Talking about the problem without a solution:

The case of climate scientists discussing climate change on Twitter.

Alejandra Revilla Cejudo

Master Thesis Series in Environmental Studies and Sustainability Science, No 2022:013

A thesis submitted in partial fulfillment of the requirements of Lund University International Master's Programme in Environmental Studies and Sustainability Science (30hp/credits)







Talking about the problem without a solution:

The case of climate scientists discussing climate change on Twitter.

Alejandra Revilla Cejudo

A thesis submitted in partial fulfilment of the requirements of Lund University International Master's Programme in Environmental Studies and Sustainability Science

Submitted May 10, 2022

Supervisor: Kimberly Nicholas, LUCSUS, Lund University

Abstract

Climate scientists are trustworthy climate change communicators. However, little research exists on how they communicate and how to better engage with their followers. This thesis focuses on Climate Twitter to better understand how often climate scientists are active, which tone they use, what content they share, and how this impact engagement. This thesis has identified that climate scientists use Twitter as a platform to share their knowledge on climate science. The tweets that are written with a negative tone have a significantly higher engagement than those written in positive or neutral tones. Currently only 3% of the tweets are dedicated to climate action and less than 2% is dedicated to specific climate actions targeting a reduction in greenhouse gas emissions. The recommendation of this thesis is that climate scientists dedicate more space in their communications to share climate solutions.

Keywords: Sentiment, Climate Action, Engagement, Text Analysis, Reducing GHG emissions, Sustainability

Word count: 11,256

Acknowledgements

"It takes a village to raise a child"

This African proverb recognizes the importance of having the support of a community for a child to grow in a safe and healthy environment. I believe this same proverb applies to most of the things we do in life. It takes a village. And like that, I recognize here that it took a village for me to come to Sweden, study LUMES, and hand in this thesis that you are about to read. And I am so grateful to have a community that supported me through this journey.

This master's might have started in August 2020, but I must thank all my professors that through their love of teaching sparked my passion for learning. An honourable mention should go to Salvador who always challenged me in my studies and supported me.

My village also includes wonderful people without whose help I wouldn't have been able to come to Sweden, thank you, Enrique, Silvia, Abraham, Lety, Lupita, and Case for believing in me. I will be forever grateful for the opportunity you gave me.

I have been blessed with the presence of people that lifted me up when I was down, that through the distance cared for me and sent me messages of love and support. To Nelly, Norma, Pilar, mi Perro Viejo, Monica & Philippe, la Tieta, Juan Pablo, Ernesto, Dani, and Betito thank you for the occasional message, meme, call, and laugh shared, you have given me the energy to keep going when I needed it the most.

Upon my arrival to Lund, my family expanded, thank you, Jenni, Gus, Moni, and Juan for being family to me. For craving the same food, missing the same culture, and sharing the same traumas. You've been a home far away from home and I couldn't thank you enough! And to my Swedish family Barbara and Chris, thank you for opening your heart and house to this Mexican. Going to your place has felt like home since the beginning of this master.

To my beautiful friends in LUMES from my lettuces to the winning hackathons, the 7 wonders, and many more thank you for being true friends. We've been through so much together and I couldn't imagine doing this without you.

A big fat THANK YOU needs to go here for my supervisor Kimberly Nicholas, thank you for your patience, guidance, and generosity. Thank you for offering your network, kind words, support, and fika in every meeting and for helping me find a way out when I was lost in my own work.

Thanks to Ragnhild, Ross, and Michael for being a true support group, for stressing through the deadlines together, lifting each other up, and trusting the process even though we had no idea what we were doing. I have no doubt my thesis wouldn't be the same without your comments. Thank you to Raul Gomez without his help my trip down coding land would've been much more terrifying and long. And to Daniel Lundgaard, your help with this thesis was invaluable.

And most importantly thank you to my parents, Maite & Enrique, for your constant support, encouragement, and infinite love. For inspiring me to dream big and helping me make those dreams come true. I couldn't wish for better parents in the world. I love you so much.

There are many names I wish I could write down because so many people have touched my journey, but I'm reaching the space limit so, as I was telling from the beginning: It took a village and I love my village. Thank you all.

Dedicated to my grandpa Ernesto, hope you are proud of me I miss you dearly, I love you.

Table of Contents

1. Introduction1
1.1 Climate Change & Twitter1
1.2 Research Aim2
1.3 Contribution to Sustainability Science3
2. Background
2.1 Why Climate Scientists?4
2.2 Why Twitter?4
3. Theory
3.1 Gateway Belief Model5
3.2 Conceptual Frameworks7 3.2.1 The role of high-socioeconomic-status people in locking in or rapidly reducing energy-
driven greenhouse gas emissions7
4. Data and Methods8
4.1 Data Selection
4.2 Data Collection8
4.2 Methodology
since 2017?
since 2017? 11 4.2.2 Research Question 2: How does emotion affect engagement? 13 4.2.3 Research Question 3: Climate action vs Climate actions 15 5. Ethical Considerations 17 6. Findings 19 6.1.1 Tweet Type 19 6.1.2 Frequency 20 6.1.3 Climate Related Tweets 21
since 2017?
since 2017?
since 2017? 11 4.2.2 Research Question 2: How does emotion affect engagement? 13 4.2.3 Research Question 3: Climate action vs Climate actions 15 5. Ethical Considerations 17 6. Findings 19 6.1 Tweet type, frequency, and climate related tweets 19 6.1.1 Tweet Type 19 6.1.2 Frequency 20 6.1.3 Climate Related Tweets 21 6.2 Sentiment Analysis and Statistics on Engagement 21 6.2.1 Sentiment Analysis 21 6.2.2 Statistics on Engagement 22
since 2017?
since 2017? 11 4.2.2 Research Question 2: How does emotion affect engagement? 13 4.2.3 Research Question 3: Climate action vs Climate actions 15 5. Ethical Considerations 17 6. Findings 19 6.1 Tweet type, frequency, and climate related tweets 19 6.1.1 Tweet Type 19 6.1.2 Frequency 20 6.1.3 Climate Related Tweets 21 6.2 Sentiment Analysis and Statistics on Engagement 21 6.2.1 Sentiment Analysis 21 6.3 Support to reduce GHG emissions versus Climate Actions 25 7. Discussion 26
since 2017?

10. References	
1. Appendix	
11.1 Appendix A. Stop words for Text Analysis	
11.2 Appendix B. List of Climate Related Words	41

List of Tables

Table 1. Structure of the dataset. (Table created by the author)	9
Table 2. General support for reducing emission words to identify in the Text Analysis. (Table	
created by author)	15
Table 3. Table of the different domain and actions with the key words used to identify climat	te
actions on the code to answer RQ3. (Table created by author)	16
Table 4. Table of most frequently used words and their categorization as climate related	
(coded 1) and non-climate related (coded 0) words. (Table created by the author)	20
Table 5. Descriptive statistical analysis performed on the engagement metrics Retweets and	
Replies for the three possible scenarios – positive, negative, or neutral. (Table created by	
author)	22
Table 6. Descriptive statistical analysis performed on the engagement metrics Likes and	
Quotes for the three possible scenarios – positive, negative, or neutral. (Table created by	
author)	23
Table 7. Results from the inferential statistics tests performed on the engagement metrics	
Retweets, Quotes, Replies and Likes. (Table created by author)	24

List of Figures

Figure 1. A visual representation of the Gateway Belief Model in climate change, showing how having messages of consensus in the scientific community affects the perceived scientific agreement which in turn affects belief in climate change, belief in human causation and worry about climate change. These lead to the support for public action. Note. This model was produced by van der Linden et al. 2019. From "The Gateway Belief Model (GBM): A review and research agenda for communicating the scientific consensus on climate change, by S. van der Linden, 2021, Current opinion in Psychology, 42, p. 8. Copyright Current Opinion in Psychology. Figure 2. Visualization of a tweet and the fields publicly visible. (Figure created by the author). Figure 3. Visualization of the Research Design. Different data collection and analysis was used Figure 4. Example of a Sentiment Analysis process from retrieving the text to assigning the polarity score. (Figure created by the author)......14 Figure 5. The different roles in which high-SES can influence their emissions. Note. From "The role of high-socio-economic status people in locking in or rapidly reducing energy-driven greenhouse gas emissions" by Nielsen et al., 2021, nature energy, 6, p. 1012. Copyright 15 Figure 6. Percentage of tweets from the dataset that correspond to the three different types Figure 7. Percentage of the tweets that are climate related or not. (Figure created by the Figure 8. Number of tweets with a positive, neutral, and negative polarity score from the Figure 9. Number of tweets dedicated to support to reduce GHG emissions versus different climate actions throughout the years 2017-2022 by the top 50 climate scientists on Twitter. The complete dataset was analysed with words from the two lists in Table 2 and Table 3.

Abbreviations

- ACA Automated Content Analysis
- AGU American Geophysical Union
- API Application Programme Interface
- GHG Greenhouse Gases
- IPCC Intergovernmental Panel on Climate Change
- NGOs Non-Governmental Organizations
- NPL Natural Language Processing
- RQ Research Questions
- SES Social Economic Status

1. Introduction

1.1 Climate Change & Twitter

As reported by the Intergovernmental Panel on Climate Change (IPCC) approximately 3.6 billion people live in contexts that are highly vulnerable to climate change (IPCC, 2022). With global warming reaching 1.5°C above preindustrial times, irreversible damages to ecosystems and biodiversity are very likely to happen, threatening human way of life.

Climate change, it's impacts, causes and the responses to it are challenging issues to communicate (Schäfer, 2012). Several actors are involved in those communications: governments, NGO's, journalists, and scientists are the main participants. "What has received little attention in climate change communication is the supply side: how climate scientists are engaging with the public" (Entradas et al., 2019).

Grand challenges like these require social participation, cultural changes are equally as necessary as policies, market, or practice changes (von Wirth et al., 2019). Programmes where science meets citizens and equip them with the knowledge to contribute to systemic changes have increased participation (König, 2015). Different possibilities to engage with a topic and systemic changes often opens room for public discussion.

There are different scenarios for public discussion, one that has become popular is social media. With more than 217 million active users, Twitter is a social media platform for micro-blogging where users learn about and discuss the most recent news topics (Twitter, 2022). According to a study by the American Press Institute, 9 out of 10 Twitter users, use the platform to be informed about the news, and 74% of the surveyed do so daily (Rosenstiel et al., 2015).

Previous studies of climate change communications on Twitter agree that Twitter presents an opportunity to discuss and analyse climate change communications, but there are differences in how they approach the platform and what they try to understand (Fownes et al., 2018; Jang & Hart, 2015; Kirilenko & Stepchenkova, 2014; Segerberg & Bennett, 2011). For example, Jang and Hart (2015) focused their analysis on climate change frames finding that hoax frames are more frequent in the US than in Canada, UK, or Australia. They also analysed the use of the term "global warming" finding that it is more frequently accompanied by hoax frames and not by impact or action frames (Jang & Hart, 2015). Fownes et al. (2018) found that NGOs have the potential to influence Twitter discussions of climate change through external content such as sharing hyperlinks to trusted websites or high quality videos. They also discuss the influence that celebrities have on the topic, although highlighting the concern that celebrity discussions might

trivialise behavioural change. Finally, Kirilenko and Stepchenkova (2014) studied the climate change discussion on Twitter finding that the US and UK dominate the conversation with 41% and 13% daily discussion coming from these countries respectively.

The role of emotion in how climate change communication is interpreted and acted upon has been unclear. Some scientists have argued that calling upon certain emotions, for example fear, can be damaging when trying to spark action (Mann et al., 2017). Other scientists argue that the desired emotion to spark action can be triggered by connection to nature, and that is the positive feeling after connecting with nature that leads to a pro-environmental attitude (Zelenski & Desrochers, 2021). However, this is a simplistic view of how emotions trigger action. Emotions by themselves do not trigger action, they are part of a system of education, beliefs and context that guide our behaviour. For this reason, viewing emotions as an immediate solution for behavioural change is perilous. The truth is that emotions work overtime and depending on the context of the recipient, as Chapman et al. (2017) argue what's important is that emotions trigger cognitive responses – like information seeking – that might in turn change our behaviour. Thus, emotions cannot be categorized as good or bad, and knowing which emotion to aim for when conveying a climate change message will vastly depend on your targeted audience.

"Engagement requires connections and interactions that take place between individuals and organizations and these are due to the participation of individuals [...]" (Muñoz-Exposito et al., 2017, p. 1129). Following this definition, allowances can also be called engagement, the amount of replies, likes, quotes and retweets form part of the user's engagement. These engagement metrics have been used to measure citizen interaction with local governments (Bonsón et al., 2019), and to measure consumer engagement with a brand (Muñoz-Exposito et al., 2017) and monitoring public opinion about certain topics like the COVID-19 vaccination (D'Andrea et al., 2019). In this thesis I will use Twitter's engagement metrics to deduct people's feedback on different forms of communication from climate scientists.

1.2 Research Aim

This thesis aims to describe how climate scientists use Twitter for climate communication and identify which emotional and action-based strategies increase engagement from their followers. Recognizing that major behavioural and systemic changes need to happen to reduce global warming and that there is already enough information on climate action, this can serve as a guide for climate scientists to improve the engagement with their followers on Twitter and/or

increase their number of followers. By analysing the contributions over the past 5 years of the most followed climate scientists on Twitter, this thesis seeks to contribute to the study of public engagement to climate change.

More specifically, it aims to recognize different patterns in the way the scientific community, and particularly the 50 most followed climate scientists, share their thoughts and findings, and what engagement they get in response. This thesis will answer the following research questions (RQ) to achieve the research aim:

- 1. What frequency and content characterizes the 50 most followed climate scientists' tweets since 2017?
- 2. How does the emotional affect climate scientists use in their tweets impact audience engagement?
- 3. How frequently and which climate change actions do climate scientists share?

1.3 Contribution to Sustainability Science

According to the Mitigation Report "Many options available now in all sectors are estimated to offer substantial potential to reduce net emissions by 2030" (IPCC, 2022, p. 51). This hints to a reality where we don't lack solutions to climate change, what we lack is, among other things, public engagement to act upon those solutions.

This thesis aims to build on previous research about climate scientists' participation in the public climate debate by Entradas et al. (2019). In their study they show that it is the most published authors, not the more senior authors, who engage in public conversations and those conversations are intrinsically driven by the scientists' own interest in public communication, in other words there is not an extrinsic reward. This study was performed on climate scientists' members of the American Geophysical Union (AGU) and the public debate they participate in were mainly at public events such as public lectures, talks at school, events by municipalities or councils. They also discuss social media participation, with Twitter and Facebook being the most used, however they note that the participation on social media is very limited compared to public events (Entradas et al., 2019).

This thesis further aims to serve as a guide for climate scientists that wish to engage audiences with their research, studying patterns in sentiment, engagement metrics and content of the

tweets, as well as analysing the impact of sharing actionable climate advice to encourage their followers to reduce emissions.

2. Background 2.1 Why Climate Scientists?

The discussion about climate change in social media mainly revolves around the trustworthiness of the communicator, who can be considered an authority when talking about climate change and climate action (Pearce et al., 2014). This was the reason behind focusing on climate scientists for this thesis. By selecting a pre-existing Twitter list of the 50 climate scientists with the largest Twitter followings (Rohde, n.d.), I selected for influential people holding higher education degrees in disciplines related to climate change and sustainability. Most of them also hold positions within academia, producing research and periodically publishing it. Their scientific knowledge gives them the authority to talk with conviction about the impacts, and solutions to climate change.

Climate change is a very contested topic on Twitter, a core part of the conversation revolves around the scientific evidence used to justify action (Pearce et al., 2014). In the Twitter discussions analysed for this thesis, I assumed that the conversations revolving climate action are justified and have enough evidence behind them to be endorsed as good climate action recommendations. This assumption relies on the fact that the climate scientists that form part of the study have authority on their topic and would share information that comes from verifiable sources. Thus, the focus does not lay on whether the solutions are good solutions but more on the engagement of the followers to such actions.

2.2 Why Twitter?

A study by the American Press Institute mentions that "three quarters of Twitter news users follow individual journalists, writers and commentators (73%) and nearly two thirds follow institutional accounts (62%)" (Rosenstiel et al., 2015). This shows that Twitter is an excellent platform where individual voices have an opportunity to be heard and have an impact and are even more valued than institutional accounts.

There is a debate on the impact that social media, and particularly Twitter has on contentious politics. Since Twitter is a place where everyone with internet access and an account can interact, and every user can decide who to follow, it presents an opportunity for civil organization. There is a debate around whether Twitter played a role in 2009's revolutions, such

as the Moldova's Twitter Revolution and the Iranian Revolution (Segerberg & Bennett, 2011). In this section I will follow arguments by Segerberg and Bennett to present Twitter as the platform that can spark revolutions and how this could be useful applied to climate change communications.

Segerberg and Bennett argue that Twitter played a role in two important topics: 1) publicizing local causes to distant audiences and 2) it's importance in logistical communication between protesters on the ground. Even though the full impact of Twitter in the revolutions is contested as it is not a source of professional journalism and the overload of information can overwhelm the followers it can bring international attention to different causes. The main conclusion of the impact that Twitter has had on these two cases of revolutions is that it cannot spark revolutions as an isolated event, but that it serves as a catalyst effect for the context (Segerberg & Bennett, 2011).

When making the parallel to climate change: some political spheres recognize climate change for example, member states of the UN (Nightingale, 2017), also many companies are making changes on their products to offer the consumer more sustainable alternatives (Thies et al., 2019), and activists are flourishing from different parts of the planet calling to action (de Moor et al., 2021). This is what constitutes the climate change context, with all the attention the topic has received, it can be a good catalyst for a climate revolution. A "revolution" where we recognize the importance of a systemic change as well as changes of individual behaviour. The role of scientists framing climate change, presenting solutions to their followers, and speaking up for the climate on Twitter is the idea behind this thesis.

When discussing audience reaction on Twitter, we have to discuss *affordance*, according to Shahin and Dai "affordance is an action possibility available in the environment to an individual, independent of the individual's ability to perceive this possibility" (Shahin & Dai, 2019, p. 1686). In this scenario Twitter allows users to tweet text or audio-visual content, share external content through hyperlinks, reply to other users, retweet other user's tweets or quote them with a comment of their own, and lastly to like tweets. These allowances that exist on the Twitters' environment can have different interpretations.

3. Theory

3.1 Gateway Belief Model

The Gateway Belief Model refers to a framework that has its foundation on the psychological experience of consensus. It is a theory that confirms what many have suspected before, that

perceived scientific agreement is a priority in changing people's attitudes about contested scientific topics. (van der Linden, 2021).

Climate change has been a contested scientific issue, and there have been attempts to fuel the perception that the scientific community disagrees on the anthropogenic causes of climate change or on the possible solutions to climate change (Braungardt et al., 2019).

Talking specifically about how the Gateway Belief Model theory could impact climate change, van der Linden (2017) explains that a change in the public perception of the scientific consensus is the first step to change the public ideas on climate change. The feeling that the scientific community agrees opens the door to them believing in climate change, starting to believe that it is human caused, and regulates how people worry about it. These three changes in judgement then lead up to support for public climate change action.

I used the Gateway Belief Model in my overall research design first to find out in RQ1 if the climate scientists on their Twitter accounts were tweeting frequently about climate change and the anthropogenic causes of climate change. Second, when answering RQ3 to discuss about climate solutions. What I wanted to see is if there is consensus messaging over some of the proposed climate solutions or if there isn't, and if this affects engagement metrics of the tweets.



Figure 1. A visual representation of the Gateway Belief Model in climate change, showing how having messages of consensus in the scientific community affects the perceived scientific agreement which in turn affects belief in climate change, belief in human causation and worry about climate change. These lead to the support for public action. *Note.* This model was produced by van der Linden et al. 2019. From "The Gateway Belief Model (GBM): A review and research agenda for communicating the scientific consensus on climate change, by S. van der Linden, 2021, *Current opinion in Psychology*, 42, p. 8. Copyright Current Opinion in Psychology.

As seen in Figure 1, it's scientific consensus that sparks the support for public action. The existing scientific consensus that climate change is real, human-caused, and worrisome (IPCC, 2022) creates support for public action. Not directly, however, but through changing people's beliefs on whether climate change is real, that climate change is human caused and then through worrying about the topic. Now, there is another issue that requires scientific consensus and is the solutions proposed to help alleviate climate change. The model seems to point that the scientific consensus of the topic is enough to gather public support for climate action. But if there is not a consensus of the solutions that should be implemented that support proves hard to capitalize. There seems to be a disagreement between what the solutions to climate change should be and the potential they have to reduce GHG emissions (Creutzig et al., 2016).

For example, when pointing out the scientific consensus people update their belief system, which can then cause people to become more supportive of policies to address climate change (Goldberg et al., 2019). This model is believed to be a good foundation to design persuasive climate messages, although there is a recognition that consensus messages can have different results depending on the context of the audience.

3.2 Conceptual Frameworks

3.2.1 The role of high-socioeconomic-status people in locking in or rapidly reducing energydriven greenhouse gas emissions

For this thesis, I used a conceptual framework to identify and categorize climate actions in RQ3. The purpose of that question is to find out the frequency in which climate scientists discuss in their tweets some of the climate change solutions that already exist. In this framework developed by Nielsen et al. (2021), they demonstrate that the impact caused by high-socioeconomic status (SES) people is higher than that of the rest of the population. Therefore, they argue a shift in their behaviour could result in a rapid reduction of GHG emissions.

The Nielsen et al. frameworks identify five different roles of the high-SES: Consumer, Investor, Role Model, Organizational Participant, and Citizen. As consumers, the authors discuss the technical potential of actions which is the reduction in GHG emissions resulting from everyone taking that action. As investors, high-SES people can serve as a driver investing in low-emission companies and mutual funds, potentially creating more climate-related investment opportunities. As role models, they highlight the capacity of high-SES people to diffuse new technologies and behaviours in their social circles. In their role as organizational participants, they can exert pressure to have more focused climate goals, develop low emissions products and decarbonize the supply chain among others. Finally, in their role as citizens, there are different actions such as voting, lobbying, and participating in social movements (Nielsen et al., 2021).

To answer RQ3, I took into consideration these different actions when analysing the tweets from the climate scientists and looking for how often they share specific climate actions like the ones mentioned above or when they mention climate action as a more general concept without direction.

4. Data and Methods

4.1 Data Selection

To perform this study and analyse the behaviour and patterns of climate scientists' communication on Twitter, I based the selection of candidates on an already existing list put together by PhD Robert Rohde a lead scientist at Berkley Earth (Rohde, n.d.). He compiled the names and handles of 49 scientists who work on climate science and have the greatest number of followers on the platform. The list named by PhD Robert Rhode as the "Top 50 Climate Scientists" includes only 49 members, no exclusion was made on my part.

The scientists compiled on the list check all the marks that previous studies on influence and Twitter have argued for (Pearce et al., 2014). They are considered experts about climate change due to their academic record; they also are supported by strong trustworthy institutions by being a part of them or participating in projects with them. Both arguments give them the authority to discuss the topic, inform about climate change, the challenges that arise from it and give advice on how to fix it.

4.2 Data Collection

The data collection of this research was sourced from the authorized Twitter Application Programme Interface (API) to ensure the dataset was from the official account of the climate scientists and complete. The data analysis involved a Frequency Analysis, Text Analysis and Sentiment Analysis of the tweet's text, as well as analysing how the engagement metrics and the tweet type varies.

Due to Twitter's restrictions on the information that can be retrieved from the API the variable reply count is not available to fetch automatically from an author's timeline, it can be requested individually with a limit of 300 tweets every 15 minutes. For this reason, a small sample of the dataset was selected to collect the number of replies those tweets got and include this engagement metric on the emotion analysis. Because of time restrictions the small sample

consists of 96,058 tweets from 31 of the 49 authors. The rest of the analysis is performed on the complete dataset.

The complete dataset includes 1,379,617 tweets scraped from the climate scientists' official accounts on Twitter. For fetching the tweets, the dates used in Twitter API were between the 1st of January 2017, and the 4th of April 2022. These tweets include all Twitter interactions, such as tweets, replies to other users, and retweets and quotes from other accounts.

These dates were selected because I believed there could be a change in climate change communication after 2018, when Greta Thunberg helped draw a lot of attention from the public to the topic (Sabherwal et al., 2021). 2018 was also the year when the 1.5°C report came out from IPCC discussing the threats and possible scenarios of climate change on earth. Thus, this seemed to be a good scope to assess climate change communication on Twitter and include the possible effects of this events on the research.

The access that I have from Twitter API was still limited to 3,200 tweets per user, this was a small dataset. With the help of my thesis supervisor, Kimberly Nicholas, who is collaborating on a research project about climate change communication she introduced me to Daniel Lundgaard. He is a post doctorate at Copenhagen Business School that has experience researching communication in social media and has a better access to Twitter API. He was then able to assist me in building the complete dataset retrieving more than 1,3 million tweets from the 49 climate scientists in the period 2017-2022. All the analysis presented in the thesis is the result of my work, however without Daniel's help my dataset for analysis would have been much smaller.

The dataset was composed by several excel files with the following structure:

Tweet ID	Unique 64-bit unsigned integer based on time	
	assigned to each object within Twitter, in this	
	case a tweet.	
User ID	Unique 64-bit unsigned integer based on time	
	assigned to each object within Twitter, in this	
	case a user.	
Username	The desired handle each user sets up when	
	they create their account. The username can	
	be modified at any time by the user.	

Table 1. Structure of the dataset. (Table created by the author).

Date	Time stamp of the moment when the tweet
	was generated.
Tweets	The text of the tweets.
In reply to user	Returns the 64-bit integer of the user to
	whom they are replying. It is useful to
	categorize the interaction as a reply.
Quote count	Count of how many users have quoted the
	tweet.
Favourite count	Count of how many users have liked the
	tweet.
Retweet count	Count of how many users have retweeted the
	tweet.
Tweet type	It identifies between a retweet and a quoted
	tweet.
Location	If the users have activated the geolocation on
	their accounts, it returns the location from
	when the tweet was made.
Language	Returns the language of the tweet.

For anyone that might be unfamiliar with the platform here is an example of how a tweet looks like, to respect the privacy of the members of the list the example was extracted from my own timeline.



Figure 2. Visualization of a tweet and the fields publicly visible. (Figure created by the author).

From the example we can see that some users have deactivated the location for privacy reasons, therefore it is not public information. All the fields presented in Figure 2 are the fields available

to anyone that has a Twitter account and follows me on Twitter. The rest of the fields that complete the dataset is information only available through the API it is still information publicly available, but it must be retrieved from the back end of Twitter.

4.2 Methodology

In Figure 3, I give an overview of how I used the collected data to answer my research questions. In brief, I performed Text Analysis on the complete dataset of 1,3 million tweets to understand how often do climate scientists tweet about climate change, and whether those tweets are original, retweets, or quotes (RQ1). Sentiment Analysis on the tweets categorized as climate related to measure the tone – positive, neutral, or negative – expressed in each of them (RQ2). Text Analysis with a different categorization to understand how many times climate scientists discuss climate action in general versus specific climate actions (RQ3), as explain in detail below.



Figure 3. Visualization of the Research Design. Different data collection and analysis was used when answering each research question (RQ). (Figure created by the author).

4.2.1 Research Question 1: What characterizes the 50 most followed climate scientists' tweets since 2017?

With the small dataset I performed a Frequency Analysis on the text of the tweets with the objective of categorizing the words used in the tweets as climate related or not. This method ensures that all the words to be included later in the Text Analysis are words that climate scientists are using when tweeting. Consequently, a list of stop words was needed to exclude from the analysis any word that cannot be classified and should be ignored, such as "the", "an", "a", "in" ('Removing Stop Words with NLTK in Python', 2017). For this analysis I used a comprehensive pre-existing list of stop words from GitHub Gist (Bleier, 2019). The list had 2,330 words initially and after running the code and revising the frequency results, I included 231 words from my dataset that were not helpful for the analysis. The criterion to include those extra words was that they were common words such as articles, prepositions, conjunctions, and even some numbers. The whole list of stop words that were ignored in the classification can be found in Appendix A.

The frequency list resulting from the tweets on the small sample resulted in 367,732 different words including hashtags, usernames, and links. These different words needed to be classified between climate related or non-climate related, to do this all the words that have a frequency less than 50 were excluded from the analysis under the premise that not all the scientists tweeted about it once or that they were mentioned in less than 2% of the tweets sample. There was a total of 5,618 words with frequency 50 or above.

I then classified the 5,618 most frequent words tweeted as either climate-related or not using the criteria that any words that could be directly linked to environmental science words such as temperature, hurricane, clouds, climate, emissions, CO₂ ... were selected as climate related. I decided to exclude words that even though they could be related to science they could also be used for mundane activities or another topic, words like "time", "days", "public", "countries", "real". Fifteen percent of the 5,618 words in the frequency list, or 851 in total, were catalogued as climate related words, see Appendix B for the list of words.

With the climate related list of words, a Text Analysis could be performed to the complete dataset and find out the frequency of the climate related tweets from the non-related tweets.

4.2.1.1 What is Text Analysis?

Automated Content Analysis (ACA) "are a suite of statistical analysis tools that can be used to identify the thematic composition of large volumes of text" (Shetty & Ramesh, 2021, p.13921). Using this statistical tool when computing multiple texts can be helpful to categorize large amounts of information automatically. Text Analysis works with libraries of words each

12

corresponding to different categories, searches for those words amongst the different texts and presents as results all text entries that contain those specific words. The Text Analysis tool will be helpful throughout this thesis, to identify which tweets discuss climate change and what climate actions are mentioned in the tweets.

4.2.2 Research Question 2: How does emotion affect engagement?

For RQ2 I performed Sentiment Analysis on the small dataset to create the connection between the four-engagement metrics – likes, replies, retweets, and quotes- with the tone used by climate scientists on their Twitter interactions.

4.2.2.1 What is Sentiment Analysis?

"Sentiment analysis or opinion mining is the process of computationally identifying and categorizing opinions expressed in a piece of text, in order to determine whether the writer's attitude towards a particular topic, product, etc. is positive, negative, or neutral" (Preethi et al., 2015, p. 84). Sentiment Analysis has been used to determine the attitude of people when reviewing films and series (Yasen & Tedmori, 2019), and then it quickly became a tool to analyse all kind of reviews like hotel reviews (Zvarevashe & Olugbara, 2018), and purchases reviews (Yue et al., 2019).

This powerful tool became more important when analysing social media due to the low barrier to post a message the number of messages increased exponentially. Yue et al. (2019) argue that sentiment analysis is "important not only for traditional consumers and companies conducting surveys to gather opinions about corresponding products or services but it also plays an important role on national security and public opinion analysis" (Yue et al., 2019, p. 619). In this case, we are going to use Sentiment Analysis to analyse the attitude of the climate scientists when they are tweeting about climate change and the affect that has on public engagement. The more public engagement, the more opportunities to change public opinion on climate change solutions.

4.2.3.2 Method on Sentiment Analysis

With the small sample I performed a Sentiment Analysis on python. The programming language has a package called TextBlob, this is a library for processing text data, that I used to analyse the

information. Analysing text requires complex natural language processing (NPL) models, to categorize the tweets between positive, neutral, or negative accordingly to the language they are using. The way of categorizing it is through a polarity score with the range of [-1,0,1], where -1 stands for negative, 0 stands for neutral and 1 stand for positive. The way the analysis works is first tokenizing the tweet, which means breaking the tweets into a list of words, after the code has the list of words the next step is cleaning the list from any special character like emojis, exclamation marks, question marks, etc and cleaning stop words. This leaves only the words that are important for the sentiment classification. Each word is assigned a polarity, Figure 4 illustrates an example of the process to assign polarity:



Figure 4. Example of a Sentiment Analysis process from retrieving the text to assigning the polarity score. (Figure created by the author).

In this example the words "Food" and "Restaurant" are assigned a polarity score of 0 because they are not useful words to define the general feeling of the tweet, whereas "Great" is assigned polarity 1 because it reveals a positive sentiment. These scores follow a list of words that are already included in the library, in this case I did not have to train the algorithm and decide which words are positive, neutral, or negative.

With a sentiment result assigned to each of the tweets the last step to answer RQ2 was to pair each tone with their respective engagement metrics and perform a statistical test of Median Comparisons to see if there is any significant difference between the engagement when tweets are written in different tones. Before testing the means, I tested the normalcy of the data with the Kolmogorov-Smirnov test, to know if I would perform parametric or non-parametric mean comparison tests. Because the data was not normally distributed, I performed non-parametric test to compare the means. This result will tell me if the tone used by climate scientists when writing tweets about climate change makes a difference in how their followers engage.

4.2.3 Research Question 3: Climate action vs Climate actions

For this research question I compared how many times climate scientists have tweeted about support for reducing emissions, and how often they give clear actions that individuals might act on to reduce emissions. The words included in the analysis to look for tweets discussing support to reduce emissions in general were:

Table 2. General support for reducing emission words to identify in the Text Analysis. (Table created by author).

Solutions words included in the code			
Climate Action	#ClimateAction	Solution	reduce emissions
Climate action	#climateaction	solutions	Reduce emissions
climate action	solution	Solutions	Reduce Emissions

The code is case sensitive, this means that if a word is written in capital letters or lower case the code would not identify them, that is the reason why many of the terms were repeated in Table 2.

To look for the words related to specific climate actions I created a list derived from the 5 roles through which people from high social economic status can lower their emissions (Nielsen et al., 2021). In this article the authors propose that there are different ways in which people from



high social economic status can influence their behaviour to reduce greenhouse gas (GHG) emissions. These different ways are divided into 5 roles that individuals have in society and the market such as: In the text, the authors make a special mention of 3 consumer related domains that could have a great impact on the GHG emissions, those domains were: Air Travel, Motor Vehicle

Figure 5. The different roles in which high-SES can influence their emissions. Note. From "The role of high-socio-economic status people in locking in or rapidly reducing energy-driven greenhouse gas emissions" by Nielsen et al., 2021, nature energy, 6, p. 1012. Copyright Nature Energy 2021.

Use and Housing. These domains can be acted upon differently, for example Air Travel the actions within the domain would be reduce flights, increase train travels, reduce unnecessary business meetings, etc. From the other four roles different articles helped me comprise a list of solution words to include all the roles, the list is included in Table 3 below (*Changing Behavior to Help Meet Long-Term Climate Targets*, 2019; Hargreaves et al., 2018; Kuss, 2021; McWhinney, 2021).

Table 3. Table of the c	different domain and actions with	h the key words used t	o identify climate a	actions on the code
to answer RQ3. (Table	e created by author)			

Consumer	Domain	Air Travel
	Key Words	Reduce flight, less flight, no flight, no flying, less flights,
		online meetings, visit your country, home vacation,
		business travel, online meetings, remote meetings
	Domain	Motor Vehicle Use
	Key Word	Public transit, Buses, Use the bus, cycling, cycle to work,
		cycle to school, cycle paths, walking, walkable
		neighbourhoods, electric cars, EV, electric vehicles, car
		sharing, car-free, reduced car use, less car use, reduce
		car use, hybrid cars, hybrid car
	Domain	Housing
	Key Words	Ownership of larger homes, large home, multiple residence, summer residence, summer house, winter
		house, winter cottage, suburb house, energy consumption of households, central air conditioning,
		heating, home retrofits, solar panels, reuse water,
		home-work commute, smart house, smart home, smart
		home technologies, heating system, energy monitors,
		energy management, reduce energy consumption
Investor	Action	Green Investing
	Key Words	Green funds, green mutual funds, ETF, green ETF, anti- fossil-fuel investment, fossil-fuel investment, divestment, reinvestment, EU Taxonomy, green finance, green bonds, climate bonds, green bond tax, green Equity, Green equities, climate commitment equities, green investment, ESG investment, pure-play green investments, water investments
Citizen	Action	Voting
	Key Words	Vote, go to vote, vote for the green party, vote for green policies, informed vote, vote green
	Action	Active Participation
	Key Words	Demonstrations, hold your representatives accountable,
		accountability, government accountability, protests,
		green protests, green government, green lobby
	Action	Financial and Social Support
	Key Words	Finance campaigns, financing green campaigns, support
		green politicians, green board, influence boards
	Action	Individual Actions

	Key Words	Having one fewer kid, recycling, wash clothes in cold water, plant-based diet, hang dry clothes,
Organizational	Action	Business Owner
Participant	Key Words	Green business owner, greening the company, greening our company, green start-up, environmental start-up
	Action	Business Manager
	Key Words	Greening the supply chain, greening the company, shorten operation hours, reduce office temperature, energy audit, energy efficient equipment, smart meters, waste audit, measure waste, identify source of waste, e- waste, prints per capita, reduce prints, office fleet, staff commute, electric shuttle, green mobility providers, telecommuting, vegetarian menus, vegan menus, locally produced, refillable stationary,
Role Model	Action	Social and social media influence
	Key Words	Share behaviours, share ideas, influencer, influential power, influence, influence others, ripple effect, conversations, debate, discussions, values, shared values, media coverage, environmental talks, talk about the environment, raise awareness, talk environment,

With the two different lists ready, one for support to reduce emissions and another one for the climate actions, the last step was including them in the Text Analysis to be able to differentiate throughout the years the evolution of mentions of climate action versus climate actions.

5. Ethical Considerations

There are many ethical considerations when research relies on big data, mainly because the information is often collected without the user's approval or knowledge. Some of the concerns that need to be addressed before including any big data information in research are: considerations on whether it is a public or a private space, legal concerns involved around the information, potential harm to participants and data confidentiality, and lastly informed consent (Ahmed et al., 2017; Lundgaard, 2021).

To determine whether Twitter is a private or a public space the conversation turned on the legal aspect of Twitter and the fact that most of the content that belongs to the platform is publicly accessible and free via the Application Programming Interface (API). In contrast with other social

media platforms like Facebook where the developers do not allow retrieving information on their users. Quoting Ahmed et al. (2018)

"It is also important to note that Twitter profiles and tweets are, by default, set to public visibility and, consequently, Twitter could be considered more of a public space compared to Facebook. However, the extent to which individual users of Twitter are aware of this or moderate their behaviour on Twitter to account for this is debatable" (Ahmed et al., 2017, p. 86)

When retrieving public information there are legal considerations. In this case it was important to determine if there is a specific restriction on using the data. This is one of the key messages of the current Twitter Private Policy that every user needs to sign before creating their account:

"Twitter is public, and Tweets are immediately viewable and searchable by anyone around the world. We give you non-public ways to communicate on Twitter too, through protected Tweets and Direct Messages. You can also use Twitter under a pseudonym if you prefer not to use your name" (Twitter, 2021).

Therefore, Twitter is informing users in their Private Policy that the information users post is available and can be used from anyone around the world. On the same document Twitter states that "Keep in mind that search engines and other third parties may still retain copies of your public information, like your profile information and public Tweets, even after you have deleted the information from our services or deactivated your account" (p. 16).

Thus, tweets are considered public information and are available for research without formally acquiring individual user consent. However, to avoid any conflicts the information was not streamed. Streaming is a technique of retrieving information available online that is set to retrieve it as soon as it is published. Thus, giving the authors no chance to erase publications after they have been done. The only tweets immediately retrieved in this thesis were the last day of the research period. This is to give the users the opportunity to delete any tweets they are no longer comfortable in having play a part of their public image on Twitter.

Other aspect included in the research was data confidentiality and potential harm to the climate scientists studied in this thesis. Regarding data confidentiality the raw information – without any analysis – on this thesis was stored temporarily on a cloud service with restricted access to the postdoc who helped acquiring the data, Daniel Lundgaard, and

18

the author. After that, the information was stored on one password-protected laptop alongside with a BitLock encrypted USB device only accessible to the author of this thesis.

To prevent any potential harm to a participant the information will be managed on an aggregated level, without mentions to particular users, unless strictly necessary. In the case that anyone wants to identify someone with de-identification techniques through hashtags using a search engine the risk this study poses to the climate scientists is minimal because these tweets and opinions are personal and public information available to anyone.

6. Findings

6.1 Tweet type, frequency, and climate related tweets

(RQ1.) What frequency and content characterizes the 50 most followed climate scientists' tweets since 2017?



6.1.1 Tweet Type

Figure 6. Percentage of tweets from the dataset that correspond to the three different types of tweets – original, quotes and retweets.

From the total 1,3 million tweets that form the dataset, 45% of those tweets were original tweets created by the climate scientists, 48% were retweets from other climate scientists,

organizations, and other accounts and 6% were quotes. The quotes are a different version of retweet since the author of a quote shares another person's tweet with a comment of their own. If we add up retweets and quotes, 54% of the content found in the timelines of the climate scientists corresponds to content created by someone else.

6.1.2 Frequency

Table 4 . Table of most frequently used words and their categorization as climate related (coded 1) and non-climate related (coded 0) words. (Table created by the author).		
Word	Frequency	Climate Related
climate	13,015	1
change	1 900	1

	woru	Frequency	Climate Nelateu
	climate	13,015	1
	change	4,809	1
	people	4,739	0
	time	3,843	0
	emissions	3,496	1
	global	2,866	0
	Climate	2,705	1
	science	2,432	1
	data	2,359	0
	ice	2,338	1
	fossil	2329	1
	energy	2155	1
	carbon	2140	1
	record	2121	0
	warming	2053	1
	sea	2009	1
	day	1837	0
	die	1826	0
	CO2	1820	1
	it's	1712	0
	temperature	1591	1
	scientists	1568	1
	report	1523	1
	it	1492	0
	2021	1468	0
	fossil	2329	1
	energy	2155	1
	carbon	2140	1
	record	2121	0
	warming	2053	1
12			

Table 4 contains the ten most frequently used words in the tweets, result of the Frequency Analysis conducted in the small sample. As it can be seen the analysis is case sensitive therefore, "climate" appears twice in the list. If we add up both appearances of the word, we have a grand total of 15,720. This means that "climate" is the most frequent word, it is used 3,2 times more frequently than the second most frequent word, "change". Throughout all the analysis I had to include all the repeated words to see which were the most frequent words. Climate Related is a binary variable that assigns the value 1 to the words that are climate related and 0 to the words that are not climate related. Out of the list showed in Table 3, 63% of the words are considered climate related, whereas the other 37% are not considered climate related words. "Climate" and "change" are the most common words however, they are not used in the same proportion which means climate scientists discuss more about the climate than climate change.



6.1.3 Climate Related Tweets

Figure 7. Percentage of the tweets that are climate related or not. (Figure created by the author)

From the complete list of climate related words, the Text Analysis on the complete dataset shows that 75% of the tweets, regardless of the type – original, replies, retweets or quotes – are climate related tweets. The other 25% are tweets about sports, holidays or other topics that have nothing to do with climate or climate change. This confirms that the climate scientists use their Twitter accounts primarily to share information and create and contribute to conversations about climate change.

6.2 Sentiment Analysis and Statistics on Engagement

(RQ2.) How does the emotional affect climate scientists use in their tweets impact audience engagement?

6.2.1 Sentiment Analysis



Figure 8. Number of tweets with a positive, neutral, and negative polarity score from the complete dataset. (Figure created by author).

Figure 8 shows the number of tweets with a positive, neutral, and negative sentiment. As can be appreciated, the most common tone in which climate scientists' tweet is positive, followed by neutral in second place and negative as a far third. There are 233 thousand tweets written in negative tone, this means only 16,9% of the tweets. From this information I can state that more than 80% of the tweets are written in a positive or neutral way. Climate scientists seem to prefer communicating facts – neutral – or positive messages when discussing climate change.

6.2.2 Statistics on Engagement

Table 5. Descriptive statistical analysis performed of	on the engagement metrics Retweets and Replies for the three
possible scenarios – positive, negative, or neutral.	(Table created by author)

Descriptive Statistics		Mean	Median	St. Deviation
Retweets	Positive	233.95	2.0	4929.2
	Negative	262.86	3.0	2774.03
	Neutral	262.75	2.0	5285.85
Replies	Positive	1.82	0.0	8.71
	Negative	2.48	0.0	10.96
	Neutral	1.82	0.0	9.58

Although positive tweets are almost three times as common as negative ones (Figure 8), negative tweets were slightly more likely to be widely shared (Table 4). Table 4 holds the descriptive statistics analysis performed on the variables Retweet and Replies, as we can see there is a difference on the behaviour dependant on the scenario. This means that the tone in which the climate scientist tweet, has an impact on the follower's engagement metrics.

For the Retweets the mean is slightly higher when the sentiment of the tweet is negative than when it is neutral, and the positive tone mean is lower. One could argue then that the positive and neutral tones data have more outliers, tweets that for an arbitrary reason became more popular but there is more consistency on the negative tone ones. Because there are outliers in the data the median can be a better measure to interpret the results. The median for the retweets with negative sentiment is 3 which means that half of the tweets have 3 or less retweets, whereas for the positive and neutral sentiment the median is 2. This means that half of the tweets in the dataset – approximately 690 thousand tweets – are retweeted 2 times or less.

For the Replies the mean is higher when the sentiment of the tweet is negative, and it remains the same for positive, and neutral sentiment. Like in the Retweet, the maximums of the positive and neutral have higher values than the negative. The standard deviation is lower in the tweets with positive sentiment which means that the values are not as dispersed from the mean as they are in the negative and neutral sentiment. Even though there are not as many outliers we will use the median value and interpret it because it is showing us that half of the tweets written by climate scientists go by without any reply from their followers. The median is constant for the three sentiments, so it appears the tone has little influence on the reply count.

Descriptive Statistics		Mean	Median	St. Deviation
Likes	Positive	44.08	2.00	330.85
	Negative	71.60	2.00	853.39
	Neutral	40.45	1.00	309.70
Quotes	Positive	1.01	0.0	8.14
	Negative	1.51	0.0	11.42
	Neutral	0.91	0.0	90.98

Table 6. Descriptive statistical analysis performed on the engagement metrics Likes and Quotes for the three possible scenarios – positive, negative, or neutral. (Table created by author)

Table 5 holds the descriptive statistics analysis performed on the variables Likes and Quotes, as we can see there is a difference on the behaviour dependant on the scenario. Meaning that the tone in which the climate scientist tweet, has an impact on the follower's engagement metrics. Likes and Quotes were both not normally distributed data, this means that when I perform inferential statistics it must be with non-parametric tests. The result from the descriptive statistical analysis is like the results on Retweets and Replies.

For the variable Likes the mean is higher on the negative sentiment than the positive, and neutral. Both positive and neutral have a very similar mean value. The standard deviation is higher on the negative sentiment which tells us that there are outliers on that variable and the data disperses more from the mean. This is consistent with the range that is much higher for the negative sentiment and quite similar for positive and neutral sentiment. The median tells us that half of the tweets receive 2 or less likes for the positive and negative sentiment and barely 1 like or less for the neutral sentiment.

Finally, for the Quotes variable it is a very similar result to that of the Replies. The average remains below 2 quotes per tweet in all the scenarios. The median tells us that more than half of the tweets have 0 quotes. The standard deviation is considerably higher for the neutral sentiment than for positive and negative which means that there are more outliers. Followers reacted quoting more facts – tweets in neutral tone – than any tweet containing a climate scientists' opinion.

To make the analysis more robust I performed inferential statistical analysis, the test I chose was the Median Comparison between groups because I wanted to see if there is a significant statistical difference between the sentiment of the tweets and the engagement metrics, Table 6 has the results for the four engagement variables and the significance of the test.

Hypothesis Test Summary						
Null Hypothesis	Test	Significance	Decision			
The medians of Retweets are the same across categories of Retweet Groups.	Independent Samples Median Test	0.000	Reject the null hypothesis			
The medians of Quotes are the same across categories of Quote Groups.	Independent Samples Median Test	0.000	Reject the null hypothesis			

Table 7. Results from the inferential statistics tests performed on the engagement metrics Retweets, Quotes, Replies and Likes. (Table created by author).

The medians of	Independent	0.000	Reject the null
Replies are the same	Samples Median Test		hypothesis
across categories of			
Reply Groups.			
The medians of Likes	Independent	0.000	Reject the null
are the same across	Samples Median Test		hypothesis
categories of Like			
Groups.			

I performed four Independent Samples Median Tests to analyse whether there is a significant statistical difference between the engagement metrics when the sentiment of the tweet used by the climate scientist changes. According to the results all null hypotheses were rejected meaning that there is a significant statistical difference. With these results and the descriptive statistics, I can state that on average and median the engagement of the followers is significantly higher when the sentiment of the tweet is negative.

6.3 Support to reduce GHG emissions versus Climate Actions

(RQ3.) How frequently and which climate change actions do climate scientists share?

Figure 9 indicates the number of tweets dedicated to climate actions corresponding to the five roles of high-SES – consumer, investor, role model, organizational participant, and citizen compared to the number of tweets with a mention to climate action in general throughout the years 2017 till 2022.



Figure 9. Number of tweets dedicated to support to reduce GHG emissions versus different climate actions throughout the years 2017-2022 by the top 50 climate scientists on Twitter. The complete dataset was analysed with words from the two lists in Table 2 and Table 3. (Figure created by author).

As it can be seen in Figure 9, there are some actions that have received more attention from climate scientists than others. For example, the results of Organizational Participant and Air Travel are so little that they can barely be seen on this scale.

The trends overtime seem to point to a strong increase in support to reduce GHG emissions, the drop off 2022 cannot be considered as a drop since only 4 months are considered. Citizen participation peaks in 2020, possibly related to the US elections since it was an important topic for the scientific community. There is very little action mentioned about investment, organizational participant, or air travel. On average, climate scientists mention the support to reduce GHG emissions 43 times more than specific actions on investment. A big takeaway from here is that climate scientists don't seem to tweet much about climate actions and when they do, they don't name specific actions, except presumably to vote in 2020.

The largest mentions correspond to General Climate Action on 2021, followed by the same variable in 2020 and Citizen 2020. Even though they seem to be mentioned often if we consider that on average each year the climate scientists' tweet 230 thousand tweets, this means that they dedicated less than 3% of their tweets to discuss General Climate Action in 2021 and less than 2% in 2020. Figure 10 shows a visual representation of the number of tweets dedicated to



Figure 10. Visual representation of the number of tweets dedicated to General Climate Action contrasted with the total number of tweets in 2021. (Figure created by author).

General Climate Action contrasted with the total number of tweets retrieved from the climate scientists accounts in 2021.

7. Discussion

This thesis aimed to create a better understanding of the way in which climate scientists use Twitter to communicate climate change and what engagement they receive from their followers. The results show that 75% of the climate scientists' interactions on Twitter are related to climate change, which means that climate scientists use Twitter primarily to discuss climate. Out of all their interactions, 45% corresponds to original content created by the climate scientists and the other 55% corresponds to retweets and quotes. The majority of tweets (45%) are written with a positive sentiment, almost three times as many as negative (17%), with the remaining (38%) with neutral sentiment. There is a statistically significant difference between the sentiment employed by the climate scientists and the engagement metrics results, with the negative sentiment tweets the ones with an average and median higher than the rest in all four of the engagement metrics – retweet, replies, likes and quotes. Climate scientists at best have dedicated less than 3% of their twitter interactions to discuss their support to the reduction of GHG emissions, and less than 2% to specific actions. These results seem to hint that there is a need to discuss more solutions.

With the results presented above I have established that Twitter is a platform climate scientists use to share their knowledge. And that more than 50% of their interactions are the result of supporting other's messages – retweeting and quoting. Lastly that their followers engage more when a negative tone is used on the communications. This presents an opportunity to discuss how, without altering too much the way climate scientists already use the platform, they can persuade their followers to act on climate solutions.

The results presented above show that the top 50 climate scientists do not use their timeline space in Twitter to share climate actions, more like they use it as a space to share knowledgeable information about their disciplines. Climate scientists discuss the climate, and this opens a question about who is responsible to talk and discuss climate solutions? Should that responsibility lay on policy experts?

If we are to follow the GBM which states that the first step for popular support on climate actions falls on the consensus of the scientific community then, it is perhaps the lack of consensus towards which actions would be best that is impeding full support on climate action. There does not seem to be consensus on which climate actions are best, this I can say because of the little mention of any of the climate actions from the 5 roles shown in Figure 9. This is not to say that the responsibility of bringing up solutions to the table lies on the portion of the scientific community that were the centre of this study. Rather, shows that the consensus is missing and that all scientists with an interest in climate change have an opportunity to participate.

There are climate scientists that are already focusing on proposing solutions to climate change. The scientists collaborating on the IPCC reports are divided into three working groups, the third working group "focuses on climate mitigation, assessing methods for reducing greenhouse gases from the atmosphere" (*Working Group III — IPCC*, n.d.). If there already are scientists working on presenting climate solutions, a recommendation might be that scientists across all climate change disciplines devote a space of their communications to these solutions. In hopes that presenting themselves as a united front might increase the perceived scientific agreement and therefore increase the public support for climate action.

The IPCC reports have three working groups, working group one assesses the "physical scientific basis of the climate system and climate change" (*Working Groups* — *IPCC*, n.d.), working group two assesses "the vulnerability of socio-economic and natural systems to climate change, negative and positive"(*Working Groups* — *IPCC*, n.d.) and working group three that, as stated above, focuses on mitigation. However, in climate twitter there seems to be a disproportionate attention to working groups 1 and 2, given what the climate scientists tweet with more frequency about. The findings of working group 3 receive less than 3% of the climate twitter space. If the calls of the IPCC are for more climate action to reduce greenhouse gas emissions, these results show that there is a gap in climate change communication.

As for the results of this thesis that state that engagement is slightly higher when the sentiment of the tweet is negative, this is in agreement with Dahal et al. (2019) who found that when there is significant climate change discussion on Twitter the sentiment of the tweets is negative. One possible explanation, they argue, is that the topic of climate change is treated as a political issue. The results of this study can support and discourage this statement. On one hand we have seen that climate scientists focus on sharing information about the climate and in that sense, one could not argue that the discussion is political at all. However, we can also see in Figure 9 how when it came to climate action recommendations in the role of citizens, the discussion spiked in year 2020 presumably for the US election when climate scientists decided to encourage people to vote thinking about the climate. There is an implication if climate scientists support climate action merely on the political sphere, they are leaving aside all the other roles individuals must reduce GHG emissions.

There is an important remark to make about the recommendations, the results of this thesis do not mean that the communication of climate scientists from now on should be negative. Communicating the scientific basis of climate change as well as the vulnerabilities of socioeconomic and natural systems in negative tones might help to convey the seriousness of the

28

situation. Most of the negative tweets that form part of the dataset are tweets referring to "terrible natural disasters", "loss of biodiversity", "bad weather for crops", "tropical monsoons destroying islands", "people being displaced", and these catastrophes are difficult to convey with a positive tone. It is also logical that people react more to the gravity of the situation when they see the impacts of it. More studies should be made of climate scientists that share information on climate action to see if the engagement metrics of the tweets that are sharing specific climate actions are also higher when the sentiment is negative.

A mention should be made that social media platforms are owned by individuals whose interests commonly lay far away from sustainability. As in many other industries the content producers – all of those who hold a Twitter account and tweet – do not own their writing. This poses a threat that the platform and the way into which they interact with their community of followers can disappear from one day to another. However, the above recommendations are not made merely considering social media, but they are recommendations for climate scientists communications. They can be followed across different platforms, podcasts, blogs, and public events to mention some of the other stages in which climate scientists participate.

8. Limitations and Pathway for future studies

There are some limitations in the study regarding the tools used to extract and analyse information. Regarding the extraction the limitation of the study was that the climate scientists selected for the study had to be active participants on Twitter. Perhaps other climate scientists have a major role sharing climate solutions and were left out of the study because they don't have a Twitter account. Other limitation in selecting the climate scientists is that there might be other scientists with less followers that are dedicated to sharing climate solutions that were left out of this thesis.

Regarding the Sentiment Analysis, a remark must be made since the algorithm cannot understand sarcasm, when scientists tweet about the climate crisis in a sarcastic way, using otherwise positive words it gets classified as positive. This might be good to consider since one of the results of the analysis was that followers engage more in negative conversations than positive ones, sarcasm is ruled out as a negative way to convey messages in this study.

As stated by Chapman (Chapman et al., 2017) the importance of emotions is that they trigger cognitive responses. However, with the results presented in this study I cannot be certain that

29

people's environmental attitudes increase the more they interact with climate scientists' tweets. That might also be considered as a limitation of the study. It would be interesting to follow a group of people that interact with climate change content and perform surveys to see if their environmental attitudes change the more, they are exposed to climate action recommendations from climate scientists.

Another limitation that is important to mention is that on this analysis I am not reading the replies to the tweets and therefore I am only presenting what causes more engagement, but I have no way of knowing if all the attention is positive or negative. This leaves an interesting pathway for future studies that may take the lead to study the most replied tweets from some of the climate scientists and analyse whether their followers agree with the messages conveyed or if they are or not persuaded by the solutions presented.

9. Conclusions

To contribute on the studies of climate change communication by climate scientists this thesis has analysed the twitter interactions of the 50 most followed climate scientists on the platform during the years 2017 to 2022. I analysed the complete dataset with more than 1,3 million tweets on their type – original, retweet or quote – sentiment, engagement metrics and content regarding climate action, looking for patterns that increase engagement.

This thesis has identified that climate scientist does use Twitter as a platform to share their knowledge on climate change. The tweets that are written with a negative tone have a statistical significantly higher engagement than those written in positive or neutral tones. Currently only 3% of the tweets are dedicated to climate action and less than 2% is dedicated to specific climate actions targeting a reduction in greenhouse gas emissions.

The recommendations of this thesis are that to increase the audience engagement with climate solutions, climate scientists should dedicate more space in their communications to share climate solutions, for example, the ones proposed by the IPCC working group three. Following the Gateway Belief Model, presenting a united front within the academic society about climate solutions might be the first step to increasing consensus, giving the followers the perception of an agreement, and influencing them to believe, support, and act upon climate solutions to reduce greenhouse gas emissions.

10. References

- Ahmed, W., Bath, P. A., & Demartini, G. (2017). Chapter 4 Using Twitter as a Data Source An Overview of Ethical, Legal and Methodological Challenges. In *The Ethics of Online Research* (Vol. 2, pp. 79–107). Emerald Publishing Limited.
 https://doi.org/10.1108/S2398-60182018000002004
- Bleier, S. (2019, October 18). *NLTK's list of english stopwords*. Gist. https://gist.github.com/sebleier/554280
- Bonsón, E., Perea, D., & Bednárová, M. (2019). Twitter as a tool for citizen engagement: An empirical study of the Andalusian municipalities. *Government Information Quarterly*, *36*(3), 480–489. https://doi.org/10.1016/j.giq.2019.03.001
- Braungardt, S., van den Bergh, J., & Dunlop, T. (2019). Fossil fuel divestment and climate change: Reviewing contested arguments. *Energy Research & Social Science*, 50, 191– 200. https://doi.org/10.1016/j.erss.2018.12.004
- Changing Behavior to Help Meet Long-Term Climate Targets. (2019, March 20). World Resources Institute. https://www.wri.org/climate/expert-perspective/changingbehavior-help-meet-long-term-climate-targets
- Chapman, D. A., Lickel, B., & Markowitz, E. M. (2017). Reassessing emotion in climate change communication. *Nature Climate Change*, 7(12), 850–852.

https://doi.org/10.1038/s41558-017-0021-9

- Creutzig, F., Fernandez, B., Haberl, H., Khosla, R., Mulugetta, Y., & Seto, K. C. (2016). Beyond Technology: Demand-Side Solutions for Climate Change Mitigation. *Annual Review of Environment and Resources*, *41*(1), 173–198. https://doi.org/10.1146/annurevenviron-110615-085428
- Dahal, B., Kumar, S., & Li, Z. (2019). Spatiotemporal Topic Modeling and Sentiment Analysis of Global Climate Change Tweets. *Social Network Analysis and Mining*. https://doi.org/10.1007/s13278-019-0568-8

- D'Andrea, E., Ducange, P., Bechini, A., Renda, A., & Marcelloni, F. (2019). Monitoring the public opinion about the vaccination topic from tweets analysis. *Expert Systems with Applications*, *116*, 209–226. https://doi.org/10.1016/j.eswa.2018.09.009
- de Moor, J., De Vydt, M., Uba, K., & Wahlström, M. (2021). New kids on the block: Taking stock of the recent cycle of climate activism. *Social Movement Studies*, *20*(5), 619–625. https://doi.org/10.1080/14742837.2020.1836617
- Entradas, M., Marcelino, J., Bauer, M. W., & Lewenstein, B. (2019). Public communication by climate scientists: What, with whom and why? *Climatic Change*, *154*(1–2), 69–85. https://doi.org/10.1007/s10584-019-02414-9
- Fownes, J. R., Yu, C., & Margolin, D. B. (2018). Twitter and climate change. *Sociology Compass*, 12(6), e12587. https://doi.org/10.1111/soc4.12587
- Goldberg, M. H., van der Linden, S., Ballew, M. T., Rosenthal, S. A., Gustafson, A., & Leiserowitz, A. (2019). The Experience of Consensus: Video as an Effective Medium to Communicate Scientific Agreement on Climate Change. *Science Communication*, *41*(5), 659–673. https://doi.org/10.1177/1075547019874361
- Hargreaves, T., Wilson, C., & Hauxwell-Baldwin, R. (2018). Learning to live in a smart home. Building Research & Information, 46(1), 127–139.

https://doi.org/10.1080/09613218.2017.1286882

IPCC. (2022). Summary for Policymakers. In *Climate Change 2022: Impacts, Adaptation and Vulnerability* (H.-O. Pörtner, D.C. Roberts, E.S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem (eds.), p. 37).
 Cambridge University Press.

https://report.ipcc.ch/ar6wg2/pdf/IPCC_AR6_WGII_SummaryForPolicymakers.pdf

Jang, S. M., & Hart, P. S. (2015). Polarized frames on "climate change" and "global warming" across countries and states: Evidence from Twitter big data. *Global Environmental Change*, *32*, 11–17. https://doi.org/10.1016/j.gloenvcha.2015.02.010 Kirilenko, A. P., & Stepchenkova, S. O. (2014). Public microblogging on climate change: One year of Twitter worldwide. *Global Environmental Change*, 26, 171–182. https://doi.org/10.1016/j.gloenvcha.2014.02.008

König, A. (2015). Towards systemic change: On the co-creation and evaluation of a study programme in transformative sustainability science with stakeholders in Luxembourg. *Current Opinion in Environmental Sustainability*, *16*, 89–98.

https://doi.org/10.1016/j.cosust.2015.08.006

- Kuss, P. (2021). Urban transition experiments for global climate goals: Learning from effective interventions to reduce car use in Lund municipality. *Master Thesis Series in Environmental Studies and Sustainability Science*. http://lup.lub.lu.se/studentpapers/record/9046766
- Lundgaard, D. (2021). Using Social Media to Discuss Global Challenges: Case Studies of the Climate Change Debate on Twitter. Copenhagen Business School [Phd]. https://research.cbs.dk/en/publications/using-social-media-to-discuss-globalchallenges-case-studies-of-t

Mann, M. E., Hassol, S. J., & Toles, T. (2017, July 12). Opinion | Doomsday scenarios are as harmful as climate change denial. *Washington Post*.
https://www.washingtonpost.com/opinions/doomsday-scenarios-are-as-harmful-as-climate-change-denial/2017/07/12/880ed002-6714-11e7-a1d7-9a32c91c6f40_story.html

McWhinney, J. (2021, May 17). *Top Green Investing Opportunities*. Investopedia. https://www.investopedia.com/articles/stocks/07/green-industries.asp

Muñoz-Exposito, M., Oviedo-García, M. Ángeles, & Castellanos-Verdugo, M. (2017). How to measure engagement in Twitter: Advancing a metric. *Internet Research, 27*(5), 1122– 1148. https://doi.org/10.1108/IntR-06-2016-0170 Nielsen, K. S., Nicholas, K. A., Creutzig, F., Dietz, T., & Stern, P. C. (2021). The role of highsocioeconomic-status people in locking in or rapidly reducing energy-driven greenhouse gas emissions. *Nature Energy*, 6(11), 1011–1016. https://doi.org/10.1038/s41560-021-00900-y

- Nightingale, A. J. (2017). Power and politics in climate change adaptation efforts: Struggles over authority and recognition in the context of political instability. *Geoforum, 84*, 11– 20. https://doi.org/10.1016/j.geoforum.2017.05.011
- Pearce, W., Holmberg, K., Hellsten, I., & Nerlich, B. (2014). Climate Change on Twitter: Topics, Communities and Conversations about the 2013 IPCC Working Group 1 Report. *PLOS ONE*, 9(4), e94785. https://doi.org/10.1371/journal.pone.0094785
- Preethi, P. G., Uma, V., & kumar, A. (2015). Temporal Sentiment Analysis and Causal Rules Extraction from Tweets for Event Prediction. *Procedia Computer Science*, *48*, 84–89. https://doi.org/10.1016/j.procs.2015.04.154

Removing stop words with NLTK in Python. (2017, May 22). GeeksforGeeks.

https://www.geeksforgeeks.org/removing-stop-words-nltk-python/

- Rohde, R. (n.d.). @RARohde/Top 50 Climate Scientists / Twitter. Twitter. Retrieved 24 February 2022, from https://twitter.com/i/lists/1056149988605116416
- Rosenstiel, T., Sonderman, J., Loker, K., Ivancin, M., & Kjarval, N. (2015). *Twitter and the News:* How people use the social network to learn about the world. 44.

Sabherwal, A., Ballew, M. T., van der Linden, S., Gustafson, A., Goldberg, M. H., Maibach, E. W.,
Kotcher, J. E., Swim, J. K., Rosenthal, S. A., & Leiserowitz, A. (2021). The Greta
Thunberg Effect: Familiarity with Greta Thunberg predicts intentions to engage in
climate activism in the United States. *Journal of Applied Social Psychology*, *51*(4), 321–
333. https://doi.org/10.1111/jasp.12737

Schäfer, M. S. (2012). Online communication on climate change and climate politics: A literature review. WIREs Climate Change, 3(6), 527–543. https://doi.org/10.1002/wcc.191

Segerberg, A., & Bennett, W. L. (2011). Social Media and the Organization of Collective Action: Using Twitter to Explore the Ecologies of Two Climate Change Protests. *The Communication Review*, *14*(3), 197–215.

https://doi.org/10.1080/10714421.2011.597250

- Shahin, S., & Dai, Z. (2019). Understanding Public Engagement With Global Aid Agencies on Twitter: A Technosocial Framework. *American Behavioral Scientist*, 63(12), 1684–1707. https://doi.org/10.1177/0002764219835248
- Shetty, S. J., & Ramesh, V. (2021). pyResearchInsights—An open-source Python package for scientific text analysis. *Ecology and Evolution*, 11(20), 13920–13929. https://doi.org/10.1002/ece3.8098
- Thies, C., Kieckhäfer, K., Spengler, T. S., & Sodhi, M. S. (2019). Operations research for sustainability assessment of products: A review. *European Journal of Operational Research*, 274(1), 1–21. https://doi.org/10.1016/j.ejor.2018.04.039

Twitter. (2021). *Twitter Privacy Policy* (p. eng). https://cdn.cmstwdigitalassets.com/content/dam/legal-twitter/site-assets/privacy-aug-19th-2021/Twitter_Privacy_Policy_EN.pdf

Twitter. (2022). *Selected Metrics and Financials Q4'21_V3* (Metrics and Financials No. 3; p. 3). https://s22.q4cdn.com/826641620/files/doc_financials/2021/q4/Final-Q4'21-Selected-Metrics-and-Financials.pdf

van der Linden, S. (2021). The Gateway Belief Model (GBM): A review and research agenda for communicating the scientific consensus on climate change. *Current Opinion in Psychology*, 42, 7–12. https://doi.org/10.1016/j.copsyc.2021.01.005

- von Wirth, T., Fuenfschilling, L., Frantzeskaki, N., & Coenen, L. (2019). Impacts of urban living labs on sustainability transitions: Mechanisms and strategies for systemic change through experimentation. *European Planning Studies*, *27*(2), 229–257. https://doi.org/10.1080/09654313.2018.1504895
- Working Group III IPCC. (n.d.). Retrieved 2 May 2022, from https://www.ipcc.ch/workinggroup/wg3/
- *Working Groups—IPCC*. (n.d.). Retrieved 8 May 2022, from https://www.ipcc.ch/workinggroups/
- Yasen, M., & Tedmori, S. (2019). Movies Reviews Sentiment Analysis and Classification. 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), 860–865. https://doi.org/10.1109/JEEIT.2019.8717422
- Yue, L., Chen, W., Li, X., Zuo, W., & Yin, M. (2019). A survey of sentiment analysis in social media. *Knowledge and Information Systems*, 60(2), 617–663. https://doi.org/10.1007/s10115-018-1236-4
- Zelenski, J. M., & Desrochers, J. E. (2021). Can positive and self-transcendent emotions promote pro-environmental behavior? *Current Opinion in Psychology*, *42*, 31–35. https://doi.org/10.1016/j.copsyc.2021.02.009
- Zvarevashe, K., & Olugbara, O. O. (2018). A framework for sentiment analysis with opinion mining of hotel reviews. *2018 Conference on Information Communications Technology and Society (ICTAS)*, 1–4. https://doi.org/10.1109/ICTAS.2018.8368746

1. Appendix

11.1 Appendix A. Stop words for Text Analysis.

The table lists the words used for the frequency code, excluding these words ensures the results from the frequency table are non-common words that can easily be classified between climate and non-climate related words.

1	abst	alongside	approximately	backing	Big	сс
100%	accordance	already	aq	backs	bill	cd
2	according	als	ar	backward	billion	се
3	accordingly	also	Are	backwards	biol	certain
4	across	Also	are	bb	bit	certainly
5	act	Also,	area	bd	bj	cf
6	actually	although	areas	be	bm	cg
10	ad	always	aren	became	bn	ch
15	add	am	aren't	because	bo	changes
20	added	amid	arise	become	both	check
30	adj	amidst	around	becomes	bottom	ci
39	adopted	among	arpa	becoming	br	ck
2020	ae	amongst	As	been	brief	cl
-	af	amoungst	as	before	briefly	clear
	affected	amount	a's	beforehand	, bs	clearly
_	affecting	an	aside	began	bt	click
_	affects	And	ask	begin	but	cm
"är"	After	and	asked	beginning	But	cmon
"lt's"	after	announce	asking	beginnings	buy	c'mon
1	afterwards	another	asks	begins	by	cn
&:	ag	Another	associated	behind	bw	сп со
(and	again	any	at	heing	by	0
	ago	anybody	att	heings	bz	com
	ab	anybow	20	believe	62	come
	ahaad	anymore	auth	below		comes
· •		anyone	20	beside		computer
-	aint	anyone	av	besides	camo	con
-	aint ain't	anyunay		best	can	concerning
		anyway		better	cannot	concerning
		anyways	aw	between	cant	consider
<u>``</u>	all	anywhere	away	bevond	can't	considering
a	allow	apart	27	beyond	cantion	contain
ableabout	allows	apart	a2	ba	caso	containing
ableabout	allows	apparentiy	b	bb	case	containing
about	alinost	appear	back	bi	causo	contains
above	along	appreciate	backad	bia	cause	copy
abioau	diolig dida't	appropriate	Dackeu	big	causes	bodet
coulda	diffor	ee	ex	för	give	hadn't
couldnt	different	offoct	exactly	forever	given	half
	difforently		example	former	giver	hannons
could'se	directly	⊂g ob	f	formerly	giving	har
	directly	en	1	forth	giving	hardly
course	dj	eight	face	forth	gi	hardiy
Cr	dK dise	eignty	faces	forty	gm	has
	do	either	facto	found	gmt	hash
	do	eleven	facts	found	gn	nasht
CS	does	else	fairly	TOUR	go	nasnit
cu	doesn	elsewhere	Tar	Tr	goes	nave
currently	doesnt	empty	Tarther	tree	going	naven
CV	doesn't	en	Telt	trom	gone .	navent
СХ	doing	En .	few	front	good	haven't
су	don	end	tewer	tull	goods	having

CZ	don't	ended	ff	fully	got	he
d	done	ending	fi	further	gotten	hed
dare	dont	ends	fifteen	furthered	gov	he'd
darent	don't	enough	fifth	furthering	gp	hell
daren't	don't	entirely	fifty	furthermore	gq	he'll
date	doubtful	er	fify	furthers	gr	hello
De	down	es	fill	fx	great	help
de	downed	especially	find	g	greater	hence
dear	downing	et	finds	ga	greatest	her
definitely	downs	et-al	fire	gave	greetings	Here
der	downwards	etc	first	gb	group	here
des	du	ett	five	gd	grouped	here:
describe	due	even	fix	ge	grouping	hereafter
described	during	evenly	fj	general	groups	hereby
despite	dz	ever	fk	generally	gs	herein
det	е	evermore	fm	get	gt	heres
detail	each	every	fo	gets	gu	here's
did	early	everybody	followed	getting	gw	Here's
Did	ec	everyone	following	gf	gy	hereupon
didn	ed	everything	follows	gg	h	hers
didnt	edu	everywhere	For	gh	had	herse"
herself	i	inside	itself	1	long	means
hes	i.e.	insofar	ive	la	longer	meantime
he's	l'm	instead	l've	La	longest	meanwhile
het	l've	int	i've	large	look	med
hi	id	interest	l've	largely	looking	meet
hid	i'd	interested	j	last	looks	member
high	I'd	interesting	jag	Last	lot	members
higher	ie	interests	je	late	low	men
highest	lf	into	jm	lately	lower	merely
him	if	invention	јо	later	lr	mg
himse"	ignored	inward	join	latest	ls	mh
himself	ii	io	јр	latter	lt	microsoft
his	ik	iq	just	latterly	ltd	might
hither	il	ir	Just	lb	lu	mightnt
hk	ill	ls	k	lc	lv	mightn't
hm	i'll	is	kan	Le	ly	might've
hn	1'11	isn	ke	le	m	mil
home		icet	kaan	lead	ma	mill
h a 10 a 10 a 10 a	im	ISHL	кеер	leau	1110	
nomepage	im i'm	isn't	keeps	least	made	million
hopefully	im i'm I'm_	isn't it	keeps keept	least length	made	million mine
hopefully how	im i'm I'm immediate	isn't it it	keeps keeps kept keys	least length les	made mainly mais	million mine minus
hopefully how How	im i'm I'm immediate immediately	isn't it it It	keeps keeps kept keys kg	least length les less	made mainly mais make	million mine minus miss
hopefully how How howbeit	im i'm I'm immediate immediately importance	isn't it it It it	keep keeps kept keys kg kh	least length les less lest	made mainly mais make makes	million mine minus miss mk
homepage hopefully how How howbeit how'd	im i'm I'm immediate immediately importance important	isn't it it It it it	keeps keeps kept keys kg kh ki	least length les less lest let	made mainly mais make makes making	million mine minus miss mk ml

how'll	In	lt's	km	let's	Many	mn
how's	inasmuch	it's	kn	li	many	mo
hr	inc	itd	knew	like	many	more
ht	inc.	it'd	know	liked	may	moreover
htm	indeed	itll	known	likely	maybe	most
html	index	it'll	knows	likewise	maynt	mostly
http	indicate	its	kp	line	mayn't	move
hu	indicated	it's	kr	little	mc	mp
hundred	indicates	it's	kw	lk	md	mq
1	information	it's	ky	II	me	mr
1	inner	itse"	kz	'	mean	mrs
ms	needs	novel	open	particularly	presenting	regardless
msie	neither	now	opened	parting	presents	regards
mt	net	nowhere	opening	parts	presumably	related
mu	netscape	np	opens	pas	previously	relatively
much	never	nr	opposite	past	primarily	research
mug	neverf	nu	or	рау	probably	reserved
must	neverless	null	ord	ре	problem	respectively
mustnt	nevertheless	number	order	per	problems	resulted
mustn't	New	numbers	ordered	perhaps	promptly	resulting
must've	new	nz	ordering	pf	proud	results
mv	newer	0	orders	pg	provided	right
mw	newest	obtain	org	ph	provides	ring
mx	next	obtained	other	pk	pt	ro
My	nf	obviously	others	pl	put	room
My	ng	och	otherwise	place	puts	rooms
my	ni	of	ought	placed	pw	round
myse"	niet	off	oughtnt	places	ру	RT
myself	nine	often	oughtn't	please	q	ru
mz	ninety	oh	Our	Please	qa	run
n	nl	Oh	our	plus	que	rw
na	no	ok	ours	pm	quickly	S
name	No	okay	ourselves	pmid	quite	sa
namely	nobody	old	out	pn	qv	så
nay	non	older	outside	point	r	said
nc	none	oldest	over	pointed	ran	same
nd	nonetheless	om	overall	pointing	rather	saw
ne	noone	omitted	owing	points	rd	say
near	no-one	On	own	poorly	re	saying
nearly	nor	on	р	possible	readily	says
necessarily	normally	once	ра	possibly	really	sb
necessary	nos	One	på	potentially	reasonably	SC
need	Not	one	page	рр	recent	sd
needed	not	ones	pages	pr	recently	se
needing	noted	one's	part	predominantly	ref	sec
neednt	nothing	only	parted	present	refs	second

needn't	notwithstanding	onto	particular	presented	regarding	secondly
seconds	show	sometime	tc	thence	things	together
section	showed	sometimes	td	there	think	too
see	showing	somewhat	tell	There	thinks	too
seeing	shown	somewhere	ten	thereafter	third	took
seem	showns	soon	tends	thereby	thirty	top
seemed	shows	sorry	test	thered	this	toward
seeming	si	specifically	text	there'd	This	towards
seems	side	specified	tf	therefore	this	tp
seen	sides	specify	tg	therein	this,	tr
sees	significant	specifying	th	therell	thorough	tried
self	significantly	sr	than	there'll	thoroughly	tries
selves	similar	st	thank	thereof	those	trillion
sensible	similarly	state	Thank	therere	thou	truly
sent	since	states	Thanks	there're	though	try
serious	sincere	still	thanks	theres	thoughh	trying
seriously	site	stop	thanx	There's	thought	ts
seven	six	strongly	that	there's	thoughts	t's
seventy	sixty	su	That	thereto	thousand	tt
several	sj	sub	That's	thereupon	three	turn
sg	sk	substantially	thatll	thereve	throug	turned
sh	sl	successfully	that'll	there've	through	turning
shall	slightly	such	thats	These	throughout	turns
shant	sm	sufficiently	That's	these	thru	tv
shan't	small	suggest	that's	they	thus	tw
she	smaller	sup	thatve	They	til	twas
shed	smallest	sur	that've	theyd	till	'twas
she'd	sn	sure	The	they'd	tip	twelve
shell	So	sv	The	theyll	tis	twenty
she'll	SO	sy	the	they'll	'tis	twice
shes	some	system	the	theyre	tj	two
she's	somebody	SZ	their	they're	tk	tz
should	someday	t	theirs	theyve	tm	u
shouldn	somehow	t	them	they've	tn	ua
shouldnt	someone	take	them	thick	То	ug
shouldn't	somethan	taken	themselves	thin	to	uk
should've	something	taking	then	thing	today	um
un	van	we	when	who'll	world	your
und	various	web	whence	whom	would	youre
under	VC	webpage	when'd	whomever	wouldn	you're
underneath	ve	website	whenever	whos	wouldnt	you're
undoing	've	wed	when'll	who's	wouldn't	yours
unfortunately	y versus	we'd	when's	whose	would've	yourself
unless	very	week	where	why	WS	yourselves
unlike	vg	welcome	whereafter	Why	www	youve
unlikely	vi	well	whereas	why'd	х	you've

until	via	we'll	whereby	why'll	У	yt
unto	viz	wells	where'd	why's	уе	yu
up	vn	went	wherein	widely	year	z
upon	vol	were	where'll	width	years	za
ups	vols	we're	wheres	will	Yes	zero
upwards	von	weren	where's	Will	yes	zm
us	voor	werent	whereupon	willing	Yes,	zr
use	VS	weren't	wherever	wish	yes,	zu
used	vu	weve	whether	with	yet	
useful	w	we've	which	With	You	
usefully	want	wf	whichever	within	you	
usefulness	wanted	What	while	without	you	
uses	wanting	what	whilst	won	you,	
using	wants	what'd	whim	wonder	youd	
usually	was	whatever	whither	wont	you'd	
ииср	wasn	whatll	who	won't	youll	
uy	wasnt	what'll	whod	words	you'll	
uz	wasn't	whats	who'd	work	young	
v	way	what's	whoever	worked	younger	
va	ways	whatve	whole	working	youngest	
value	We	what've	wholl	works	Your	

11.2 Appendix B. List of Climate Related Words

The table lists the words used for the Text Analysis, including these words in the analysis ensures that I can find all the tweets related to climate change and mark then to find the frequency with which climate scientists' tweet about climate change.

climate	extreme	hurricane	lost	observed
change	Global	cold	risks	Energy
emissions	land	role	range	marine
Climate	Tropical	levels	#GreatBarrier	systems
			Reef	
science	models	rain	Change	methane
ice	#ClimateEmerg	analysis	environmenta	protect
	ency		1	
fossil	human	political	space	rate
energy	planet	project	economic	increased
carbon	storm	person	satellite	conversation
warming	#COP26	local	transition	scenario
sea	social	response	normal	Carbon
CO2	including	change,	Data	green
temperature	model	care	annual	trend
scientists	students	community	rainfall	approach

report	scientist	Sea	warmest	changing
gas	map	tropical	building	rising
water	industry	potential	process	burning
future	life	worth	pressure	national
fuel	fuels	forecast	answer	variability
weather	based	natural	provide	reports
IPCC	Storm	adaptation	#climatechan	experts
			ge	
action	Science	reason	long-term	car
snow	surface	CO2	electricity	temps
policy	solar	winds	nuclear	coast
average	impact	food	save	critical
impacts	Join	expected	growth	emissions,
power	share	coral	flooding	safe
ocean	idea	loss	development	discuss
oil	winter	#climate	resources	net-zero
risk	issue	solutions	Pacific	leading
study	evidence	scale	effects	effective
article	government	World	updated	cycle
coal	Atlantic	atmosphere	fall	Report
Hurricane	clean	warm	Gulf	1.5C
air	#ClimateBrawl	review	observations	positive
#ClimateCrisis	season	view	2030	pollution
current	crisis	colleagues	species	expect
heat	scientific	greenhouse	field	caused
level	times	records	damage	finance
Arctic	rise	policies	#IPCC	maps
#Arctic	health	mitigation	student	specific
temperatures	scenarios	Ocean	budget	#ClimateChange
Earth	conditions	atmospheric	warmer	wave
event	summer	anomalies	period	efforts
light	panel	benefits	concentration	earth
society	trees	consequences	mag	produced
trends	pattern	renewables	bike	diversity
emergency	solution	cars	technologies	Assessment
nature	expert	Green	cutting	1.5
capacity	reducing	ecological	cuts	causing
UN	coastal	Bay	forests	Environmental
iustice	precipitation	movement	seasonal	investments
sustainable	mph	ground	measure	rights
threat	developing	forest	sustainability	hurricanes
world	estimates	activities	walk	force
vote	breakdown	oceans	monitoring	transport
science	Coast	dioxide	nrevent	factor
forcing	reduction	resilience	covered	extremes
TOTCINE	reduction	resilience	covereu	EAUCINES

challenge	capture	CH4	animals	Temperature
drought	emission	ecosystems	driving	Marine
heating	hottest	deep-sea	respond	flying
situation	Water	Ice	burn	invest
individual	plant	planetary	shared	agreement
tax	researchers	outcomes	reef	projected
Scientists	humans	reductions	lightning	pathway
degrees	urban	vulnerable	grow	eruption
severe	studies	target	Planet	modelling
1.5°C	environment	uncertainties	coverage	#ClimateReport
assessment	world's	cities	activists	stream
reporting	COP26	regions	cloud	tackle
hot	plants	data,	fish	waves
uncertainty	GHG	Weather	Warming	predicted
production	Adaptation	degree	temp	system
decision	climate,	Research	physics	feedbacks
AR6	removal	melting	Reef	sensitivity
funding	tipping	flood	#CAfire	glaciers
academic	#ClimateAction	commitments	choices	Extreme
storms	reefs	world,	subsidies	warming,
landfall	investment	biodiversity	responsibility	collapse
physical	Nature	cooling	driven	tornado
progress	waste	wildfires	reduced	scientists,
melt	drive	river	conservation	consumption
projections	corals	Oil	floods	diverse
infrastructure	produce	2C	sun	catastrophic
anthropogenic	tech	plastic	responses	institutions
knowledge	market	polar	Action	losing
challenges	Lake	wildfire	change?	ecosystem
renewable	targets	Fossil	Agreement	report,
offshore	Land	Clean	imports	#AdaptationWithoutB
				orders
Fire	academics	hydrogen	wind,	temperatures,
Scientist	offsets	coldest	framework	Data:
#hurricane	"climate	research	albedo	lakes
energy,	human-caused	academia	input	recommendations
snowfall	scientist,	Wind	Temperatures	policymakers
freezing	Environment	emit	AR5	#AR6
#water	summit	Coal	mapping	1,5
NASA	measurements	peer-reviewed	large-scale	evacuation
1%	Hemisphere	research,	committee	islands
modeling	Cyclone	drivers	Institute	Islands
lake	acting	Earth's	wildlife	tips
challenging	disasters	2°C	Development	sky
СОР	accelerating	CO2,	impacts,	profit
water,	coal,	Scientific	Force	stock

fund	radiative	soil	vehicle	scale,
Summary	MBARI	Resilience	housing	#drought
Net	ENSO	#Hurricane	wood	planting
EV	flows	deforestation	rivers	pricing
Zero	resilient	zero	transformatio n	sciences
behavior	models,	Human	Methane	#energy
fuels,	latitude	Centre	equitable	mines
EVs	footprint	centre	humidity	constraints
Emissions	gases	volcanic	#GreenNewD eal	demonstrate
ET	warmth	strategies	home	#deepsea
individuals	hotter	#SDGs	life,	experiments
cyclone	Niño	4C	efficient	worldwide
°C	vehicles	tonnes	thunderstorm s	lights
animal	GHGs	observation	legislation	atmosphere,
methods	1.5-2°C	threshold	sea-level	barriers
feedback	clouds	mountains	panels	financing
gas,	scenarios,	scales	partnership	taxes
Summit	waters	meters	#FridaysForFu ture	utility
Sustainable	agriculture	organizations	advisory	emitted
#ClimateAction Now	initiative	permafrost	politically	preliminary
captured	boundaries	geoengineerin g	threats	season,
Policy	Planetary	Solutions	seafloor	collected
policy,	system,	voters	frame	outdoor
"Climate	Food	heatwaves	#GlobalWarm ing	volcano
Earth's	UNFCCC	Commission	restoration	seminar
sinks	System	density	elements	Analysis
heatwave	oil,	expand	researcher	meat
#ocean	mining	decarbonizati on	habitat	short-term
Solar	pipeline	investing	assessments	reviewed
Atmospheric	#ClimateStrike	process,	bills	Glacier
NETs	hazards	biosphere	demands	#ParisAgreement
dramatic	weather,	poverty	catastrophe	intensification
temporary	seasons	WG2	measuring	feasible
climate	ocean,	justice,	motion	rains
conclusions	level,	changes	scenario,	information,
problematic	harmful	stats	SO2	#GreenStimulus
ESG	implement	Winds	substitution	#IPCCReport
organization	Natural	cyclones	theories	Policymakers
flights	reverse	non-CO2	drops	communications
Earth,	refuse	whale	Impacts	fossil-fuel

Hot	method	seas	#adaptation	Finance
#Climate	productive	biomass	droughts	temperature,
analyses	tropics	Urban	victims	garbage
ECS	mitigate	crop	alternatives	journals
farm	corporations	improvements	stratospheric	
freshwater	priorities	damages	frozen	
landscape	destroying	discourse	Cities	
Rainfall	investors	ecology	dependence	
bus	credibility	frequency	solutions,	
variety	co2	barrier	Sciences	
experiment	demonstrated	demonstrates	Crisis	
toxic	endangered	incentives	healthcare	
#biodiversity	geospatial	decreasing	ozone	
#COP26,	winter,	#GreatBarrier	interactions	
impacted	removing	Reel,	CLIMATE	
	inchiration	Lakes	Vulporability	
2050,		offoot	threatened	
systemic	GICOZ	enect	threatened	
concrete	accumulation	governance	plane	
Coral	#NewClimateW ar	SNOCKING	Flooding	
cycling	streams	thermal	#seaice	
beach	Panel	record-	hi-emitters	
		breaking		
irreversible	rise,	engineering	denying	
bioenergy	anxiety	technology,	fishing	
Justice	mechanisms	model,	mandate	
eating	inequality	activism	solving	
metrics	policies,	meteorologica I	emissions)	
household	reaction	whales	emitting	
food,	traffic	Island,	Technical	
health,	roles	migration	meteorologist	
		C	s	
solar,	regulatory	Fuel	decarbonize	
solar, initiatives	regulatory UNESCO	Fuel mortality	decarbonize decarbonisati on	
solar, initiatives Sustainability	regulatory UNESCO generating	Fuel mortality systems,	decarbonize decarbonisati on restrictions	