-3']=NOL_m14['12-3 Followers']
FOL['13-3']=NOL_m14['13-3 Followers']
FOL['14-3']=NOL_m14['14-3 Followers']
FOL['15-3']=NOL_m14['15-3 Followers']
```

```
FOL['16-3']=NOL_m14['16-3 Followers']
FOL['17-3']=NOL_m14['17-3 Followers']
FOL['18-3']=NOL_m14['18-3 Followers']
FOL['19-3']=NOL_m14['19-3 Followers']
FOL['20-3']=NOL_m14['20-3 Followers']
FOL['21-3']=NOL_m14['21-3 Followers']
FOL['22-3']=NOL_m14['22-3 Followers']
FOL['23-3']=NOL_m14['23-3 Followers']
FOL['24-3']=NOL_m14['24-3 Followers']
FOL['25-3']=NOL_m14['25-3 Followers']
FOL['26-3']=NOL_m14['26-3 Followers']
FOL['27-3']=NOL_m14['27-3 Followers']
FOL['28-3']=NOL_m14['28-3 Followers']
FOL['29-3']=NOL_m14['29-3 Followers']
FOL['30-3']=NOL_m14['30-3 Followers']

FOLT=FOL.T

#############################################################


x=['2-3', '3-3', '4-3', '5-3', '6-3', '7-3', '8-3', '9-3', '10-3', '11-3',
'12-3', '13-3', '14-3', '15-3', '16-3', '17-3', '18-3', '19-3', '20-3',
'21-3', '22-3', '23-3', '24-3', '25-3', '26-3', '27-3', '28-3', '29-3',
'30-3']
event=['17-3', '17-3', '17-3']
eventviral=['18-3', '18-3', '18-3']
secondevent=['25-3', '25-3', '25-3']
y=[0,50,100]
z=[0,2000,5000]

#1#1#1#1#1#1#1#1#1#1#1#1#1#1# Figure 1

plt.stackplot(x, ABL_m14['fear'], ABL_m14['sadness'], ABL_m14['anger'],
ABL_m14['disgust'], ABL_m14['surprise'], ABL_m14['anticipation'],
ABL_m14['trust'], ABL_m14['joy'], labels=['fear', 'sadness', 'anger',
'disgust', 'surprise', 'anticipation', 'trust', 'joy'], colors=['salmon',
'gold', 'firebrick', 'darkorange', 'lightskyblue', 'palegreen',
'limegreen', 'seagreen'])
plt.plot(event,z,label='Event', color='k')
plt.plot(eventviral,z,label='Event went viral', color='k')
plt.xlabel("Time intervals (per 24 hours)")
plt.ylabel("Number of tweets")
plt.legend(bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.subplots_adjust(left=0.15, bottom=0.2, right=0.8, top=0.9)
plt.title("Figure 1: Emotion distribution (24 hours) for the word
'Antarctica'",
          fontsize = 8, loc='left')
plt.xticks(rotation=90)
plt.xticks(rotation=90)
#get handles and labels
handles, labels = plt.gca().get_legend_handles_labels()
#specify order of items in legend
order = [8,7,6,5,4,3,2,1,0]
#add legend to plot
plt.legend([handles[idx] for idx in order],[labels[idx] for idx in order],
bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.show()
plt.savefig("1Figure1.jpg")
```

```
#2#2#2#2#2#2#2#2##2#2#2#2#2#2#2#2#2#2# Figure 2

plt.stackplot(x, EML_m14['fear'], EML_m14['sadness'], EML_m14['anger'],
EML_m14['disgust'], EML_m14['surprise'], EML_m14['anticipation'],
EML_m14['trust'], EML_m14['joy'], labels=['fear', 'sadness', 'anger',
'disgust', 'surprise', 'anticipation', 'trust', 'joy'], colors=['salmon',
'gold', 'firebrick', 'darkorange', 'lightskyblue', 'palegreen',
'limegreen', 'seagreen'])
plt.plot(event,y,label='Event', color='k')
plt.plot(eventviral,y,label='Event went viral', color='k')
plt.xlabel("Percentage (%)")
plt.ylabel("Number of tweets")
plt.subplots_adjust(left=0.15, bottom=0.2, right=0.8, top=0.9)
plt.title("Figure 2: Emotion distribution (24 hours) for the word
'Antarctica'",
          fontsize = 8, loc='left')
plt.xticks(rotation=90)
#get handles and labels
handles, labels = plt.gca().get_legend_handles_labels()
#specify order of items in legend
order = [8,7,6,5,4,3,2,1,0]
#add legend to plot
plt.legend([handles[idx] for idx in order],[labels[idx] for idx in order],
bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.show()

#3#3#3#3#33#3#3#3#3#3#3#3#3#3#3# Figure 3


#stackplot
plt.stackplot(x, RELT['fear'], RELT['sadness'], RELT['anger'],
RELT['disgust'], RELT['surprise'], RELT['anticipation'], RELT['trust'],
RELT['joy'], labels=['fear', 'sadness', 'anger', 'disgust', 'surprise',
'anticipation', 'trust', 'joy'], colors=['salmon', 'gold', 'firebrick',
'darkorange', 'lightskyblue', 'palegreen', 'limegreen', 'seagreen'])
plt.plot(secondevent, y, label='Second event', color='0.8')
plt.plot(event, y, label='Event', color='k')
plt.plot(eventviral, y, label='Event went viral', color='k')
plt.legend(bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.subplots_adjust(left=0.15, bottom=0.2, right=0.8, top=0.9)
plt.xlabel("Time-interval (per 24 hours)")
plt.ylabel("Number of tweets")
plt.title("Figure 3: Normalized distribution of retweet for the word
'Antarctica'",
          fontsize = 8, loc='left')

plt.xticks(rotation=90)
#get handles and labels
handles, labels = plt.gca().get_legend_handles_labels()
#specify order of items in legend
order = [8,7,6,5,4,3,2,1,0]
#add legend to plot
plt.legend([handles[idx] for idx in order],[labels[idx] for idx in order],
bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.show()
#bijzonder figuur, uitbreiding figuur 3b andere manier weergave

#OR stackplot
plt.stackplot(x, LILT['fear'], LILT['sadness'], LILT['anger'],
RELT['disgust'], LILT['surprise'], LILT['anticipation'], LILT['trust'],
LILT['joy'], labels=['fear', 'sadness', 'anger', 'disgust', 'surprise',
```

```
'anticipation', 'trust', 'joy'], colors=['salmon', 'gold', 'firebrick',
'darkorange', 'lightskyblue', 'palegreen', 'limegreen', 'seagreen'])
plt.plot(secondevent, y, label='Second event', color='0.8')
plt.plot(event,y,label='Event', color='k')
plt.plot(eventviral,y,label='Event went viral', color='k')
plt.legend(bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.subplots_adjust(left=0.15, bottom=0.2, right=0.8, top=0.9)
plt.xlabel("Time-interval (per 24 hours)")
plt.ylabel("Number of tweets")
plt.title("Figure 4: Normalized distribution of likes for the word
'Antarctica'",
          fontsize = 8, loc='left')
plt.xticks(rotation=90)
plt.xticks(rotation=90)
#get handles and labels
handles, labels = plt.gca().get_legend_handles_labels()
#specify order of items in legend
order = [8,7,6,5,4,3,2,1,0]
#add legend to plot
plt.legend([handles[idx] for idx in order],[labels[idx] for idx in order],
bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.show()
#bijzonder figuur, uitbreiding figuur 3b andere manier weergave

#OR stackplot
plt.stackplot(x, FOLT['fear'], FOLT['sadness'], FOLT['anger'],
FOLT['disgust'], FOLT['surprise'], FOLT['anticipation'], FOLT['trust'],
FOLT['joy'], labels=['fear', 'sadness', 'anger', 'disgust', 'surprise',
'anticipation', 'trust', 'joy'], colors=['salmon', 'gold', 'firebrick',
'darkorange', 'lightskyblue', 'palegreen', 'limegreen', 'seagreen'])
plt.plot(secondevent, y, label='Second event', color='0.8')
plt.plot(event,y,label='Event', color='k')
plt.plot(eventviral,y,label='Event went viral', color='k')
plt.xlabel("Time-interval (per 24 hours)")
plt.ylabel("Number of tweets")
plt.legend(bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.subplots_adjust(left=0.15, bottom=0.2, right=0.8, top=0.9)
plt.title("Figure 5: Normalized distribution of followers for the word
'Antarctica'",
          fontsize = 8, loc='left')
plt.xticks(rotation=90)
plt.xticks(rotation=90)
#get handles and labels
handles, labels = plt.gca().get_legend_handles_labels()
#specify order of items in legend
order = [8,7,6,5,4,3,2,1,0]
#add legend to plot
plt.legend([handles[idx] for idx in order],[labels[idx] for idx in order],
bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
plt.show()
```

```
#bijzonder figuur, uitbreiding figuur 3b andere manier weergave


#################overig
# plt.figure()
# plt.stackplot(x, EML_m14['fear'], RELT['fear'], LILT['fear'],
FOLT['fear'], labels=['original', 'retweet', 'like', 'follower'],
colors=['darkslategrey', 'cornflowerblue', 'darkorange', 'red'])
# plt.legend(bbox_to_anchor=(0.95, 1.0), loc='upper left', prop={'size':
6})
# plt.title("Figure 4c: Normalized distribution of retweet for the word
'Antarctica' from 10-3-2022",
#           fontsize = 8, loc='left')
# plt.xticks(rotation=90)
# plt.show()
#
# #4#4#4#4#44#4#4#4#4#4#4#4#4#4#4#
#
# plt.figure()
# plt.scatter(EML_m14['fear'], RELT['fear'], color='cornflowerblue',
label='retweet')
# plt.scatter(EML_m14['fear'], FOLT['fear'], color='red', label='follower')
# plt.scatter(EML_m14['fear'], LILT['fear'], color='darkorange',
label='like')
# plt.title("Figure 4b: Scatter plot 'fear', original tweet vs
follower/like/retweet for the word'Antarctica' from 10-3-2022",
#           fontsize = 8, loc='left')
# plt.legend(bbox_to_anchor=(0.95, 1.0), loc='upper left', prop={'size':
6})
# plt.xlim(0,30)
# plt.ylim(0,30)
# plt.xlabel("Original")
# plt.ylabel("Retweets/Likes/Followers")
# plt.show()
# #voor alle emoties?
#
#
# #overig
#
# ABL_m14.plot(kind="bar",stacked=True)
# plt.title("Figure 1a: Absolute emotion distribution (24 hours) for the
word 'Antarctica' from 10-3-2022",
#           fontsize = 8, loc='left')
# plt.xlabel("Time intervals (per 24 hours)")
# plt.ylabel("Number of tweets")
# plt.legend(bbox_to_anchor=(1.05, 1.0), loc='upper left')
# plt.tight_layout()
# plt.show()
#
# #2a#2a#2a#2a#2a#2a#
#
# plt.figure()
# plt.plot(EML_m14['fear'], color='g', label='Fear')
# plt.plot(EML_m14['sadness'], color='m', label='Sadness')
# plt.plot(EML_m14['anger'],color='r', label='Anger')
# plt.plot(EML_m14['trust'], color='b', label='Trust')
# plt.plot(EML_m14['surprise'],color='c', label='Surprise')
# plt.plot(EML_m14['disgust'],color='y', label='Disgust')
# plt.plot(EML_m14['joy'], color='k', label='Joy')
# plt.plot(EML_m14['anticipation'],color='0.8', label='Anticipation')
#
```

```
# plt.plot(event,y,label='Event', color='k')
# plt.plot(eventviral,y,label='Event went viral', color='k')
#
# plt.legend(bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
# plt.title("Figure 2a: Emotion distribution (24 hours) for the word
'Antarctica'",
#           fontsize = 8, loc='left')
# plt.subplots_adjust(left=0.15, bottom=0.2, right=0.8, top=0.9)
# plt.xlabel("Time intervals (per 24 hours)")
# plt.ylabel("Percentage(%)")
# plt.ylim(0,30)
# plt.xticks(rotation=90)
# plt.show()
# plt.tight_layout()
# plt.savefig('Antarctica_USA_Figure_7')
#
# #Fear figure
#
# plt.figure()
#
# plt.plot(RELT['fear'], color='salmon', label='Fear')
# plt.plot(RELT['anger'], color='firebrick', label='Anger')
# plt.plot(RELT['trust'], color='limegreen', label='Trust')
# plt.plot(RELT['surprise'], color='lime', label='Surprise')
# plt.plot(RELT['sadness'], color='gold', label='Sadness')
# plt.plot(RELT['disgust'], color='darkorange', label='Disgust')
# plt.plot(RELT['joy'], color='seagreen', label='Joy')
# plt.plot(RELT['anticipation'], color='turquoise', label='Anticipation')
#
# plt.plot(event,y,label='Event')
# plt.plot(eventviral,y,label='Event went viral')
#
# plt.legend(bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
# plt.title("Figure 3: Normalized distribution of retweet for the word
'Antarctica'",
#           fontsize = 8, loc='left')
# plt.subplots_adjust(left=0.15, bottom=0.2, right=0.8, top=0.9)
# plt.xlabel("Time intervals (per 24 hours)")
# plt.ylabel("Percentage(%)")
# plt.ylim(0,70)
# plt.xticks(rotation=90)
# plt.show()
# plt.tight_layout()
#3a#3a#3a#3a#3a#3a#3a#3a#

# #Fear figure
#
# plt.figure()
# plt.plot(EML_m14['fear'], color='darkslategrey', label='Original tweet',
marker='x')
# plt.plot(RELT['fear'], color='cornflowerblue', label='Retweets',
marker='x')
# plt.plot(LILT['fear'],color='darkorange', label='Likes', marker='x')
# plt.plot(FOLT['fear'], color='red', label='Followers', marker='x')
# plt.plot(event,y,label='Event', color='k')
# plt.plot(eventviral,y,label='Event went viral', color='k')
#
# plt.legend(bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
# plt.title("Figure 4a: Normalized distribution of emotion 'Fear' for the
word 'Antarctica' from 10-3-2022",
#           fontsize = 8, loc='left')
```

```
# plt.subplots_adjust(left=0.15, bottom=0.2, right=0.8, top=0.9)
# plt.xlabel("Time intervals (per 24 hours)")
# plt.ylabel("Percentage(%)")
# plt.ylim(0,70)
# plt.xticks(rotation=90)
# #get handles and labels
# handles, labels = plt.gca().get_legend_handles_labels()
# #specify order of items in legend
# order = [8,7,6,5,4,3,2,1,0]
# #add legend to plot
# plt.legend([handles[idx] for idx in order],[labels[idx] for idx in
order], bbox_to_anchor=(1.0, 1.0), loc='upper left', prop={'size': 6})
# plt.show()
# plt.show()
# plt.tight_layout()


# Circle diagram average emotions

y = np.array([EML_m14['fear'].mean(),EML_m14['sadness'].mean(),
EML_m14['anger'].mean(), EML_m14['disgust'].mean(),
EML_m14['surprise'].mean(), EML_m14['anticipation'].mean(),
EML_m14['trust'].mean(), EML_m14['joy'].mean()])
mylabels = ["fear", "sadness", "anger", "disgust", "surprise",
"anticipation", "trust", "joy"]
mycolors = ["salmon", "gold", "firebrick", "darkorange", "lightskyblue",
"palegreen", "limegreen", "seagreen"]
plt.pie(y, labels = mylabels, colors =
mycolors,autopct='%1.1f%%',startangle=90, counterclock=False)
plt.show()

# Circle diagram average emotions during peak

q = np.array([20.9, 9.7, 6.4, 7.5, 13.7, 18.0, 17.1, 6.7])
mylabels = ["fear", "sadness", "anger", "disgust", "surprise",
"anticipation", "trust", "joy"]
mycolors = ["salmon", "gold", "firebrick", "darkorange", "lightskyblue",
"palegreen", "limegreen", "seagreen"]
plt.pie(q, labels = mylabels, colors =
mycolors,autopct='%1.1f%%',startangle=90, counterclock=False)
plt.show()
```