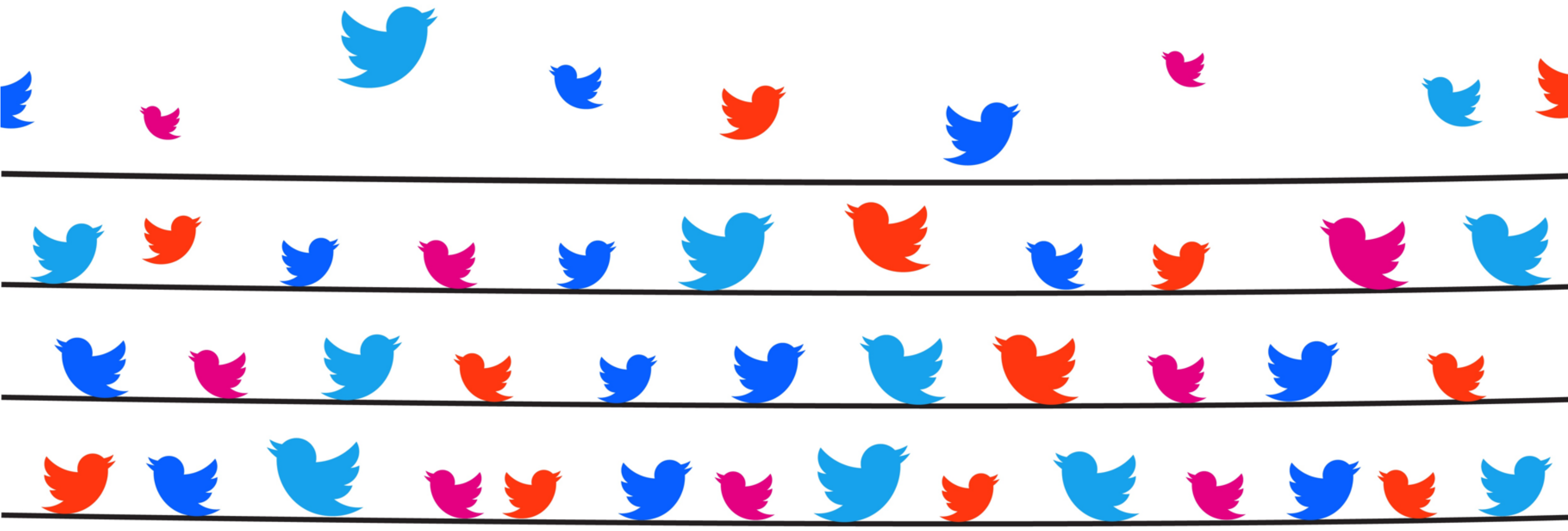

Social Media and Climate Change:

Exploring the Effects of Climate-related Events on Online Discourse Using Topic Modelling & Sentiment Analysis

By Elias Bach

Master Thesis, MSc Engineering and Policy Analysis

TU Delft

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by E. L. Bach

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Thesis committee:	Prof. dr. T. Comes,	TU Delft, supervisor
	Prof. dr. T. Filatova,	TU Delft, supervisor
	Dr. M. Sirenko,	TU Delft, advisor
	L. Houwing,	Politie Nederland, advisor
	R. Maas,	Politie Nederland, supervisor

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Executive Summary

Climate change is an omnipresent issue in politics, industry, science, and society. Scientist knew of its existence for several decades, but only recently has the perception of it shifted from a solely environmental problem to a matter of international security. Climate change is thought to impact the likelihood of extreme weather events, intensity of droughts, rising sea levels and more. In this way climate change contributes to ongoing conflicts around the world by destroying resources or forcing people out of habitats, creating tensions among groups of people.

As the impacts of climate change are being felt more directly, calls for bolder climate action are getting louder. At the same time, there is also resistance by climate skeptics in industry, government, and among voters. Although most people appear aware and concerned with the development of climate change, the attitude towards climate action is extremely broad. Political rhetoric and disinformation in the media compound the disagreement on climate change, causing polarization. Although some polarization is beneficial for democratic deliberation and for mobilizing voters, if polarization divides the electorate into mutually distrustful groups, it can trap societies in a stifling gridlock or gradually erode democratic institutions. These pernicious effects are what necessitates closer study to monitor societal polarization, prevent conflict and improve climate action efforts.

Social media offers huge amounts of textual data to study discourse on climate change, which this study leverages to make first steps in understanding what topics make up the public discourse, how it varies across linguistic regions (English, German, Dutch) and how it changes considering climate-related events, namely floods and a climate protest. Using both topic modelling and sentiment analysis on Twitter data, it could be identified that activity spiked around major events: namely the 2019 Climate Strike and the 2021 Flood in Western Europe. However, reaction to events appears to be mainly regional with reaction to floods seen only in the Dutch and German tweets. The English Twittersphere seemed to be mainly skewed towards events in America. Polarization appeared low as most tweets were neutral. Examining only tweets with high sentiment, a different behavior was detected in terms of news coverage as there existed more high negative sentiment tweets, but almost no high positive sentiment tweets. During the 2019 Global Climate Strike, extreme sentiment tweets went both positive and negative, possibly indicating more intense discourse and a more polarized atmosphere.

Overall, results show that conflict-triggering climate events are very likely to be domestic events. Thus, from a security perspective, it suggests on the short-term to focus on the monitoring of domestic actors. On the long-term however, policies need to be implemented which address underlying factors that make society susceptible to polarization, such as socioeconomic inequalities and exclusion, disinformation in media or corruption. Lastly, from an academic perspective, more research on other dimensions of polarization needs to be conducted. Polarization is a complex phenomenon, whose full implications cannot be captured by the sentiment metrics. Thus, research moving forward should strive towards a more refined multi-method approach to further investigate climate change polarization and its conflict potential. A better understanding could benefit practitioners in many areas such as security and social policy, for strategic planning regarding climate change.

Acknowledgements

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1 Introduction

1.1 A Very Brief History of Climate Change

Climate change is considered by many as the defining challenge of the modern era; an unprecedented one, that is unique in the potentially irreversible consequences which it poses on the planet on both a geographical and temporal scale (Wagner and Weitzman 2016). Climate itself refers to the long-term weather-related patterns, including primarily temperature and precipitation, but also all other meteorological phenomena such as snow, wind, or thunder. Over the course of its 4.5-billion-year history, the Earth has had climactic oscillations on a geological scale, shifting between glacial and interglacial periods, as repeatedly evidenced by geological analysis of soil, sediments and rock formations, archeological findings of fossils or chemical composition of polar ice bubbles (Smithsonian National Museum of Natural History 2022). It is clear that the climate on Earth is and has always been dynamic in nature, yet the modern age marks a turning point, both in terms of the speed and magnitude of these changes.

Contemporary climate change is by and large an anthropogenic phenomenon. Its starting point is commonly dated to the start of the First Industrial Revolution around 1750-1840 where a series of technological innovations, most notably the steam engine spurred the transition from hand production to mechanized production, fueled by the chemical combustion of coal (Mohajan 2019a; Rosen 2012). Following with the Second (~1860-1914) and Third Industrial Revolution (~1950-present), which are mainly characterized by the invention and mass adoption of electricity (Gordon 2000; Mohajan 2019b) and digital technology respectively, energy demands exploded. These were met through coal, oil, and gas (Jänicke and Jacob 2009; Mohajan 2021). Within a couple of centuries, human activities have significantly altered global atmospheric chemistry. The burning of fossil fuels increased concentrations of greenhouse gases (GHG), particularly carbon dioxide, but also methane, nitrous oxides, and chlorofluorocarbons.

1.2 Climate Change: Not Just an Ecological Issue

A rapid change in mean global temperature could overwhelm the adaptive capacity of the Earth's climate system and drive the biosphere into massively disruptive patterns (Dietz, Shwom, and Whitley 2020). By the end of the 1980s it had become clear that this would change planetary conditions, by decreasing the albedo, i.e. reflectivity, of the Earth's surface, causing global warming (Weart 2003). The major concern of global warming are its cascading effects, including self-reinforcing feedbacks that could push the Earth System toward a planetary threshold leading to irreversible changes, at least in a timeframe that matter to human society. For example, melting ice not only increases sea-levels, but due to reduced ice coverage further reduces the Earth's albedo. More atmospheric CO_2 interacts with water to make carbonic acid, causing ocean acidification affecting thermohaline ocean currents, which in turn affects annual weather patterns. Interaction with further global environmental changes, including biodiversity loss and modification of biogeochemical cycles, could adversely impact ecosystems, but also disrupt services on which humans are dependent for survival (Steffen et al. 2018).

According to the most recent report by the Intergovernmental Panel on Climate Change (IPCC), the "Sixth Assessment Report" (AR6), which was drafted by 234 leading climate scientists and compiling over 14,000 scientific articles, global temperatures are set to rise by 1.6 at least °C by 2050, even in the most optimistic of scenarios where carbons emissions cease in 2050 (IPCC 2022). In any case, with a warmer mean global temperature scientists expect for more intense desertification (exacerbating by deforestation and unsustainable farming practices) and increased frequency of extreme weather events, such as droughts and storms, on top of sea level rise and ocean acidification (IPCC 2022). These biophysical changes would not only affect the natural world but would also lead to a wide range of consequences, upsetting the relative stability of human society. A sea level rise alone, threatens the habitat of roughly 600 million to 1 billion people in coastal regions (Hauer et al. 2020). Desertification could also threaten livelihoods in regions such as the Mediterranean, Northern Africa, Arabian Peninsula, Central & Southeast Asia, and the Sahel region (Mirzabaev and Wu 2019; Rodrigo Comino 2022), making them unsuitable for living and/or disrupt agricultural activities. The security threats posed by climate change were well-summarized in a G7-commissioned report "A Climate for Peace" as so-called “climate fragility risks". These include local resource competition, volatile food prices and provision, livelihood insecurity and migration (Rüttinger et al. 2015). In fact, climate change-induced conflicts have already been identified, with several United Nations Security Council resolutions pertaining to ongoing conflicts, such as civil wars and communal conflicts in Africa, where these risks play a central role (Busby 2021).

1.3 Dire Consequences, yet Slow Climate Action

Despite UN Chief António Guterres describing AR6 as "code red for humanity", the most dire warning yet, climate action efforts continue to progress slowly in all sections of society (McGrath 2021).

An undeniably large portion of global GHG emissions can be attributed to industrial activities (Frumhoff, Heede, and Oreskes 2015). Numbers differ depending on definition and method of allocation. For 2014, the American Environmental Protection Agency estimates roughly 24% of global GHG emissions to originate from industry alone (US EPA 2015), while the European Environmental Agency estimates roughly 19% (EEA 2016). At the 26th session of the Conference of the Parties (COP26) corporations and businesses have committed themselves to strive towards net-zero emissions, yet these promises are subject to much doubt and scrutiny, as many remain full of loopholes, such as the continued investment in fossil fuels, and are met with accusations of green-washing (Laybourn-Langton and Smith 2021). Due to continued corporate reliance on fossil fuel-based energy, business goals, a. k. a. profits, are generally at odds with environmental goals, making businesses unlikely to drastically shift towards renewable practices (Wright and Nyberg 2017). Moreover, economists may deflect responsibility, pointing towards the idea that ultimately it is consumption which drives activity, not production (Cho 2020).

Calls are growing louder for bolder initiatives from governments to reduce emissions and ensure sustainable use of resources, such as carbon taxes, electric cars, switch to renewable energy, circular economy etc. More controversial ideas include geo-engineering (Lawrence et al. 2018), as well as the full decoupling of economic growth from environmental sustainability (Parrique et al. 2019). Most countries have made official pledges to significantly reduce carbon emissions in order to keep global mean temperature below 1.5°C, without offering concrete policy measures. Even so, taken collectively, these pledges are insufficient in reaching this target (Laybourn-Langton and Smith 2021). Before COP26, the United Nations estimated that current policies will lead to an increase of 2.6°C, while pledges made at COP26 would still result in an increase of 1.9°C, resting on the assumption they are fully adhered to (CAT 2021).

Focusing mostly on Western, industrialized nations (i.e. Europe & North America) which are responsible for at least a third of global emissions in 2017 (Ritchie, Roser, and Rosado 2020) even larger if historical emissions are included (Lazare 2020), various influences undermine effective climate action and justice efforts. On one hand, there is meddling, lobbying and corruption, that purposefully drive decision-making processes to favor economically powerful interest groups, i.e. wealthy citizens, businesses and corporations (Kuhner 2021).

Another crucial influence comes from the socio-political landscapes in these industrialized nations. Climate action in democratically ruled states oftentimes targets short-term benefits rather than long-term adaptation. Elected officials want to provide visible outcomes for voters and ensure electoral victory, rather than prioritize solving global problems that may not receive recognition from voters. Scholars refer to this as "democratic myopia", resulting from the temporal asymmetry of policy action (political time, i.e. electoral cycles) and long-term impacts (ecological timescale) (Gheuens and Oberthür 2021). Additionally, economic interests, which are often at odds with environmental interests, can have influence on political decisions in democracies, stirring decision-makers away from formulating and implementing emission reduction regulations or policies (Povitkina 2018).

1.4 Societal Relevance

Climate change will continue to push earth systems to their limits and strain natural and human systems. This creates real potential for erupting conflicts and instability worldwide, which poses a threat particularly to less developed nations with weaker economies and institutions. However, also in the developed world there is a growing potential towards conflict on a social level. On top of the physical dangers that climate change poses, there are also societal and political implications that require attention. People have a wide array of attitudes towards the problem, and these broad attitudes towards political action often prevent concerted action to combat climate change, as democratic governments must appease voters to avoid political backlash, mass demonstrations or social polarisation and unrest (Gheuens and Oberthür 2021).

This is why climate change perception, rather than simply the natural phenomenon of climate change should be an important focal point of analysis. The steady presence of climate change as a topic discussed in different forms of media creates research opportunities (and necessities) to understand public perceptions and discourse, and how these relate to conflict, most notably polarization, between those who demand more immediate and forceful climate action and those who propose a more modest approach, or even deny the problem to begin with.

Situations of polarization can create severe problems of governance, as communication between groups ceases, diverging into two main camps that become unwilling and unable to negotiate and compromise. Polarization changes the way political institutions operate. Consensus-promoting mechanisms break down when the two camps refuse to cooperate; for example, rules requiring a legislative supermajority. Such a political gridlock paralyzes governments, and in some cases leads to national instability if neither side can prevail in the long run. Alternatively, one camp may become hegemonic and authoritarian. All the while citizens become divided spatially and socially. (McCoy and Rahman 2016). Thus institutions must be aware of the controversies at hand to formulate effective depolarization strategies. (McCoy and Somer 2021)

Studying this complex phenomenon requires understanding of causal mechanisms behind conflict, as well as methods and metrics that can be used to interpret, analyze, and monitor the debate, including for example language, topics and ideas that are floating around the public realm. Knowledge about these attitudes could be used to increase political support and spur practitioners and policymakers in making more prudent investments and policies that minimise global conflict (Mach and Kraan 2021). Social media has become the dominant news sharing platform for a variety of social, political, and cultural issues. Twitter in particular provides a useful tool for studying public conversations about climate change, an issue that crosses international boundaries and stirs political and scientific debate (Fownes, Yu, and Margolin 2018). Combined with newly refined computational techniques to process textual data, there lies great potential to study public polarization and its growing conflict potential and interdependence with climate change. The results could be used in areas of security, social policy or even by social media developers, for strategic planning in regard to climate change.

1.5 Research Questions

The general purpose of this paper is to explore whether social polarization is a potential conflict driver in the developed world and to what degree it poses a security threat. For polarisation the definition by Chakravarty (2015) is used as a guiding concept. They define polarisation within society a ”widening of gap between subgroups of people in society in terms different factors such social circumstances, opportunities or political stances” (Chakravarty 2015). (In this thesis, this is ultimately translated into a quantitative metric: a ratio between the number of positive tweets and extremely negative tweets.

The main research question, followed by relevant sub-questions are defined as:

How may climate-related events create or amplify polarization within a country?

1) How do reactions differ in different countries?
2) Are certain topics more controversial/polarizing than others?
3) How do reactions differ to climatic events and political events?
4) Does online (Twitter) activity on climate change, translate to offline activity?
5) Are there any distinguishable trends that could aid future policy makers in strategic planning?

2 Literature Review

The literature is structured as follows: section 2.1 begins with a short historical recounting of the connection between the main topics of conflict and climate change. In section 2.2 the systematic literature collection process is explained.

Sections 2.3, 2.4, and 2.5 discuss three "branches" of literature that help set the context for this thesis. Section 2.3 discusses the direct impacts climate change has on the environment that may lead to conflict. Section 2.4 focuses on the social aspects and discusses the narratives and perception that society has on the climate change impacts highlighted previously, so that then in section 2.5 and 2.6 the various methods and metrics that are used to analyze these, can be examined.

The content of the prior four paragraphs is briefly summarized in 2.7, in order to explicate the research gap in section 2.8 and build a conceptual framework in section 2.9, which forms the basis of the methodological approach.

2.1 Climate-Conflict Research

Research on the connection between climate and contemporary civil conflicts began towards the end of the 1980s (Rønnfeldt 1997), although very niche. It gained prominence in the mid-2000s, as warnings surrounding climate change became more severe and the paradigm began to shift. Governments began seeing climate change not only as an environmental or developmental issue, but also as a matter of national and international security (Brzoska 2012).

Since then, the field has produced a large number of studies focusing on a range of different types of climate effects and conflict types. In terms of climate effects, research can be divided into two types: climate variability and climate change. The former relates to extreme weather events (e.g. floods, droughts, natural disasters), while the later refers to changing trends of weather patterns over longer time scales. Conflict is the broader term, which encompasses both small-scale strikes, demonstrations, political attacks as well as larger-scale riots, violent crime and civil wars (von Uexkull and Buhaug 2021). Over the past few decades, climate-conflict research has produced a substantial literature, branching into various research avenues including resource management (most prominently water), refugees and migration, political ecology, civil war, media (perception, narratives, framing etc.), totaling to more than over 4400 articles on Web of Science alone, (Sharifi, Simangan, and Kaneko 2021).

For this research the most pertinent lines of research are (1) conflict drivers and causal mechanisms for context, and (2) narratives, perceptions, discourse for identification of the research gap and methodology. The actual literature overview on climate-conflict, related discourse and methods is presented from section 2.3 onwards.

2.2 Literature Collection & Selection

2.2.1 Collection Process

Articles for literature review were collected in several steps. The first included formulating key search terms. Then, the returned articles were analyzed, looking mainly at the introduction and discussion sections. Important reference articles from the papers providing relevant theories, insights or claims were also included in the literature collection. Special attention was given to prominent literature reviews, as this allowed for additional snowballing (and reverse snowballing) of relevant articles using the open-source tool ConnectedPapers, which generates an interactive network visualization connecting papers that cite one another. This collection process is summarized in Figure 2.1 and was carried out threefold. The first two concern the two lines of research mentioned in section 2.1 above.

The third time concerned the types of methods that were used in the second line of research to analyze text data in narratives and discourse.

The 3 searches were carried out successively, using independent lists of key terms.

1) For the climate conflict line, the list included various security- and climate-related key terms. In full, the search included: armed conflict, violent conflict, civil conflict, security in various combinations with climate change, climate variability, climate variation, extreme weather events, extreme climate events, natural disasters.
2) For the climate discourse and perceptions line, the list included various terms relating to controversy such as discourse, debate, framing, perception, polarization, denial, skepticism after the central term climate change.
3) For literature review on methods, the search included terms pertaining to methods: text analysis, discourse analysis, natural language processing in combination with the central term climate change.

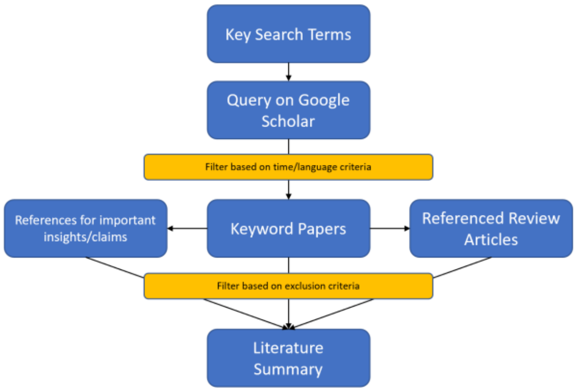


Figure 2.1. Steps in the literature collection process

2.2.2 Selection Criteria

The range of papers was limited to English-language peer-reviewed articles that were published between 2012 and 2021 on Google Scholar. Even with said criteria in place, each search process produced more results than could realistically be analyzed and summarized. Therefore, a few criteria concerning content were formulated, to reduce the literature volume to a manageable volume.

The criteria for each search were:

1) Causal Mechanisms
    a. Article must contain at least one of the key search terms in its title.
    b. Research must be focused on environmental drivers / damages identified as the main cause of conflict, not ones, which are the result of human land use change.
2) Climate Change Discourse
    a. Research needs to analyze at least one country in a developed (anglophone) region, North America, Europe, or Australia.
    b. Research needs to concern climate change directly, not adjacent topics like sustainability, pollution, public health, or animal rights.
3) Methods for analyzing discourse
    a. Article must analyze data from online social media*

*Studies on social media and twitter in particular were selected because Twitter is the largest global social media platform by userbase and is used extensively for the sharing and discussion of social and political news and information. This use of Twitter can provide clues about the topics that are associated with mentions of climate change, as well as gauge the awareness and prominence of climate change as a discussion topic on the platform (Fownes et al. 2018).

Overall, the approach described in section 2.2 previously provided comprehensive overviews of (1) the overarching research themes, theories and ideas within climate-conflict research, (2) key contributions and authors within the field and (3) current state-of-the-art methods. These could then be used to explicate the knowledge gaps under section 2.8.

2.3 Literature Summary: Conflict Drivers & Causal Mechanisms

Climate science is characterised by its sheer complexity. The global climate system is interlinked with natural ecosystems and human activity, each hugely complex in itself. Because of this, it is incredibly challenging to isolate clear causal effects, and it also makes it challenging to summarize climate science in a fully consistent manner. I have chosen to summarize the literature using some guiding questions for structure.

2.3.1 Is Climate Change linked to Conflict?

2.3.1.1 Important Theoretical Frameworks

There exists a range of plausible hypotheses and theoretical frameworks on how climate change can affect conflict within human societies. Two important papers incorporate these contextual factors and causal pathways into a theoretical framework. The first is seen in Figure 2.2 and was devised by Sakaguchi et al. (2017). It depicts the hypotheses concerning the climate-conflict pathway. Path A depicts a direct pathway of climate-induced violence. These theories are not widely researched and only suggest few mechanisms, the most prominent of which posits that warmer temperatures have physiological effects on the body which increases tendency of aggression and violent response. Path B postulates interacting pathways, where climate interacts for instance with resources or economic factors that lead to migration and/or violence. Path C is similar to path B but focuses on social circumstances, i.e. conditional effects such as distribution of wealth that mediate disputes and violence. Path D denotes a combination of the mediation and interaction pathways (Sakaguchi, Varughese, and Auld 2017). The framework is useful for classifying literature, as well as a guide to structure empirical studies exploring the different variables important in understanding the climate-conflict relationship.

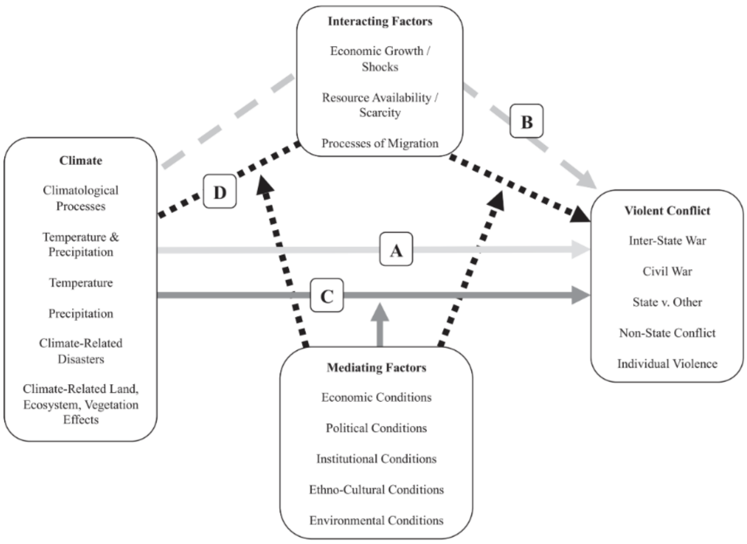


Figure 2.2. Climate-conflict framework by (Sakaguchi et al. 2017)

The second theoretical framework was conceived by Sellers et al. (2019), seen in Figure 2.3. It includes both interacting and mediating factors, however putting greater emphasis on the role of health systems as well as the interplay of natural environment and human environment. Moreover, factors are grouped differently. Authors make a distinction between drivers, stressors and shocks. Drivers lie at the center, these are seen as main factors that undermine the local context, which are somewhat comparable to mediating factors seen in the framework by Sakaguchi et al. (2017). Surrounding the drivers are stressors largely composed of social parameters that can be used to form a "baseline conflict potential". The outer ring denotes shocks that can act as triggers of conflict events. This arrangement is used to highlight temporal aspects, where innermost factors, i.e. drivers, are least likely to change. The middle ring represents medium to long-term stressors, and the outer ring represents near-term shocks. This framework was intended to serve as a starting point of conceptualizing explanatory and predictive models, in order to facilitate testing and assessing security policy in the future (Sellers, Ebi, and Hess 2019).

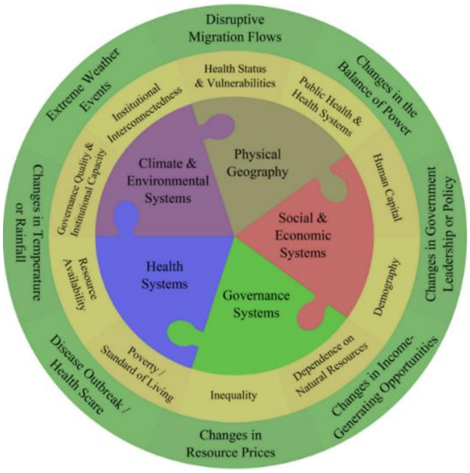


Figure 2.3. Climate-conflict framework by (Sellers et al. 2019)

2.3.1.2 Empirical Studies

A central piece of work in the climate-conflict field is the meta-study by Hsiang et al. (2013) which sought to establish relationships between various climate variables (e.g. temperature, precipitation, floods, storms) and different types of violence at various spatial (e.g. pixel-based, municipality, regional, national, etc.) and temporal scales (daily, weekly, monthly, annually, etc.). The main claim from the analyses was that for each one standard deviation of change towards warmer temperatures or more extreme rainfall, the median estimate for frequency of interpersonal violence increases by 4% and that of intergroup conflict by 14% (Hsiang, Burke, and Miguel 2013). In response, the aforementioned study was heavily scrutinized in its findings by Buhaug et al. (2014), who published a response article. Heavy critiques included the lack of cross-study independence, causal heterogeneity and non-representative sampling strategy. Studies were assumed to be independent, however a majority, in fact more than half of these, are limited to post-1980 Sub-Saharan Africa. The presented studies also cover a wide range of social and climactic phenomena, from non-violent land grabbing via urban riots to major civil war, but it is highly unlikely that their causal mechanisms are the same. Lastly, the authors argue that the adopted sampling strategy did not constitute a representative subset of all relevant scientific research, thus the aggregated and generalized results were invalid (Buhaug et al. 2014). Studies of this sort remain inconsistent, which is why researchers continuously stress the need for data triangulation employing multi-method approaches (both qualitative and quantitative), in order to integrate different lines of evidence, to establish greater confidence in the causal mechanisms of the climate-conflict connection (Ide et al. 2020; von Uexkull and Buhaug 2021).

2.3.2 What are the potential Causal Pathways for Climate-Conflict?

Although many case studies exist which report statistically significant correlation between different climate and conflict variables, these are often limited to a specific area in the world, and thus contextual societal elements are the more critical factors that allow for this relationship to arise. Climate has been described as a "threat multiplier", that significantly increases conflict potential under certain social, economic or political conditions (Asaka 2021; Okpara, Stringer, and Dougill 2016). Recalling the theoretical framework of Sakaguchi et al. (2017), this is most similar to paths C & D. This again shows that climate change may not act as the primary or direct driver of unrest or conflict, but rather as an interacting factor that indirectly influences the remaining factors. Qualitative study seems to support this as well. An expert elicitation study interviewed a range of domain experts from political science, economics, geography and environmental sciences. They ranked various conflict drivers in magnitude and uncertainty of their impact. These are presented in Figure 2.4.

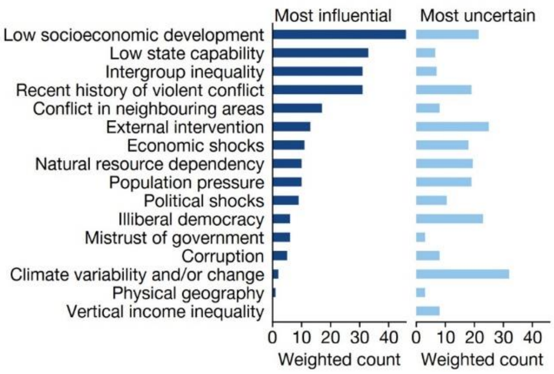


Figure 2.4. Conflict drivers with weighted rank by experts in study of (Mach et al. 2019).

Although climate change and variability was ranked relatively low, it was also ranked as the most uncertain of the factors examined (Mach et al. 2019). Climate change may be behind other examined factors, such as physical geography and natural resource dependency, which will be discussed in subsequent paragraphs. Uncovering causalities remains a challenge in this field, due to the interconnected and overlapping nature of social, political and economic spheres. The most prominently discussed climate-conflict mechanisms are presented below.

2.3.2.1 Resource Scarcity

A prominently discussed causality in climate discourse and policy is informed by the neo-Malthusian narrative, named after Thomas Malthus (1798), who argued that humankind would need to deliberately curb population growth to avoid depleting resources. The Malthusian argument posits that resource scarcity is a key driver of conflict as different groups compete to acquire resources for themselves (Gleditsch 2021). A 2019 IPCC report warns that higher temperatures will lead to harsher droughts and increase the probability of natural disasters such as storms, hurricanes, and floods, destroying agricultural livelihoods and resources, particularly rain-fed agriculture across Africa and the Middle East. Moreover warming oceans threaten marine ecosystems, another important food resource for many communities around the world (IPCC 2019). Modern day security debates on climate change bear similarity to this simple argument, as it would cause scarcities particularly for food, water and inhabitable land (Gleditsch 2021).

2.3.2.2 Migration and Inter-ethnic Conflict

A related conflict driver that arises from scarcity is migration. The same 2019 IPCC report forecasts that excessive temperatures will trigger migration, as people are driven out of their traditional homelands due to them becoming uninhabitable (IPCC 2019). In turn, this could inadvertently lead to conflict in the host countries, as there would be increased competition for scarce geographically stationary resources (Hsiang et al. 2013). Capture of natural resources (including ecosystem services and/or political power) by a specific, often ”elite”, group can breed resentment, increasing the risk of instability. Inequalities, perceived or real, particularly between established ethnic groups within countries, have been identified as another potential conflict driver (Sellers et al. 2019). Resources however need not play a role, as the political powers may simply act out of a populist desire to prevent the arrival of unwanted migrants (Sakaguchi et al. 2017).

2.3.2.3 State Capacity: The Role of Institutions

Effective governance or lack thereof may be another crucial pillar in understanding the climate-conflict relation. Some research emphasise that conflict does not need to automatically follow scarcity. In fact, in the wake of climate-related events, social cohesion may increase (Slettebak 2012). It is thought to do so by generating a sense of ”shared suffering” within a community or country, resulting in spontaneous communitarian actions and generating solidarity (Nardulli, Peyton, and Bajjalieh 2015). The strength of a government is difficult to quantify and thus often relies on composite indicators, e.g. corruption, service provisions, emphasis on equity and institutional interconnectedness (Sellers et al. 2019).

2.4 Literature Summary: Perceptions, Narratives & Discourse

As exemplified by the theoretical frameworks in the previous section, it is much more difficult to draw a direct connection between climate and conflict in the developed world, due to more resource abundance and stronger institutions. Therefore, other social and political factors such as perceptions and polarisation surrounding climate discourse may be a more pertinent to the issue.

2.4.1 What are current Public Perceptions of Climate Change?

Despite the general acknowledgment in mainstream media and overwhelming consensus from academia and international organisations that anthropogenic climate change will have increasingly severe consequences on international security, public risk perception of climate change does not match the warnings by experts and researchers (Lewandowsky et al. 2016). A significant proportion of Europeans are either skeptical of the existence of climate change, doubtful of its consequences, or unwilling to make meaningful concessions to address them (Poortinga et al. 2019). Examining survey data may give an indication why climate action has not been a priority for a majority of decision-makers. The eighth round of the biennial European Social Survey (ESS), found that across 42 000 respondents in 23 countries, roughly 10% did not believe that human activity is the main driver behind climate change, while about 25% indicated they are not worried about the possible consequences (ESS 2016).

However, attitudes do seem to be shifting. Roughly 93% of Europeans believe that climate change is a serious problem, including 78% who qualify it as a “serious problem” and 15% as a “fairly serious problem” (Eurobarometer 2021). A recent study by Mildenberger (2019), found that most of the US public does believe in anthropogenic climate change with a plurality of respondents concerned, but unsure about mitigation measures, see Figure 2.5. It should also be noted that there exists misperceptions of the relative awareness and belief in climate change It should also be noted that there are misperceptions about the relative awareness and belief in climate change. A study showed that people in the US, including a sample of American academics, underestimate the proportion of Chinese residents who believe in climate change, and vice versa. As a result, despite a majority supporting climate action, the belief that others do not lowers willingness to act (Mildenberger and Tingley 2019).

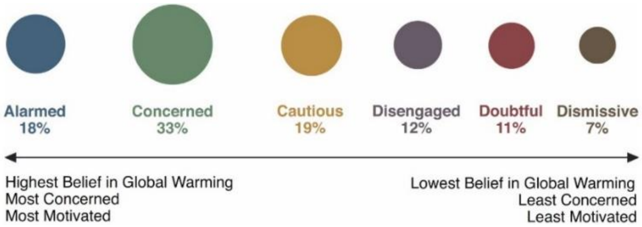


Figure 2.5. Climate Change Attitude Spectrum taken from (Leiserowitz et al. 2021)

2.4.2 How are Positions on Climate Change argued?

Climate change is referred to as a so-called "wicked problem" because people cannot agree how serious of a problem it is, nor how to tackle it (Incropera 2016). Worse yet, there still exists numerous groups who either question whether climate change is a problem at all, i.e. skeptics, or whether it even exists, i.e. deniers (Schreurs 2019). Skeptics will often question the effectiveness of climate responses, including the willingness and capacity to respond to climate change at the individual, political, and societal levels (Haltinner and Sarathchandra 2021b). Arguments revolves around common ethical themes (Nisbet 2014), most prominently justice (e.g. Are policies fair?) (Baatz and Voget-Kleschin 2019) and freedom (i.e. do policies hurt individual or collective freedoms?) (Palm, Bolsen, and Kingsland 2020; Pinto 2021). Moreover they often stress the uncertainty of research to undermine the validity of scientific fact, falsely equating uncertainty to lack of consensus (Haltinner and Sarathchandra 2021a). Climate denial, which can be viewed as the most extreme form of climate skepticism, is characterized by the rejection of science and scientific evidence all together. This includes the personal and professional attacks on experts, as well as the spread of conspiracy theories (Lewandowsky et al. 2016).

The idea of climate skepticism and supporting arguments have been elegantly summarized by Van Rensburg (2015) and is presented in Figure 2.6. It distinguished three types of climate change skepticism: 1) evidence skepticism: towards scientific evidence regarding trend, cause and/or impact of anthropogenic climate change, 2) process skepticism: towards the scientific, bureaucratic, and political processes behind mainstream climate science, and 3) response skepticism: towards public and private responses to the climate issue.

Core objects of scepticism (arguments that define scepticism)			Concomitant objects of scepticism (arguments that strengthen scepticism)			
Evidence			Processes		Response	
Trend	Cause	Impact	Scientific knowledge generation processes	Climate decision-making processes	Policy instruments	Policy style
No postindustrial warming Data inconclusive Unexceptional warming Warming stopped	No CO2 causal mechanism Entirely "natural" causes Predominantly "natural" causes Too early to tell	Negative impacts speculative Extreme weather events unexceptional Insignificant negative impacts Significant positive impacts Negative impacts only in distant future	Climate change is a hoax A lucrative climate industry now exists Climate activists seek fame and money Scientists manipulate/hide the evidence Computer modeling overrated and unreliable Peer review by "buddies"	Political interference in IPCC Socialists and Greens drive the climate agenda Wealth redistribution, world government agendas Media sensationalism distort public opinion	No problem—no response needed Need to prepare for hot or cold scenarios Better to invest in climate adaptation Carbon pricing will not cut emissions enough The costs of mitigation outweighs the benefits	Economy and jobs should not be harmed Wait for global agreement—no unilateral response A pragmatic and measured response is best

Figure 2.6. Taxonomy of generalized set of climate skeptic arguments as developed by (Van Rensburg 2015)

2.4.3 What Social Factors can influence Climate Change Perception?

Stances on climate change are dynamic and result from a variety of social factors. (Ruiz, Faria, and Neumann 2020).

2.4.3.1 Ethnography, Education and Wealth

Ethnography turns out to be one of the strongest drivers, simply because a shared natural, cultural, and political environment will shape similar perceptions. Individuals tend to form opinions compatible with the values of the groups they identify with and as such also have similar strategic reasoning (Lee et al. 2015). For example communitarian cultures tend to attribute a stronger role to the anthropogenic cause of climate change than those in more hierarchical ones (Shi et al. 2016). Perceptions vary more strongly geographically, both between and within nations (i.e. rural vs. urban areas), likely to be a result of cultural and ideological factors (Howe et al. 2015; Lee et al. 2015). Demographic variables such as race, age, and gender have also been found to have some influence on climate change perception, although much weaker than ethnography or education (Howe et al. 2015; Shi et al. 2016).

In developed nations, educational attainment has been found to be a very strong predictor of climate change risk perception worldwide. That said, higher academic literacy does not necessarily lead to a broader acceptance of anthropogenic climate change but can enhance polarization in society. (Drummond and Fischhoff 2017). Even when the public at large may recognize that scientists play a valuable role in society, public disengagement still can ensue when only a small minority of citizens are exposed to scientific work directly (Castell et al. 2014). It is argued that most people, especially in developing countries, still perceive climate change as an overly complex and distant topic (Wang et al. 2019).

Wealth is a determinant of the willingness of communities to embrace certain mitigation and adaptation policies. Even though developed countries are just as likely to experience high exposure to climate hazards as developing countries, they have a much lower vulnerability to them, resulting in an low overall risk perception and disengagement from action (Cook and Lewandowsky 2016; Hamilton et al. 2015). Again, a majority of citizen do recognize climate change as a problem and may be willing to support pro-environmental policies, but individuals, not unlike corporations, will tend to put their own immediate economic interests first. And especially in times of economic recession, priorities shift quickly and support for climate change issues dwindles (Kanbur and Shue 2018).

2.4.3.2 Media and Corporate Influence

The media adds another layer of complexity to the already intricate problem. In today's information age, where most people consume more and more news, media plays an instrumental role in how climate change is perceived and beliefs are formed (Ruiz et al. 2020).

The media are the key agents to translate information across the interfaces of experts-to-public and science-to-policy interface. They often do this using "narrative framing", which is a journalistic practice of selecting certain aspects of a complex issue to make communication to diverse audiences more effective. Yet, these frames can never be neutral, as the selection of included and excluded aspects will always promote a particular problem definition, thus shaping proposed solutions. A salient example of this is shown in an article by O'Neill et al. (2015), who investigated media framing of the IPCC Fifth Assessment Report (AR5) (O'Neill et al. 2015). Analyzing broadcast, print and social media coverage, the authors distinguished between 10 distinct frames, which are presented in Figure 2.7 below.

Frame	Brief description
Settled Science (SS)	Emphasis on the science of climate change (across any WG) and the broad expert consensus. Considerable evidence of the need for action. Science has spoken, others must act. Uncertainty or scepticism quashed.
Political or Ideological Struggle (PIS)	A conflict over the way the world should work; over solutions or strategy to address climate change (above disagreements over science). A battle for power (for example, between nations or personalities).
Role of Science (ROS)	Explores the role science plays in society. May debate transparency, funding or public awareness; especially in relation to institutions, for example, IPCC.
Uncertain Science (US)	Focus on uncertainty—in climate science, impacts or solutions. May question anthropogenic nature of climate change, or discuss natural variability. We cannot act, should not act, or will struggle to act.
Disaster (D)	Predicted impacts are dire. Impacts are numerous, discussed in detail, and threaten all aspects of life. Impacts will get worse, we are not well prepared.
Security (S)	A threat to human security. Could be energy, water or food security, or a threat to the nation state (for example, migration).
Morality and Ethics (ME)	An explicit and urgent moral, religious, or ethical call. ME1: for action. Strong mitigation, and protection of the most vulnerable. ME2: for no action. Likely to discuss scientific uncertainty.
Opportunity (O)	Climate change poses opportunities. Either O1: as a way to re-imagine how we live; for example, to further human development, to invest in co-benefits. O2: there will be beneficial impacts so no intervention is needed. Likely to mention uncertainty.
Economic (E)	Discusses growth, prosperity, investments, markets. Provides economic costs. Economics implies either E1: taking action now. Details potential economic actions (for example, divestment). E2: action is hugely expensive (or too costly in context of other priorities). Likely to mention uncertainty.
Health (H)	Climate change poses a danger to human health, for example, malnutrition, air quality. Urgent action required.

Figure 2.7. Narratives Frames used to discuss the AR5 Report as developed by (O'Neill et al. 2015)

Although general mainstream media does acknowledge the threat of climate change and frame it as such, researchers claim that in the US, between 1985 and 2017, an overall polarization in news content has taken place, in terms of news article themes and their frequency (Chinn, Hart, and Soroka 2020). Studies have shown whenever climate change polarization is high in the media, citizens will tend to rely on their political affiliation as a source of credibility to form an opinion (Bliuc et al. 2015; Hornsey et al. 2016). It leads to mutual distrust of "the other's" media and information sources, and reinforces an ideological bias in consuming and sharing online information about climate change (Cann, Weaver, and Williams 2021).

This process is partly driven by corporate funding. It not only influences governments and policy but also shapes the actual language and thematic content of polarizing discourse in the media (Farrell 2016). Powerful organizations and/or NGOs enhance public exposure to polarizing information through "disinformation campaigns" or alternate narrative framing to provoke confusion or cast serious doubt and reduce risk perception. This can ultimately undermine knowledge that was long considered established, which in turn benefits corporations, as eroding consensus means less incentive for environmental regulations and an unlikely deviation from "business-as-usual" (Dunlap and Brulle 2020; van der Linden et al. 2017).

Biases in news coverage can distort perception too. Overproportioned portrayal of climate skeptics in the media may enhance controversial, uncertain or unsettled science views (Dunlap and Brulle 2015). Moreover, sensationalist tendencies of news organization to present big one-off events such as extreme weather disasters, lend themselves well to climate skeptics' accusations of media alarmism (Haltinner and Sarathchandra 2021b), while on the other hand, proponents criticize the lack of focus on the larger trends, consequences and connections with climate change. Moreover, circulating misinformation impedes individual efforts to obtain reliable or credible information (Treen, Williams, and O'Neill 2020).

2.4.3.3 Personal Experience & Psychology

Personal experience can be another personal driver. It is believed that by witnessing climate change firsthand, concerns and support for action will develop. However, for this to occur there needs to be a cognitive association between present changes of climate and weather to the phenomenon of climate change at large. Particular for extreme weather events but also perceived recent local weather changes do seem to impact the broader perception of climate change perception, as people become more aware of the environmental threats to their communities (Howe et al. 2019). That said the association does not always form, as (Brügger et al. 2015; Howe et al. 2019; Wong-Parodi and Feygina 2020).

Several psychological biases and barriers keep us from making such a cognitive association. People in developed nations judge negative impacts due to climate change to be more likely to occur to others than to themselves, perceive climate change as a threat distant in space and time (judgmental discounting/optimism bias) (Gifford 2011; Ruiz et al. 2020). Moreover, physiologically it is argued that human brains are functionally set up to identify immediate threats, rather than a long-term uncertain risk such as climate change (ancient brain). People also tend to not want to lose out on invested resources such as money, time, and behavior patterns in light of such an uncertain/undefined risk (sunk cost bias) (Gifford 2011).

Lastly, psychology research has also suggested that policy attitudes could actually be a determinant of belief in climate science and climate change, rather than vice versa (motivated reasoning) (Cann and Raymond 2018; Hennes et al. 2016). Motivated reasoning is a goal directed goal process, whereby the desire to avoid acknowledging adverse impacts, i.e. the reality of climate change, is achieved though biased cognitive strategies (Wong-Parodi and Feygina 2020). This so-called motivated climate change denial offers a sensible explanation why conservatives and right-wing parties seem to always embrace a more climate skeptic stance, as these groups traditionally stand strong on private ownership and free market economy and thus will naturally oppose government intervention like climate change mitigation regulations (Dunlap and Brulle 2020; Lockwood 2018).

2.4.4 How may differing Climate Change Perceptions lead to Conflict?

2.4.4.1 Polarization

With the increased attention given to climate change, there is also growing concern about politicization and polarization on the issue, driven by any of the factors mentioned in section 2.4.3. Political polarization has been growing in the US for years and the correlation between the belief/attitude towards climate change and partisan affiliation can be seen very clearly, as there exist only two major political parties, with the more right-wing Republican party showing increasing skepticism on the issue of climate change (Dunlap, McCright, and Yarosh 2016). Although variations in the climate change risk perception exceed what political orientation alone can explain, it has been consistently found that these orientations influence a wide range of beliefs, including climate change (Bliuc et al. 2015; Ruiz et al. 2020). In Europe too, climate skepticism has also increased, with the successes of right wing parties in recent years (Forchtner 2019; Kulin, Johansson Sevä, and Dunlap 2021). Polarization in society over time can lead to, among others, lower social cohesion, erosion of democratic institutions, discrimination of marginalized groups and income stratification. (McCoy, Rahman, and Somer 2018).

2.4.4.2 Extremism

Polarization plays into the hands of more extreme political groups. European far-right opposition parties spread lies about climate change alongside fears of globalization and migration to feed into the anti-government / anti-establishment sentiments. This may range from attacking wind turbines being a “blight on the landscape” to attacks on climate policies for destroying the livelihood of “the little guy” (Forchtner 2019). In the US, where far right leaning politicians hold office, the term “environmental protection” is often weaponized against mainstream environmentalists, by vilifying the protections of environmental rights as an attack on individual freedom and property rights (Huq and Mochida 2018). On the other side of the climate belief spectrum activists as well are taking much more disruptive action than demonstrations, in what some refer to as eco-terrorism or radical environmentalism, where individuals used violence against properties and civil rights in defense of the environment or to direct changes in environmental policy (Spadaro 2020).

2.5 Literature Summary: Methods in Climate Discourse Analysis

For the final stage of the literature review, several articles were analyzed with focus on quantitative methods to investigate and evaluate climate change discourse, as well as the insights gained from them.

Computational research on climate change discourse has been highly fragmented. Target texts range from news articles, blogs, but mainly Twitter. Very few comparative analyses across genres or channels have been made, and there has been little attention on political arenas or on statements by individuals and interest groups that are meant to directly influence policymaking. The articles were divided in terms of methods. These mainly include network analysis for detecting communities and natural language processing, which encompasses a variety of techniques like topic modelling, classification of frames and sentiment analysis (Stede and Patz 2021).

2.5.1 Online Networks

Network properties of social media platforms are thought to be key in understanding polarizing behavior in users. A very recent paper by Falkenberg et al. (2022) focused on political polarisation of climate change that evolved in online spheres between 2014 to 2021 during COP events, employing the mathematical "latent ideology method". They found that ideological polarization is actually quite recent, as it remained very low between COP20 and COP25, with a significant increase during COP26. They attribute this to the growing engagement from right-wing parties, as well as partial overlap with the discussion around the Covid-19 pandemic (Falkenberg et al. 2022).

Häussler (2018) explored polarization of the German hyperlink network. They found that climate skeptics reside in a cluster that is largely disconnected from the domestic debate due to their weak position and inability mobilize a critical mass at the national level. The author believes that polarization is facilitated by the nature of online social networks. Actors tend to primarily link to like-minded others, abetting the formation of "echo chambers". They note that although there may be good scientific reasons why the dissenting skeptical voices in climate debates should be marginalized, there are also strong moral dimensions that need to be considered in order to distinguish between the beneficial and detrimental consequences of fragmentation dynamics and homophily effects for the political process and the public sphere (Häussler 2018).

Samantray and Pin (2019) hypothesize that polarization of the online climate change debate may be potentially caused by propagation of fake news on social media. As such they investigate homophily in communication, i.e. the tendency of people to communicate with others with similar beliefs. Quite surprisingly, in an empirical analysis of Twitter conversations on the climate change topic during 2007–2017, authors found that evolution of homophily over time negatively affects the evolution of polarization in the long run. It is suspected that among various information about climate change to which people are exposed to, they are more likely to be influenced by information that have higher credibility. Thus authors infer that anti-climate change tweets tend to be less credible (Samantray and Pin 2019).

2.5.2 Twitter Studies

Most quantitative studies focused on twitter. To present a more comprehensive overview of these papers, they were organized in Table 2.1 in chronological order. The main methods and findings are presented in the same order below.

Table 2.1. Overview of Twitter-centered studies on climate change on climate change discourse. Note: when papers have multiple datasets, “N_tweets” and “Span” refer to the largest data set.

Paper	N_tweets	Span	Main Techniques	Main Focus
(Moernaut et al. 2022)	4 919	28 Jul. 2018 – 4 Aug. 2018	Statistical and qualitative analysis	Framing
(Foderaro and Lorentzen 2022)	~30 000	23 Aug. 2018 – 6 Sept.	Crowdsourcing and statistical analysis	Argumentative practices and patterns
(Al-Rawi, Kane, and Bizimana 2021)	10 617 487	Mar. 2015 – Jun. 2018	Topic modelling	Topics in relation to global warming, political stance of users
(Koenecke and Feliu-Fabà 2020)	15 080	2 Jan. 2018 – 6 Jan. 2018	ML (Neural networks)	Climate sentiments pre- and post- events
(Roxburgh et al. 2019)	99 823	24 Oct. 2012 – 5 Nov. 2012	Geo-spatial analysis	Framing of storm events
(Yeo et al. 2017)	3,732,058	1 Jan. 2012 – 1 Mar. 2014	Statistical analysis	Linguistic patterns
(Pathak, Henry, and Volkova 2017)	4 500 000	30 Nov. 2015 – 12 Dec. 2015	Statistical and sentiment analysis	Demographic patterns
(Olteanu et al. 2015)	482 615	1 Ap. 2013 – 1 Oct. 2014	Crowdsourcing	Framing/behavior of social media vs. traditional media
(Cody et al. 2015)	~1 500 000	Sept. 2008 – Jul. 2014	Sentiment analysis and word frequency	Linguistic changes
(Jang and Hart 2015)	~5 700 000	Jul. 1 2012 – Jul. 1 2014	Statistical analysis	Framing across countries/states
(Kirilenko and Stepchenkova 2014)	~1 800 000	Jan. 2012 – Jan. 2013	Mixed statistical methods	Spatiotemporal distribution of climate change tweets
(An et al. 2014)	494 097	3 Oct. 2013 – 12 Dec. 2013	Sentiment analysis	Subjectivity vs. objectivity in tweets

Moernaut et al. (2022) focus on online twitter dialogue and investigated whether debate surrounding recent heat waves and climate change in general induced more constructive dialogue or tended towards polarization. By applying a multideterminant frame model user were into skeptics and believers. They found that both groups mostly use similar antagonistic strategies to delegitimize and denaturalize their out-groups. Such strategies include appeal to logos (“objectifying their position and painting counter arguments as illogical or unreasonable”), ethos, (“drawing on authoritative external sources, e.g. institutions, experts, legacy media, to legitimate their argumentation”), and pathos (“convincing others of the irrationality and immorality, for example using irony and sarcasm to evoke emotional responses”) (Moernaut et al. 2022).

Similarly, Foderaro & Lorentzen (2022) investigated argumentative practices of Twitter discussions about climate change. Instead of individual tweets they focused on conversational threads. These were coded following an operationalization scheme using fundamental concepts from argumentation theory. Tweets could then be analyzed in the context of the discussions and coded according to their argumentative approach, interaction type and argumentation stage. They found five typical practices involving the dynamics of the conversations, however agreements were rarely achieved. The arguers used a variety of sources to justify or support their positions, often embedding non-textual content. (Foderaro and Lorentzen 2022).

Al-Rawi et al. (2021) used a more user-centric approach to analyze polarization of climate change. Using topic modelling algorithms, they examined the twenty most active users employing the term ‘global warming’ and ‘climate change’. They found the former group to be more likely to be consisting of bots rather than the latter. Moreover, they found that of top 400 most active users that use the term ‘climate change’ and believe it is human-made or anthropogenic (82.5%) is much higher than users who use the term ‘global warming’ and believe in human causation (25.5%). The study reveals indication of polarization, reflected in terminology (Al-Rawi et al. 2021).

Koenecke and Feliu-Faba (2020) acknowledge polarization of Twitter discourse and sought to investigate whether individuals (in the US) might be prone to changing their opinions because of natural external occurrences. Using language and sentiment, relevant tweets were labeled as either accepting or denying of climate change to roughly 75% accuracy. Then applying recurrent neural networks (RNNs), a cohort-level analysis showing that the 2018 hurricanes in the US yielded a statistically significant increase in average tweet sentiment affirming climate change. But this effect does was not seen for the 2018 blizzard, nor wildfires. This implies that Twitter users' opinions that there is a preexistent association between climate change and types of natural disasters. (Koenecke and Feliu-Fabà 2020).

Roxburgh et al. (2019) also sought to compare the online Twitter discourse in light of extreme weather events, specifically Hurricane Irene, Hurricane Sandy and Snowstorm Jonas. They focused on how climate change was related to each of these disasters including argumentative framing. Each case had different responses and tended to have different dominant frame(s). The authors hypothesize that the differences in activity between the events are tied to both meteorological characteristics of the storms, but also argue that the socio-political context in which they occurred could play an important role in shaping the lenses through which climate change was viewed during each event, such as on-going elections, etc. (Roxburgh et al. 2019).

Further, Yeo et al. (2017) conducted a 2-year study on the use of #climatechange and #globalwarming to examine underlying linguistic patterns, "based on concepts identified by human coders using initial training sets and subsequently applied a learned algorithm to analyze the remaining big data sets. It was found that when temperatures fluctuated only slightly, tweets with terms climate change and global warming were in constant in rate of use. But during temperature anomalies these increased drastically. The use of the term 'global warming' became more frequent, while 'climate change' did not. More generally, the research found that the term 'global warming' tended to be related to physicality, such as changes in temperature and weather, while the term 'climate change' was utilized more often in relation to political advocacy and activism (Yeo et al. 2017).

Next, in a mixed-method study, Pathak et al. (2017), concerned themselves with the discourse around COP21 and the Paris Climate Accord. They looked at the differences, similarities, and dynamics over time in terms of frequency of mentions, tone and sentiment towards various climate-related topics was tracked globally (although English language posts only) across various user demographics. It was found that climate denial was most discussed by higher income people, but least discussed among females. Meanwhile air issues, economy, and energy were most discussed by younger, male, and lower income people. Lastly, security was most discussed among lower income people (Pathak et al. 2017).

Olteanu et al. (2015) looked into differences in media coverage for a larger variety of climate-related events, not just COP21 or natural disasters, focusing in particular comparison between social media and online news networks. Using crowd computing, they found that disaster events both natural (e.g., hurricanes and floods) and man-made (e.g., oil spills) were able to trigger news coverage and discussions on climate change. But that mainstream media focused more on events from governments, such as legal actions and publication of reports, while Twitter discussion focused more on news stories about individual actions (Olteanu et al. 2015).

Cody et al. (2015) investigated emotion in tweets with mentions of "climate". They conducted sentiment analysis on individual tweets, using a previously developed sentiment measurement tool called the Hedonometer. This was used to analyze different responses to climate change news, events, and natural disasters, measured by collective aggregate sentiment. It was found that natural disasters, climate bills, and oil-drilling can contribute to a decrease in happiness while climate rallies, a book release, and a green ideas contest can contribute to an increase in happiness. Words uncovered from the analysis also suggest that responses to climate change news are predominately from climate change activists rather than climate change deniers, indicating that Twitter is a valuable resource for the spread of climate change awareness (Cody et al. 2015).

A geographic analysis by Jang and Hart (2015) found that climate skeptic framing on Twitter was most heavily centered in ‘‘red states’’ of the US compared to the UK, Canada, and Australia or ‘‘blue. In line with the study of Yeo et al. (2017), authors note that red states prefer the use of ‘‘global warming’’ to ‘‘climate change’’, and that the term is particularly associated with hoax framing. (Jang and Hart 2015).

Kirilenko and Stepchenkova (2014) explored spatiotemporal pattern of public discourse in relation to natural and/or socio-economic events. They explored almost 2 million tweets on ‘‘climate change’’ and ‘‘global warming’’ in five major languages: English, German, Russian, Portuguese, and Spanish. They analyzed weekly and daily patterns of climate change discourse, major events that affect tweeting on climate change, frequently referenced web resources, and the most authoritative Twitter users. From a theoretical perspective, they believe for the classic two-step model of communication holds, as evidenced by high concentration of the discussion around a relatively small number of influential newsmakers. The frequency of URL references to other domains and mentions could be utilized as an indicator of the most authoritative sources of information on climate change. Additionally they found that over half of the messages with external references point to just 129 domains (0.28% of all domains at the time) (Kirilenko and Stepchenkova 2014).

An et al. (2014) used classical sentiment analysis algorithms to track opinions regarding climate change. Employing both sentiment and subjectivity metrics they detected a connection between short-term fluctuations in negative sentiments and major climate events. However, they also found that although major climate events can have a result in sudden change in sentiment polarity, when considering the variation in sentiment polarity significant uncertainty in overall sentiment persists (An et al. 2014).

2.6 Metrics of Polarization

2.6.1 Categorization

Across the aforementioned studies, polarization is conceptualized in different ways. Some studies do not directly measure polarization. Rather they categorize different terms, frames, and discourses to then make more qualitative assessments of polarization (Foderaro and Lorentzen 2022; Moernaut et al. 2022; Yeo et al. 2017).

2.6.2 Network Connectivity

Network studies can use network metrics, particularly relating to connectivity. Polarization occurs when a certain group of people becomes largely disconnected from the collective. These sorts of communities can be quite easily identified using network theory and quantified based on their connectivity to the out-group (Falkenberg et al. 2022; Häussler 2018).

2.6.3 Ideological Spectra

In the social sciences, the most common conceptualization comes through the classic Downsian left-right ideological continuum (for multi-party-political systems). Although any other form of spectra are also usable in instances where polarization occurs not on an ideological dimension (McCoy and Rahman 2016)

2.6.4 Sentiment and Emotion

For online media studies sentiment and emotional analysis to measure "opinion polarization" to a given topic, under the assumption that negative sentiment expresses disagreement and positive sentiment expresses agreement. Emotion is a slightly more fine-grained sentiment, where text is categorized according to different types of emotion, rather than simply positive and negative (Sailunaz and Alhajj 2019).

2.7 Conclusion of Literature Review

This paragraph will briefly summarize the main insights from the literature review that have guided the research. Above all climate change is characterized by interconnectedness and complexity. Any claims must be carefully considered for contextual factors and uncertainties. Climate change is thought to drives conflict in multiple ways, be that through food shortages or migration in places that cannot properly withstand those shocks.

In places where these impacts have not taken full effect, conflict may arise differently. It is hypothesized that social polarization between those who demand more immediate and forceful climate action and those who propose a more modest approach, or even deny the problem to begin with. Risk perception is complex as it is near impossible to assign clear cause-effects between social drivers and individual psychology, as they have been demonstrated to be under continuous mutual influence.

Monitoring polarization is a more realistic option, with multiple operationalizable metrics across disciplines and application. Previous studies outlined in section 2.5 have shown for polarization to take place, but usually involve only a single method to demonstrate for increasing trend of polarization to have taken place across a larger time span.

Combining measures of polarization with other methods of text analysis for specific events, it is thought to provide more fine-grained insight about the state of climate change discourse in online spaces.

2.8 Knowledge Gap

A multitude of empirical studies have linked outbreaks of or increases in civil conflicts to climatological events (Hsiang et al. 2013; von Uexkull and Buhaug 2021) A relatively large majority of these studies were conducted in less developed regions of the world such as sub-Saharan Africa or Latin America, where this link has often in big parts been attributed to institutional failure and weak economies Furthermore, research usually explores consequences in the country where the physical environmental changes occur (Busby 2021; Mach et al. 2019). In more developed nations such as the G7 that generally experience milder climate and have stronger governmental institutions and economies however, societal unrest would likely manifest in a different manner. To understand this the literature focus was shifted towards research studying discourse and polarization surrounding climate change, looking at various factors such as social demographics etc.

Twitter offers great opportunities over traditional methods such as survey, as it offers means to access wide range of textual data directly from the public, following a "people-as-sensors" paradigm. It is also conducive to communication research due to its availability, geo-distributional nature, internal structure, as well as attached auxiliary information by the Twitter API (Kirilenko and Stepchenkova 2014). A wide array of these Twitter studies report that a polarization on Twitter. Moreover many of these stress importance of events and new stories (Olteanu et al. 2015; Roxburgh et al. 2019), however few link these findings to the actual potential for conflict.

Therefore, this research seeks to climate-related events across the world to measurable effects in the countries which are generally farther removed from extreme climate-related disaster and conflict, and with relatively strong institutions. From the multiple conceptualizations of polarization, sentiment is the most fitting to apply to large data sets, such as Twitter discourse. By then combining sentiment analysis to topic modelling and sentiment analysis I seek to obtain a more fine-grained view of the state of polarization, what topics may be most controversial and investigate if climate-related events/shocks can be linked to instances of violence.

2.9 Conceptual Framework

The relevant concepts from literature review and the research questions have been gathered and assembled in a conceptual framework, seen in Figure 2.8. How these concepts translate to the methodology are elaborated upon in section 3.4.

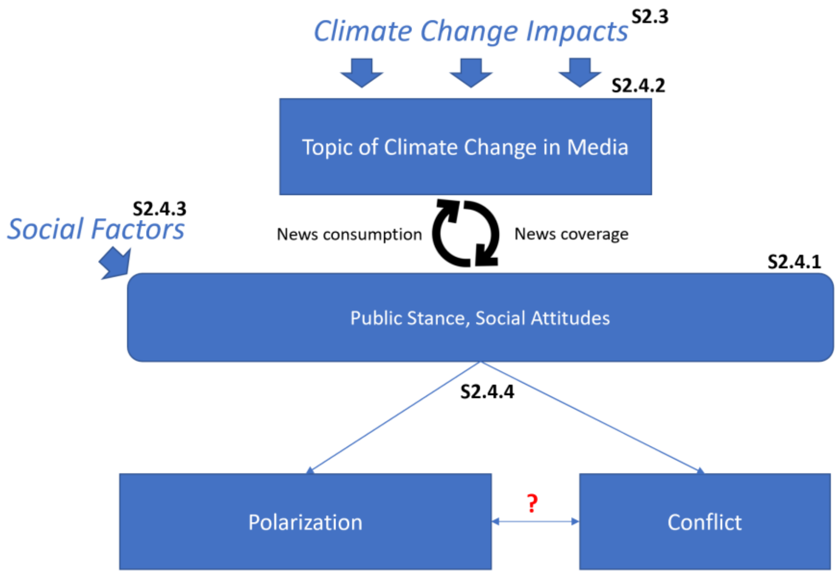


Figure 2.8. Conceptual Framework relating concepts gathered from review of climate-conflict literature

3 Methodology

3.1 Data Source: Twitter

Twitter was selected as the primary data source for text. It was chosen over other social media, because of these it is the largest platform designed to be used for the sharing and discussing of political and scientific news and information. This can provide clues about the topics that are associated with mentions of climate change, as well as gauge the awareness and prominence of climate change as a discussion topic on the platform. Moreover, it can allow researchers to gauge whether scientists agree, what topic are perceived as primary climate change causes (e.g., carbon emissions) and solutions (e.g., a carbon tax or geoengineering), Lastly, disaggregated tweets also include user-specific data, which can be used to study demographic trends or network structure, and sometimes also geo-tags that allow for geo-spatial analyses. Links to external resources such as news sites, science journals and blogs, and political sites can also be useful in identifying key players / organisations in debates (Fownes et al. 2018). This is not not the goal of this study, as the study is focused at a social level, and thus results in section 4 are exclusively presented in aggregate form. There are, however, some limitations to using Twitter data that should be considered. First and foremost, the Twitter user base is not a representative sample of the population. As such, inferring current level of attitudes and/or belief in an underlying population is problematic and cannot replace traditional surveys (Kirilenko and Stepchenkova 2014). Moreover, statistics can be skewed by over-active users or bots (Fownes et al. 2018; Leetaru et al. 2013).

3.2 Data Collection

3.2.1 Acquiring License for Twitter API

The tweet data was collected using the Twitter API (v2) with Academic Research level access. This requires an exclusive license that provides academic researchers full archive access to Twitter posts. In order to obtain it, an application is filled out on Twitter developer portal (Twitter 2022).

3.2.2 Adjusting Time Frame

The Academic Research has a monthly rate limit of 10 million tweets. Therefore, specific time periods needed to be selected to remain within the limit. Fortunately, the API includes a tweet count endpoint, found at https://api.twitter.com/2/tweets/counts/all, which simply returns the number of tweets for a given query within a specified time frame. Tweet counts do not use up the rate limit and therefore allow one to easily find the periods with the highest activity to investigate and pull tweets from. Due to pagination, tweet counts only show tweet counts over a month per request with a request rate of 30 request per 15 minutes, thus, only the tweet counts over the past half decade were pulled. Due to the time scale, the lowest granularity ”day” was used. Using python requests were sent iterative so that the daily tweet volume could be plotted, see section 4 for discussion. For the English Twitter data, the highest tweet volume per day tweets registered in September 2019 (A), whereas German and Dutch had highest volume in July 2021 (B). Event A most likely corresponds to the global climate strike that year (BBC, 2019), while Event B likely corresponds to floods that occurred in Western Europe that month (BBC, 2021). The exact time spans are presented in Table 3.1.

Table 3.1. Starting and Ending Times for selected Events

Time Span	Start Time	End Time	Likely Event
A	2019-09-08T00:00:00.000Z	2019-10-06T00:00:00.000Z	Global Climate Strike
B	2021-06-27T00:00:00.000Z	2021-08-01T00:00:00.000Z	Summer Floods

3.2.3 Adjusting Query

Language has great impact on the perception of risks and nature of climate change. Communication from experts to general public tends to favor language with connotations of certainty and confidence (Herrando-Pérez et al. 2019). Moreover, the terms global warming and climate change are often used interchangeably in popular media, however display variation in individual understanding (Lineman et al., 2015). Tweets from the US public have shown that tweets that contest the existence of climate change and frame it as a hoax are more likely to refer to the phenomenon as “global warming” than “climate change” (Schuldt, Enns, and Cavaliere 2017). Tracking the usage of climate change terminology lends potential in researching shifts in belief and support (Fownes et al. 2018). For this reason several terms that had different political connotations were queried, to see whether they displayed different patterns in activity. Terms were divided along the general stances towards climate change: 1) climate-activist, 2) neutral, 3) climate-sceptic/denier, see Table 3.2.

Three languages were selected for analysis: English, German, and Dutch, which were chosen due to the researcher’s language proficiencies, as well as availability of reliable NLP tools. Query-building requires different strategies across languages, dependent on prevalence of inflection and use of noun compounding (e.g. in German the term climate change is a single word Klimawandel). The Twitter API returns tweets with exact matches only: e.g. if term is dog, it does not return tweets with dogs or vice versa. Syntactically the API treats spaces between keywords as AND-operators, i.e. ”climate change” returns tweets that contain the exact word climate and the exact word change. The terms need not necessarily occur sequentially. For exact phrasing the terms the phrase should be enclosed in quotation marks, e.g. ”term1 term2”.

Table 3.2. Queries used for Tweet Counts

Language	Neutral query phrases	Pro-query phrases	Anti-query phrases
English (EN)	(climate change) (global warming)	(climate action) (climate justice) (climate crisis)	(climate hoax) (climate lie)
German (DE)	(Klimawandel) (Erderwärmung)	(Klimakrise) (Klimaschutz)	(Klimalüge) (Klima Lüge)
Dutch (NL)	(klimaatverandering) (opwarming aarde)	(klimaatcrisis)	(klimaatzwendel) (climategate)

3.2.4 Obtaining Tweets & Tweet Structure

Upon deciding on the exact time frame see Table 3.1 and queries see Table 3.2, the actual tweet objects were retrieved by connecting to the https://api.twitter.com/2/tweets/search/all endpoint using the Python programming language. The data sets with respective sizes are presented in Table 3.3. When pulling tweets the attributes need to be specified. These are presented in Table 3.4.

Table 3.3. Number of Tweet Objects included in Topic Modelling & Sentiment Analysis

Language	Query	# Tweets (Span A)	# Tweets (Span B)
EN	(climate change) lang:en	3 354 456	2 356 516
DE	(Klimawandel) lang:de	100 857	222 652
NL	(klimaatverandering) lang:nl	15 737	51 403

Table 3.4. Table 3.4: Selected Attributes for Tweet Objects

Field	Description	Datatype
id	unique identified of tweet	string
text	tweet content	string
date	date tweet was published	datetime UTC
like_count	number of likes on tweet	integer
retweet_count	number of retweets of tweet	integer
reply_count	number of comments on tweet	integer
author_id	unique identifier of author	string
verified	boolean whether user is verified	boolean
followers_count	number of followers of user	integer
tweet_count	number of tweets made by user	integer
user_created	time when user account was created	datetime UTC
query_time	time of query	datetime UTC
geo	geographic info about tweet	json

3.3 Methods

In the following section the employed methods are presented. Each paragraph specifies theoretical basis for each technique, programming libraries/packages used, a justification for its application over other tools and main limitations.

The 2 main methods selected were topic modelling and sentiment analysis. As mentioned previously in section 2.6, there are several conceptualizations of polarization across disciplines. Of these, sentiment analysis appears to deal with the most appropriate to cope with the vast size of social media content. Social media usage among American adults has increased near tenfold since 2005 (Dahal, Kumar, and Li 2019), and is therefore a more ubiquitous and representative source of public opinion of climate change. Social media also has a very quick reaction time, which thus might be able to give immediate insight to certain events that are impactful towards climate change perception and shifts in sentiment. Sentiment analysis is also thought to pair synergistically, as both attributes (sentiment & topic) are the attribute per tweet, whereas connectivity or stance are user attributes, and could therefore give more fine-grained insight towards the exact topics and events that are polarizing.

3.3.1 Preprocessing for Topic Modelling

Most text analyses requires some sort of preprocessing, such as spelling corrections or word filters. For topic modelling only words that contribute towards topic identification should be included. Therefore the following pre-processing timeline was applied to all tweets using a variety of different NLP python packages. First, tokenisatization was performed using the nltk.TweetTokenizer. Tokenizers split the string representation of a tweets into constituent elements, a list of strings usually either sentences or words. The nltk.TweetTokenizer in particular is the most appropriate for this case, as it has specific features that allow it to better handle emoji-characters, URLs, etc. Secondly, word filters were applied, since the chosen topic modelling technique does not use all words, but rather only includes those which are most informative towards topic identification. Non-alpha characters, such as emojis, URLs were removed first. Highly frequent words such as ”the”, ”and”, ”to”, ”I” a.k.a. stopwords were removed as these generally only serve grammatical function. Also, nouns are generally most informative topic-wise, so to reduce computation over millions of tweets, words that were not nouns were filtered out. This could easily be done using the spacy module in python, which can parse strings and tag words based on grammatical function. (Note: that although non-alpha characters and most stopwords are also not nouns and could in theory be also filtered by spacy. It is computationally much more efficient to remove them using basic python string methods before, than relying on the more-computationally expensive tagging system used by the spacy module.)

3.3.2 Topic Modelling

Topic modelling is a technique that is a performed on a collection of documents, often referred to as the corpus. Topic modelling assigns topic(s) to each document, in this case tweet. Among the most popular is latent dirichlet allocation, which has found many application in a range of disciplines such as software engineering, political science, medical and linguistic science (Jelodar et al. 2018). The technique was devised by Blei (2003) and is a generative probabilistic model of a corpus, which posits that each document can be represented as a random mixtures over latent topics. Each topic is characterized by a distribution over words (Blei 2003). This assumption is reasonable to make for medium and higherlength documents, but for shorter texts, such as 140-character tweets, it is much more plausible for text to be concerned with a single topic. Yin and Wang (2014) recognized this as well and created a modified LDA technique called ”Gibbs Sampling algorithm for the Dirichlet Multinomial Mixture model for short text clustering”, which has received the much appreciated abbreviation ”GSDM”. Documents are assigned a single topic using clustering, to obtain the representative words of each cluster (Yin and Wang 2014). Like in LDA, these word collections are human-interpreted to denote the common, overarching topic. GSDM is not a standard python library, the code was obtained from GitHub: https://github.com/rwalk/gsdmm.

3.3.3 Sentiment Analysis

Sentiment analysis (SA) techniques fall under several categories, the most common i) lexicon-based (a.k.a. rule-based) and ii) ML-based (ML=machine learning) (Qazi et al. 2017). Lexicon-based approaches are centred around the lexicon, an ideally exhaustive list of all possible words that are found within all documents to be analysed. The main premise is that words are given polarity scores between -1 and +1 associated to them, where scores closer to -1 indicate words with negative connotation (e.g. bad, lacking, disaster) and scores closer to +1 indicate words with positive connotations (e.g. exciting, success, pleasant). Following a predetermined rule to compute a weighted composite metric, an overall score for a text can be determined. The advantage of these sorts of algorithms is their simplicity and higher tractability (Hutto and Gilbert 2014). In contrast machine learning algorithms are not fully understandable to humans, but generally achieve higher accuracy (Qazi et al. 2017). This is because the quality of lexicon-based SA is is highly dependent on quality of the lexicon, for which it is time consuming to manually label across the entire list of possible words. Moreover words can have different connotations dependent on context (e.g. ”This is crazy good” vs. ”They are acting crazy”) (Indurkhya and Damerau 2010). Slang and abbreviations and non-standardised spelling would also need to be specified (e.g. different abbrevations for the coronavirus: COVID-19, Covid, corona). For this reason 2 lexicon-based sentiment libraries were used based on different lexica. These python libraries were: i) vaderSentiment and ii) pattern.en. The former is based on the acronym Valence Aware Dictionary for sEntiment Reasoning, specifically developed for shorter texts from social media. It expands typical lexica by including polarity scores for emoticons (e.g. :)), UTF-8 encoded emojis, some slang/abbreviations (e.g. lol), and also has rules for intensifiers (e.g. ”very, really, kind of”) which do not have polarity in themselves but rather modify scores thereafter. Lastly developers implemented rules to recognise full capitalisation and difference in punctuation (Hutto and Gilbert 2014). The latter is the sentiment analysis module within a larger general purpose NLP package. Documentation for each can be found at https://github.com/clips/pattern. Unfortunately limited language compatibility prevented dual use in German and Dutch. The German version of pattern.de, did not have an implemented SA module, but did have an adapted vaderSentiment package called GerVADER. The inverse was true for Dutch, pattern.nl did have a functional SA module, but no adapted vaderSentiment package. For both packages raw Twitter text could be passed as arguments and assigned a sentiment polarity score, without need for pre-processing. Mean polarity scores were aggregated at an hourly level and plotted as a time series, see section 0.

Lastly, to covert sentiment polarity into an indication of polarization, tweets were split into positive tweets and negative tweets above a certain threshold polarity. The ratio between these two values serves as a proposed metric for polarization on Twitter, see section 4.3.2.

3.4 Police Registrations

To translate online polarization into offline activity, the number of registered police incidents related to climate change was used. These incidents include things such as protests, threats, or trespassing. It was deemed an appropriate metric as unlawful behaviors translate to security threats, falling under the general umbrella term of conflict. The entries for registered incidents were obtained from a database of the Dutch National Police Database and had to be queried. Thus a list of query terms was initially composed of individual words and phrases of climate-related vocabulary and names of pro/anti climate action organizations as well as prominent individuals in Dutch climate policy. Next, the terms in the list were each queried in the database. Out of the retrieved entries, a random sample of 20 entries was validated by reading the description attribute of the entry, which gave a short summary of the incident.

Certain keywords gave false positives, meaning an incident gave hits on a query term, but were not actually related to climate action. For example perpetrators falsely claiming to be a GreenPeace member to collect donations. If the validation sample contained one or more false, positives the list of query terms was adjusted to exclude the entries from the data set. The adjustments included combining terms and look for co-occurrence. Terms with no hits were also scrapped from the list. The adjusted list was then queried again and validated until no more false positives appeared in the validation set.The final query table is presented in Table 3.5. Note that descriptions of incidents are not included due to privacy laws, only date of occurrence and type of incident. Descriptions may include details about specific individuals that cannot be publicized.

Table 3.5. Queries used to gather registrations climate-related police incidents from the Dutch National Police database

	Organizations	*Climate Terms*
Timespan: **From: Oct. 2017** **Until: Jun. 2022** * = only in combination with "Climate Terms"	• GreenPeace / Green Peace • Extinction Rebellion • Jongeren Milieu Actief • Klimaatalarm • Urgenda • Milieudefensie • Fridays for Future / Friday for Future / Friday's for Future • Fossielvrij NL • Farmers Defence • Code rood* • ExxonMobil*	• Climate action • Climate justice • Klimaatmars *(transl. "climate march")* • Klimaatprotest *(transl. "climate protest")* • Milieuactivist *(transl. "environmental activist")* • Klimaatalarm *(transl. "climate alarm")* • Klimaatactivisme *(transl. "climate activism")*

	• Shell* • BP* • TotalEnergies*	• Klimaatactivist *(transl. "climate activist")* • Broeikasteffect *(transl. "green house effect")* • Climategate • Klimaatplan *(transl. "climate plan")* • Green Deal • Stikstofcrisis *(transl. "Nitrogen crisis")* • Klimaatbeleid *(transl. "climate policy")* • CO2 uitstoot *(transl. "CO2 emissions")*

3.5 Computational Framework

To conclude this chapter, the schematic in Figure 3.1 illustrates the process in which the earlierdescribed computational methods were employed. It is intended as a complement to conceptual framework presented in Section 2.9. Polarisation will be measured in sentiment polarity, which saddles on the assumption that a more polarised debate will contain stronger language and diverge polarity.

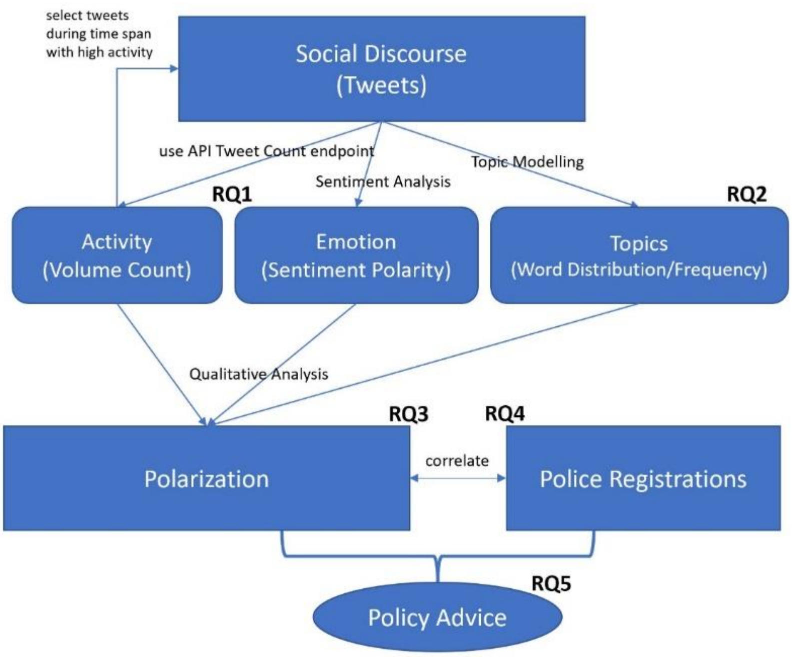


Figure 3.1. Simplified computational framework showing order of employed methods

4 Results

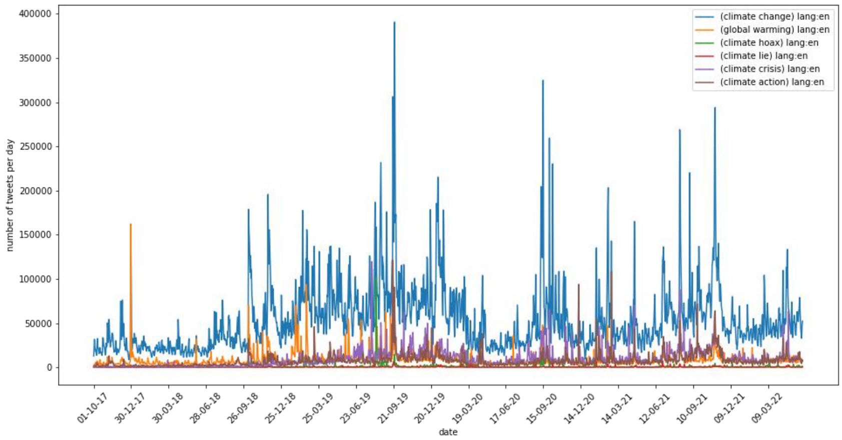
In the following section results and possible implications are discussed. These follow a similar order to how methods were introduced in section 3.3.

4.1 Tweet Counts

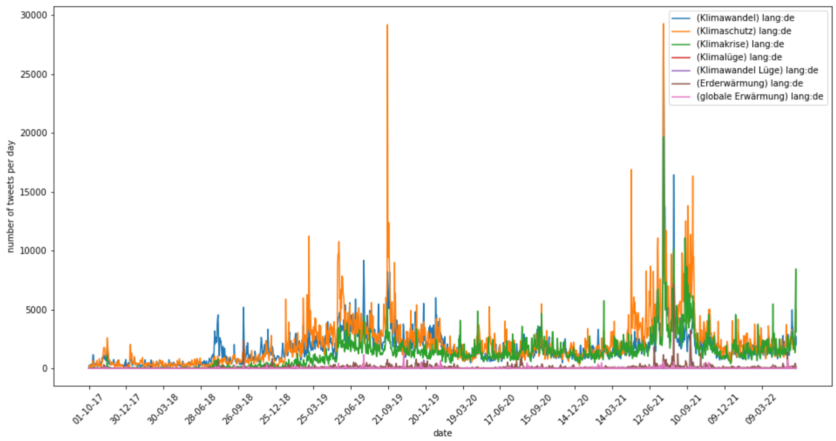
4.1.1 Differences in Language

Tweet volume was used to determine the most active periods, which are then further analysed in sentiment analysis and topic modelling. The different English, German and Dutch query counts are plotted in Figure 4.1. English had the highest levels of activity, which was expected since the greatest Twitter user base is found in the United States. Three events in particular seem to have been central in the discussion on climate change, these are discussed in more detail in 4.1.2. ”Climate change” appears to be the dominant term, with more tweet volume across virtually the entire 5 year period. The term ”global warming” had some peaks of 50 000 tweets per day prior to 2020. The term ”climate action” had virtually no mention up until mid-2018. The query for mentions of ”climate” & ”hoax” were extremely low across the entire period, apart from shortly trending on August 11th 2019. This suggests blatant climate change denial is not widespread and the level of polarization is low at the aggregate level, which suggests a high level of consensus on the existence of climate change with a certain ”baseline activity”. High levels of activity and discourse are usually brief and tied to some sort of newsworthy event.

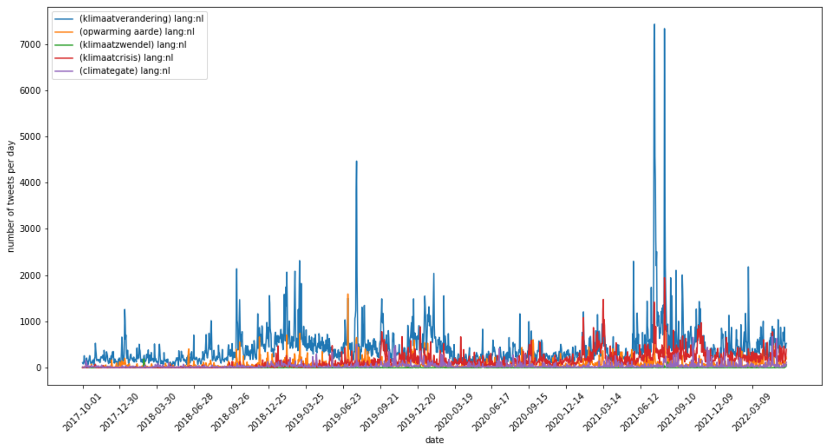
On the German Twittersphere, there is a slightly different picture linguistically. Before 2019, all query terms had very low activity, however around June 2019 discussion seems to rise. While in English ”climate change” is the dominant term compared to others, in Germany 3 terms began to be used in about equal measure. These are ”Klimawandel”, ”Klimaschutz” and ”Klimakrise”, which translate to ”climate change”, ”climate protection” and ”climate crisis” respectively. It may reflect greater consciousness towards environmental issues, in particular following the floods in 2021. However, it should be considered that the German Twittersphere is relegated in large parts to Germany, Austria and Switzerland, which are highly industrialized nations, while the English Twittersphere includes users from many regions of the world, where more pressing issues are discussed.



(a) EN



(b) DE



(c) NL

Figure 4.1. Mean sentiment polarity for Tweets mentioning various climate change related terms in three different languages between Oct. 2017 and Jun. 2022

4.1.2 Influential Events

On the English Twittersphere, three events in particular seem to have been central in the discussion on climate change. The biggest peak occurred in September 2019, followed by similarly large peaks in August and September 2020, see Figure 4.2. Searching online news stories using ”climate change” + [date], reveals for the peak of September 2019 to likely correspond to the global climate strikes (BBC 2019), which is further confirmed by different keyword queries and topic modelling. The peaks of August and September 2020 could correspond to reports of record-breaking temperatures (ECMWF 2020), though this is not further investigated.

Both Dutch and German mentions of climate change follow a very similar trajectory to each other. One peculiarity on the Dutch data set occurs on July 26th, 2019, with the third highest peak within the 4.5-year time frame, which does not seem to correspond to any global event. A likely cause was found in a local news report about a ”social media riot on Twitter” that was instigated when a prominent weather forecaster made a strong statement denouncing denial of climate change, following record-breaking temperatures in that month (Metronieuws 2019). Diving into disaggregated data corroborates this, with some sporadic activity between September 2018 and February 2020, followed by a long period of low activity. The sudden and prolonged low activity could have been caused by the overshadowing discourse and news coverage of the coronavirus pandemic.

The July 2021 floods (BBC 2021) seem to have provided considerable impetus for climate change discussions, as two peaks in activity can be seen in quick succession on both German and Dutch Twitterspheres. The first peak matches the dates of the flood. It is possible for the second peak, occurring in August 2021, to correspond to the publication of “Climate Change 2021: The Physical Science Basis”, released on 9 August 2021 (UN 2021), but this is not further investigated. As explained earlier in section 3.2.2, the periods July 2021 (Floods) and September 2019 (Climate Strikes) were chosen as they had high activity from users, but also as it would also allow for comparison between a political event and an environmental disaster.

What Figure 4.2 shows is that peaks in activity could relatively easily be tied to a news report about a major climate-related event on the same day. This implies that there is very little delay between event and response within the Twitter userbase. The potential for real time monitoring has already been recognized by scientists, in particular for disaster response efforts, where research has progressed quite extensively (Karimiziarani et al. 2022).

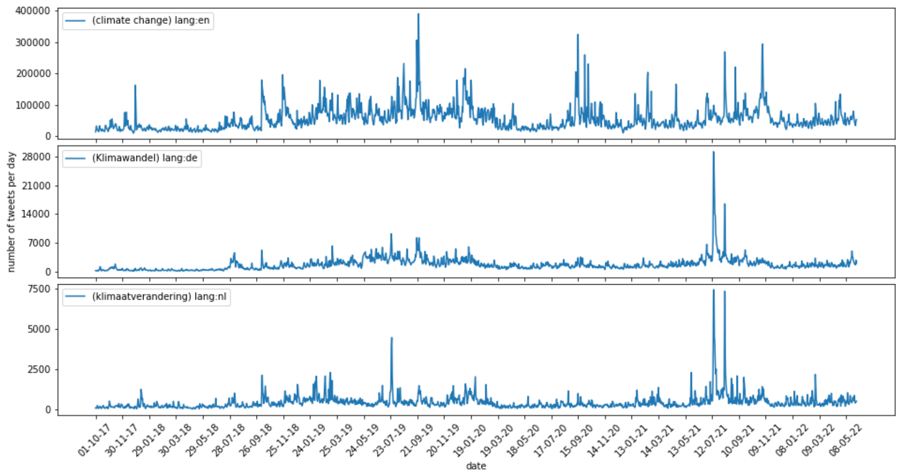


Figure 4.2. Tweet Counts per language between Oct. 2017 and Jun. 2022

4.2 Topic Modelling

Topic modelling was conducted on each of the full six data sets. The model could then be used to label tweets in the data sets and visualise the most common tokens within tweets of the same label. Figure 4.3 shows some noteworthy word clouds from English tweets mentioning climate change around July 2021. Some word clusters do mention flood-related terms (see Appendix), but it appears some other topics/stories grabbed more attention, which may be due to the fact that most English-speaking users reside outside of Europe and would not directly be affected by the flooding event. The word clouds have a somewhat consistent topic. In particular, clouds in Figures 4.3a, 4.3b, 4.3c, 4.3f could fall under topics: a) carbon, b) temperature/heat, c) people/health, f) global. Figures 4.3d and 4.3e contain some quite unusual words that do not have any apparent connection to climate. Diving into the data set and doing a word search within individual tweets reveals a single tweet that was retweeted multiple times within a short time span. For example, the tweets behind Figure 4.3d contain headlines concerning an apology video of an Exxon lobbyist outlining plans to undermine climate action.

German and Dutch topics are more similar to each other than the English data set. In July 2021 there were multiple clouds with flood related terminology, such as disaster prevention or reparation. However, Germany additionally has distinct clouds with political terminology, which comes from the fact that there was an election campaign going on at the time.

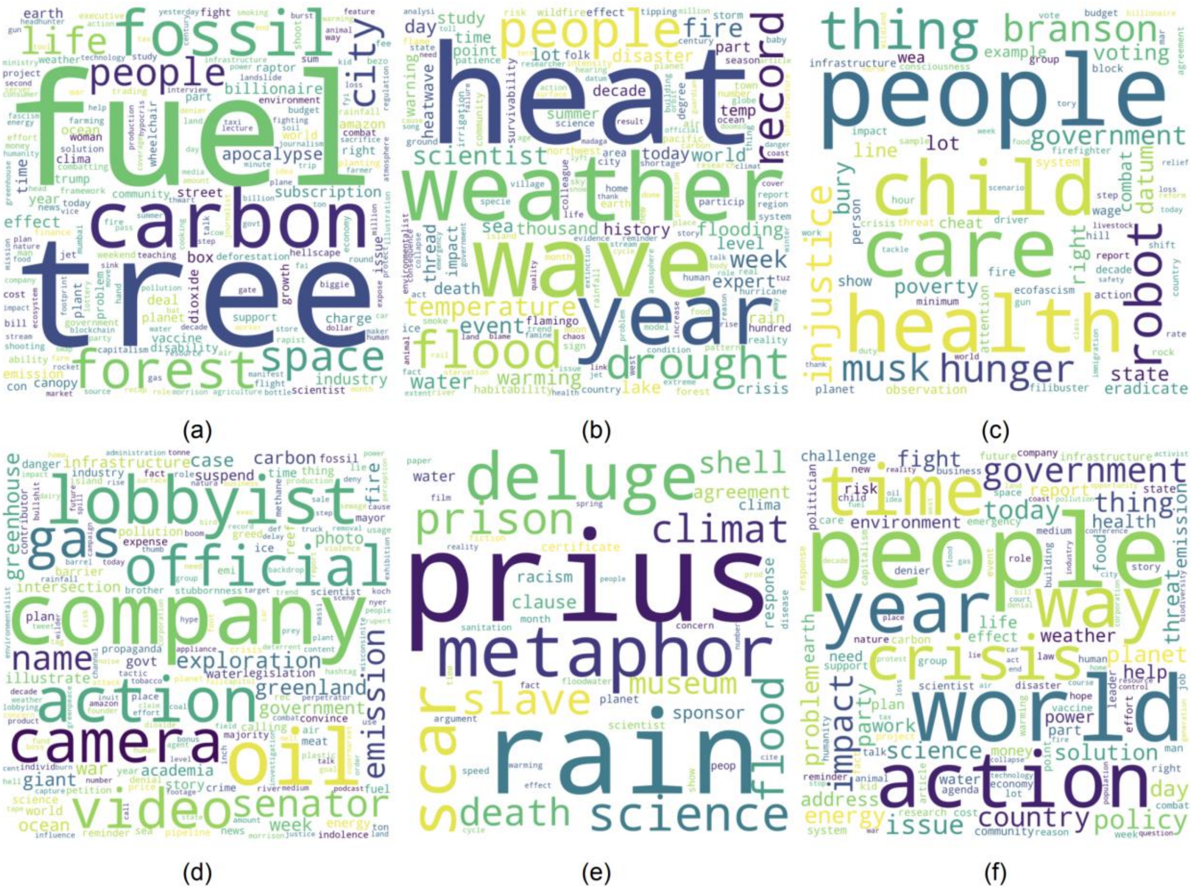


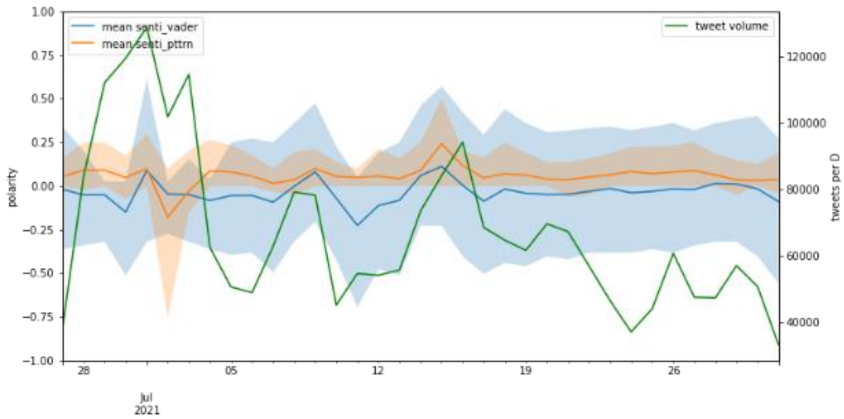
Figure 4.3. Six word clouds from English tweets mentioning climate change between 27th June and 1st August 2021

4.3 Sentiment Analysis

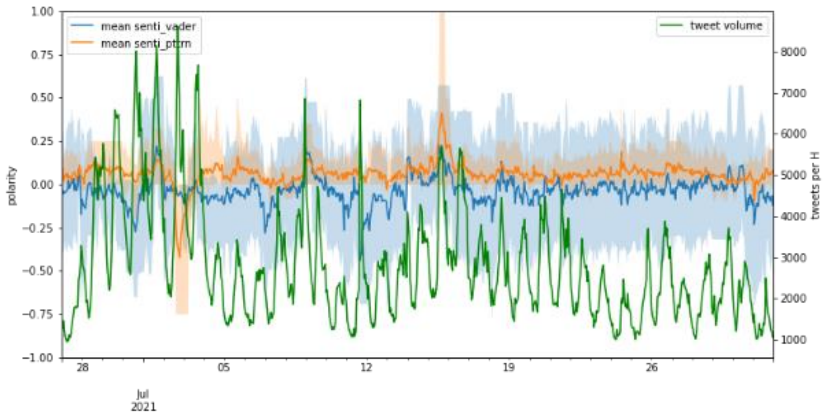
4.3.1 Mean Polarity

Sentiment analysis was performed on various subsets of the full data sets described in section 3.2 under Table 3.3. A large proportion of subsets bore very similar results in that mean sentiment polarity hovered close to 0. This is an unexpected result, of which the reasons are discussed in subsequent paragraphs.

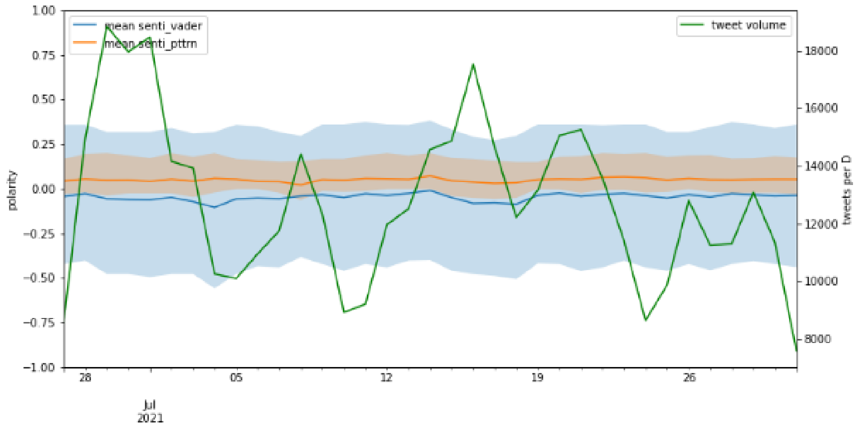
English data sets had two different measures for sentiment packages (vader & pattern), mean sentiment remained close to zero for both. However, the vader package gave a generally more negative (polarity-wise) result than the pattern package, with also a much wider interquartile range. Figure 4.4a and 4.4b show the mean sentiment of climate change tweets on July 21st at daily and hourly granularity respectively. Two peaks can be observed: one negative peak on July 3rd and one positive peak on July 26th. Positive peaks were generally not expected, as coverage on natural disasters would naturally contain more negative language. When subsetting tweets to only contain original tweets and no retweets, as seen in figures 4.4c and 4.4d, peaks are no longer visually recognizable. Mean sentiment across both measures flattened, with a little variance. This supports the idea that retweeting likely caused spikes in sentiment if the tweet in question contains particularly strong language. The tweet topics shown in Figure 4.3e have a large subset of retweets containing the phrase ”perfect metaphor” posted on July 16th, causing the positive peak in sentiment.



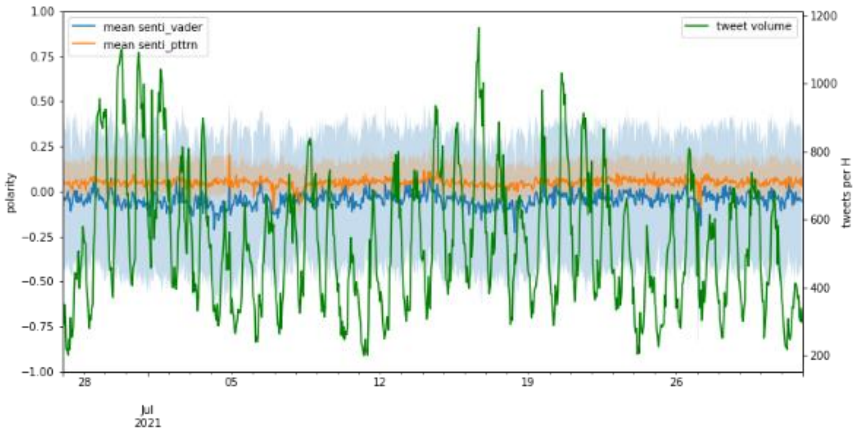
(a)



(b)



(c)



(d)

Figure 4.4. Mean sentiment polarity for Tweets query="(climate change) lang:en" between 27-06-2021 until 01-08-2021.

A significant number of Twitter users are not actual people, but rather bots that are programmed to post or share certain types of information. Verified users go through a verification procedure to ensure they correspond to a real person (usually celebrity, influencer or high office) or to an organisation. As such, subsetting by verified status should give a picture that more closely reflects news coverage of traditional media, rather than public opinion. In Figure 4.5, showing mean sentiment polarity for English tweets from verified users only, sentiments are close to zero. This is less surprising than for other subsets, since organisations are expected to be more formal in their reporting. Results are more interesting regarding volume, as there is very periodic behaviour visible, with low volumes on the 4th, 11th, 18th, 24th/25th July, which all fall on a Sunday. This may likely indicate different behaviour of verified media outlets as supposed to the mass user base on Twitter, something previously noted by Olteanu et al. (2015). It should be noted however that these observations do not hold for German and Dutch data sets, see Appendix, which in contrast may suggest low engagement of traditional media outlets in these countries on the platform.

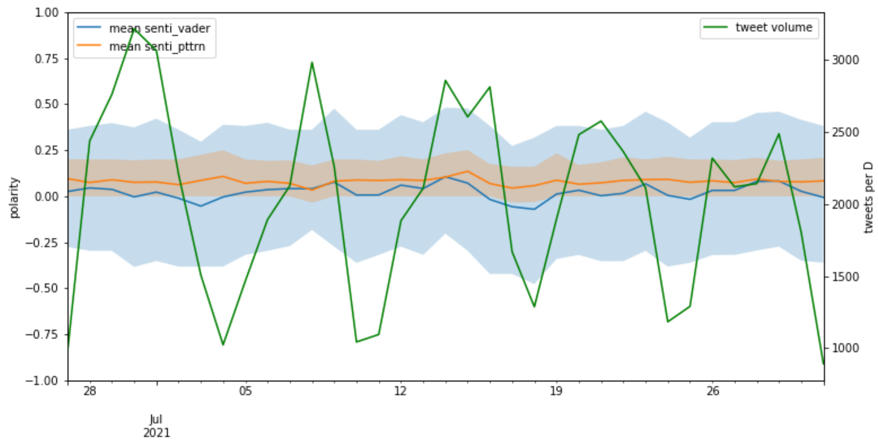


Figure 4.5. Mean sentiment polarity for English Tweets from verified users.

4.3.2 Sentiment Analysis: Extreme Sentiment

Polarization cannot be captured by the mean if the extremes are roughly of equal size and statistically cancel each other out. Furthermore, since surveys show that a large number of people are concerned with climate change but not necessarily vocal about the issue, it is logical that mean sentiment across all tweets is rather stable. This is confirmed by looking at the distribution of sentiment polarity values, seen in Figure 4.6. Across all datasets this distribution was very similar. Most tweets have zero polarity, with a relatively even spread on each side. It is worth noting that the vader package produced a smoother distribution, whereas pattern package appeared to have some bias towards ±0.5 and ±1.0. However, both metrics lead to similar conclusions.

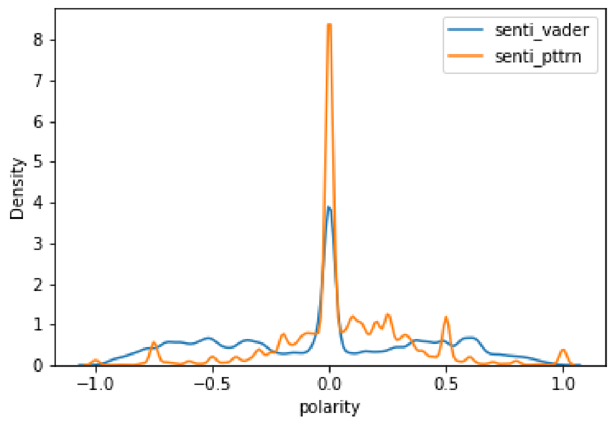


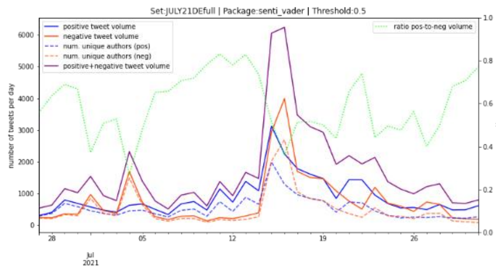
Figure 4.6. Distribution of sentiment of Tweets, query =" (climate change) lang:en" between 27-06-2021 until 01-08-2021.

Since the large number of neutral tweets caused the mean to be zero, the datasets were subset into tweets above a certain sentiment threshold. And rather than looking at the mean, the number of extreme sentiment tweets was used as the polarization metric. Plotting volume of "extreme" sentiment tweets reveals a difference in coverage of the flooding event and protesting event. Figure 4.7a and Figure 4.7b show a subset of tweets above a threshold of ± 0.5 and ± 0.9 sentiment polarity.

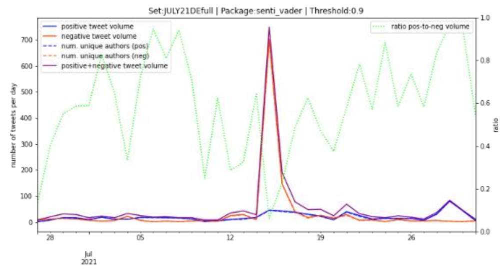
To ensure that tweets were not skewed by overactive users, or bots, data was also subset to include tweets made by unique authors. A dashed line denotes the number of tweets that came from an account that did not author another extreme sentiment tweet within the timeframe. This was done to show whether tweets originate from across the userbase or a select number of sources. At ± 0.5

minimum sentiment polarity a lower number of tweets had unique authors, whereas at highly sentimental tweets above ± 0.9 had mostly unique authors. Similar results were seen for Dutch and English, although Dutch tweets had very small volumes when threshold was greater than ± 0.5.

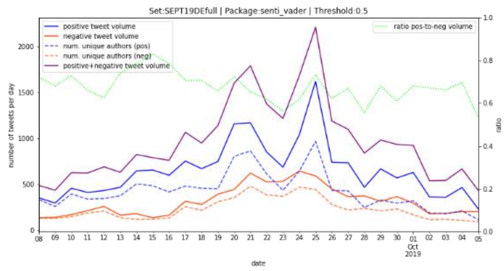
The fact that most sentimental tweets within each timeframe came from different users, may be one indicator towards polarization of the public. To further investigate this, the ratio between number of positive and negative tweets was also plotted (green line), where 0.5 would indicate a situation of maximum polarization as both positive and negative were posted in equal measure. During September 2019 this ratio is above 0.6 for both thresholds. During July 2021, the measure varied greatly, but sat at around 0.5 (max polarization) during the flooding event for threshold ± 0.5 but became 0 (minimum polarization) for threshold ± 0.9. This is contradictory result based on the threshold could show that the metric is not fit for purpose. It could however also be reflective of the dual nature of natural disasters, which on one hand can generate conflict, via fear, uncertainty, and scarcity or costs, but at the same time also generate solidarity from short-lived social and psychological support (Nardulli et al. 2015).



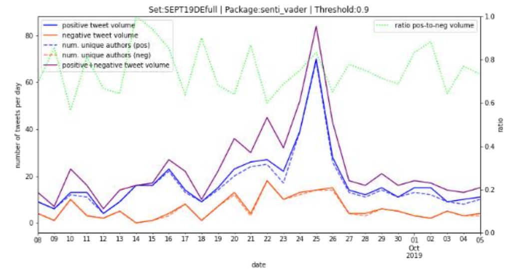
(a)



(b)



(c)

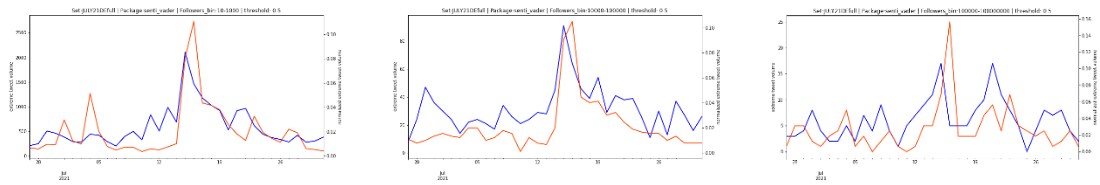


(d)

Figure 4.7. Volume of German Tweets above ±0.5 (left) and ±0.9 (right) polarity during July 2021 (above) and September 2019 (below)

4.3.3 Influential Users

The last factor that was investigated was the difference in reaction from different types of accounts. What Figure 4.8 shows, is that when normalized against the number of users within the subset, accounts with bigger following publish more sentimental and more negative content than accounts with fewer followers. Smaller accounts post negative and positive sentiment tweets in equal measure. That said all types of accounts produce both highly positive and negative tweets during the flooding event. Based on the assumption that a) sentiment is indicative on a stance towards the issue and b) follower count is indicative of social standing, these figures show that polarization is occurring at all levels of society.



(a) 10 - 100 (b) 1000 – 10 000 (c) 100 000 +

Figure 4.8. Number of extreme sentiment tweets (±0.5) from accounts with certain range of followers for German dataset July 2021.

4.4 Police Registrations

4.4.1 Incidents over Time

Now that online behavior has been analyzed, we turn to offline behavior and look at climate action related incidents. Figure 4.9 shows the frequency of registered police incidents at different time aggregations (daily, weekly, biweekly, monthly), that are seemingly related to the climate movement.

Overall it should be noted activity is still relatively speaking quite low, as the maximum number of incidents reported in one month is less than 40. It can be observed that there is very low amount of criminal activity before 2021. However, offline activity spikes in particular March-April and September-October of 2021. These peaks persist at daily aggregation, with four dates in particular accounting for a majority of incidents in the respective months. These are 12/03/2021 with 21 registries, 03/04/2021 with 22 registries, 15/09/2021 with 14 registries and 15/10/2021 with 11 registries.

Even when disregarding these incidents, there seems to be a gradual increase in registrations, as between 2018 there were many months with single incidents, with some intensification of incidents in the following years. The sharp peak in 2021 may however be some interaction with Covid-19 or general political protests.

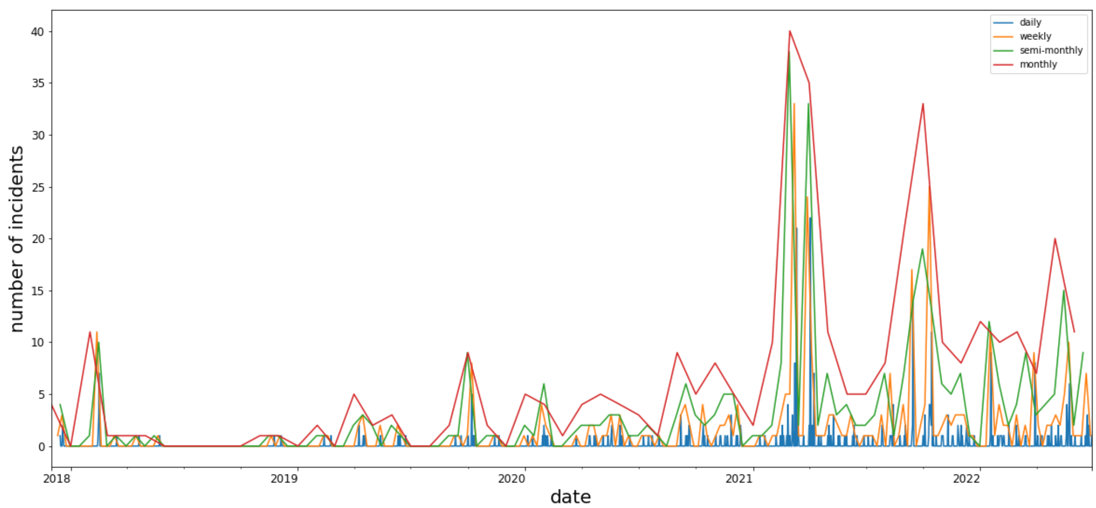


Figure 4.9. Frequency of climate-related police registration at various time aggregations between 2018 and 2022

4.4.2 Types of Incidents

Zooming in, Figure 4.10, depicts the same incidents at monthly aggregation, but as a histogram to also highlight different types of incidents. Before 2021, there are many “one-off” incidents of various types. However, when examining the peaks outlined in the previous paragraph, we this corresponds to a particular increase in one type of crime.

Looking at the types of incidents shows a variety of crimes, such as suspicious situations, threats, and trespassing. However by far the most common type of incident is F19: “overige misdrijven tegen het openbaar gezag”, which denote cases of disorderly public behavior. Examining descriptions indicates a lot of activity by extinction rebellion, who are known for certain types of incidents that disrupt public such as blocking roads and civil disobedience (Shah 2019).

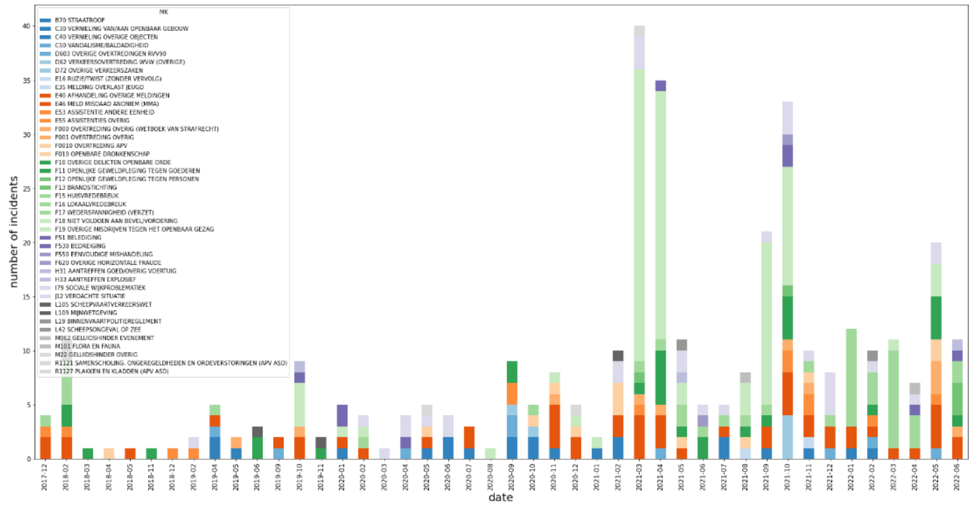


Figure 4.10. Monthly climate-related police registrations between 2018 and 2022 divided by type of incident

4.4.3 Types of Incidents

Figure 4.11 shows the tweet counts of Dutch climate change terms over the same time period as Figure 4.9 and Figure 4.10. The graphs show few commonalities. Twitter activity is high throughout 2019 and 2020 and bit lower throughout 2021. However there is quite an apparent negative correlation in July of 2021 with the highest Twitter activity but very low activity before and after, which is seemingly inverse for police registrations. The July 2021 floods may have halted activist activities, as media attention was given to the aftermath of the floods. The peak in registrations in the following months may be a delayed reaction, as the event did become politicized, sparking discussion about increased climate action.

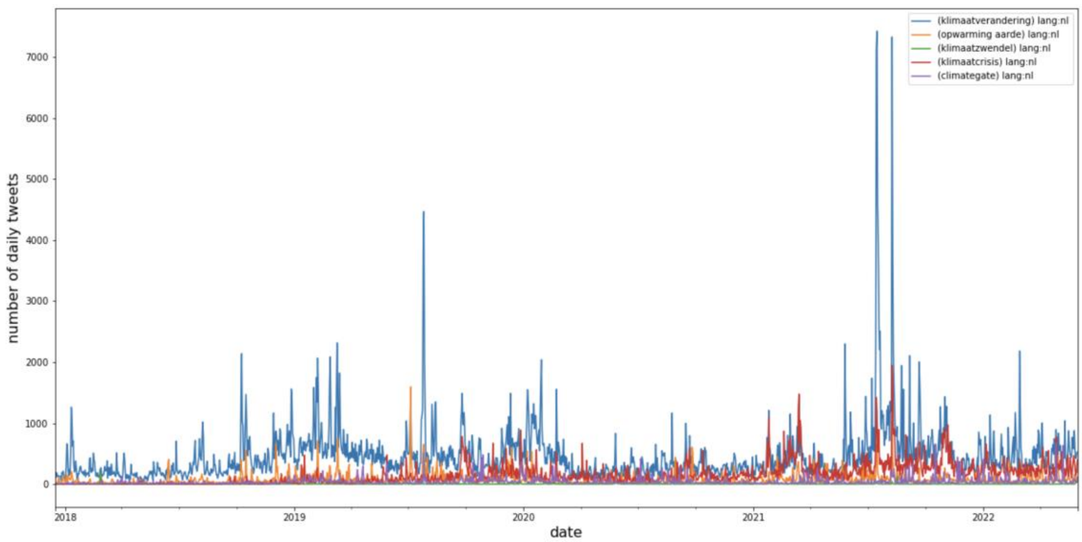


Figure 4.11. Volume of Dutch climate-related tweets between 2018 and 2022

4.5 Summary

Results have shown that climate is heavily discussed in the media and that there is an immediate reaction to large-scale climate events with increased Twitter activity, this is much in line with previous research (Dahal et al. 2019). After the events, this activity gradually reverts to a "baseline activity", or the activity before the event occurred. Looking at different queries shows that climate change is now a dominant term in the Twitterspheres of the languages studied. This is expected as most studies studying framing of climate change online, features mainly pro-action stances (Cann and Raymond 2018; Moernaut et al. 2022) Language of denial is not featured prominently, even during peaks of high activity such as the Global Climate Strike. There are several explanations for this:

Twitter may be, as accused in the past, a left-leaning platform, and thus have users from the pro-climate camp, while climate deniers avoid the platform (Fownes et al. 2018). Another possibility is that visible consequences of climate change are making it too difficult to maintain beliefs of denial among a large group of people. It is now too extreme of a belief to have and is thus more likely to arise as climate skepticism.

Moreover, sentiment analysis shows that a large majority of tweets are neutral, and that mean sentiment is largely invariant. Peaks in sentiment are often shown to be coming from one sentimental tweet that had a massive number of retweets, instead of a collection of people discussing. This dynamic makes it difficult to assess how the collective stands towards an issue or event, which hinders drawing conclusions about the state of polarization at a societal level.

Looking at counts of highly sentimental tweets exceeding a certain sentiment threshold revealed that, during both major events, there was nearly always a somewhat even split between extremely positive and extremely negative tweets. Although this could be a sign of polarization, there are certain limitations that will be discussed below in section 5.2.

5 Discussion & Conclusion

The final paragraphs conclude this project by answering the research questions, outlining limitations and recommendations for future research, as well as giving reflections on important policy implications.

5.1 Answering Research Questions

- How do reactions differ in different countries?

Many of the spikes in tweets were associated with events that most affected the country in which it occurred. Over the 4-year period, the most discussed event in Germany and the Netherlands were the flood of July 2021, a natural event, whereas in the English Twittersphere the most activity occurred during the week of the international climate protests. This could be due to over half of the dataset being from the USA. However, what seems common among most countries is that they are primarily focused on domestic events, meaning that the global issue of climate change is still viewed through a "national security lens" rather than an international one.

- Are certain topics more controversial/polarizing than others?

The topic models were able to distinguish topics to varying degrees of coherence. When sub-setting tweets by topic, no extreme differences in sentiment were observed. Interestingly, topic modelling revealed different kinds of discourse across different languages. Topics that are brought up a lot are weather, health and carbon emissions, but without any indication of controversy. Thankfully, language of denial is not seen prominently, which may actually be an indicator that polarization is not as widespread as some studies make it out to be. Interestingly, it seems that the climate-conflict linkage is not as apparent to social media users as for researchers, as terms that commonly relate to particular conflict drivers such as food security and migration are not visible within the word clouds.

- How do reactions differ to climatic events and political events?

It was expected for coverage to differ between a natural disaster and a political event such as a protest. Natural disasters would likely be covered using more negative language to convey the tragedy of the event, whereas political events would be more varied in nature as different stances are discussed. Exploring more polarized content revealed that the flooding event was covered more negatively, whereas protest events had both positive and negative content. Protest events thus pose bigger threats in term of polarization.

- Does online (Twitter) activity on climate change, translate to offline activity?

This research question cannot be answered based on current results. The culprit for the increase in police registries appears to be the Extinction Rebellion, but do not seem extraordinary security threats compared to other activist groups. Future methodologies could try to make a stronger connection between tweet queries and queries in the police database or find other data sources to investigate this further.

- Are there any distinguishable trends that could aid future policy makers in strategic planning?

Tweet volume on climate change suggests that this topic will become increasingly important. However, conclusions about the trend of polarization are difficult to proclaim, since these hinge on quite big assumptions. News coverage of events may stir a short trending discussion, but not one which persists. It should be noted that these conclusions involved a large amount of interpretations and speculation and each require more thorough analysis to build more credibility.

5.2 Limitations & Recommendations

To improve future work, the limitations, and recommendations for each step of the data processing pipeline are discussed.

5.2.1.1 Query Strategy

The query strategy was kept simple to capture a wide discourse space, with the intention for topic modelling to distill relevant topics. This was unfortunately not realised, possibly for two reasons: 1) The simple query did not cover enough discourse space, as there are different terms that pertain to climate change, such as ”climate action” or ”global warming”, that do not explicitly mention climate change, but still very much pertain to the topic. And 2) climate change could have alternate expressions such as ”the changing climate” or ”the change in climate”, which are not included in the analysis. Another example: in German, the term ”global warming” has multiple valid formulations that are commonly used: i) globale Erwärmung = ”global warming” (used for this analysis), ii) (globale) Erderwärmung = ”(global) earth warming”, iii) Erwärmung der Erde = ”warming of the earth”. More careful adjustment of the query may include a wider, more representative sample of the Twitter discourse.

That said, as seen in section 4.1.1, Figure 4.2, climate change is still the dominant term, so for no patterns to emerge at all is unexpected. It is more likely that the discourse space is in actuality too broad and many patterns are evened out when analysing their aggregation. This is elaborated upon when talking about topic modelling later. Narrowing the discourse space should be done by looking not only at the mention of climate change, but also at its co-occurrence with other keywords such as drought, storm, or floods by making use of the AND operator when formulating Twitter API queries.

5.2.1.2 Preprocessing for Topic Modelling

Another potential misstep could have occurred during text preprocessing for topic modelling. Here, a large amount of words were filtered out, retaining only nouns to reduce computational load. Nouns were deemed most informative for topic identification. However, verbs and adjectives can also give an indication of the topic at hand, particularly in regards to climate change. For example, words such as protect, invest or lying could be substantial indication towards the topic and the political stance of the user. In addition, preprocessing did not include lemmatization nor bigram/trigram detection, which are common steps in a NLP pipelines, but also computationally expensive. Both steps are concerned with how words should be treated syntactically and are explained below.

A bigram/trigram is either a 2 or 3-set of words that occur after one another. In languages such as English it is typical for new ideas to be formulated as a bigram of existing words (e.g. climate change). The idea of bigram detection is that although bigrams are composed of separate words, they refer to a single idea, so they should be treated as such. Lemmatization is the process of trimming words to their root. Words such as ”protection”, ”protect” and ”protective” all share the same root words and provide similar indication to a topic, but only the first is currently included in topic modelling. Some phrases should definitely be treated as one idea e.g. industrialised world, environmental protection laws etc., as they lose meaning when separated into individual words. The current python packages nltk, gensim and spacy have pretrained bigram/trigram and lemmatization modules that could be integrated to improve the pipeline in the future, and improve coherence of topic models.

5.2.1.3 Topic Modelling Limitations

Topic modelling could be improve to disentangle more comprehensive topic streams. As already touched upon previously, the data set may be too broad. The general topic of climate change may be too large or interconnected to provide fully distinct topic clusters. Furthermore, the settings of the topic modelling algorithm were not optimized due to lack of computational power. These parameters include k - the number of clusters i.e. topics, alpha & beta - convergence constants and n - the number of iterations. Better hardware, coupled with an evaluation metric would be helpful to better the quality of results.

For topic modelling, a different approach may be worthwhile. Firstly, the current methodology could include more iterative steps, which would begin with querying a set of tweets, applying topic modelling, identifying keywords and readjusting the query, to slowly narrow down towards a topic area. Secondly, simple histograms may not be sufficient to outline a topic area, especially when there is a lot of interconnections. Results could be drawn by using network visualisations to show word collocations, rather than showing word frequencies and distributions. This would have the added benefit that collocations would likely reveal common bigrams as well. If this fails, the last option would be to switch to different topic modelling methods. GSDM is a so-called bag-of-words approach, where documents (i.e. tweets) are treated as a collection of words without regard for word order. Clustering is simply based on similarity of word distribution (Yin and Wang 2014). More recent advances in this area include a ”Bidirectional Recurrent Attentional Topic Model” which accounts for word order and sentences before and after in making a topic inference (Li, Zhang, and Pan 2020). Deep neural network techniques were not attempted due to logistical limitations with acquiring a labelled data set, but hold promise and could be considered in future research (Jansson and Liu 2017).

5.2.1.4 Sentiment Analysis Limitations

For the full data sets and most subsets regardless of language, mean sentiment polarity and inter-quartile range were relatively stable with only minor exceptions. Examining sentiment distributions across tweets reveals that most tweets are classified as neutral, i.e. with no polarity at all. One reason for this may be that lexica were incomplete, given that the quality of lexicon/rule-based sentiment analysis depends heavily on the completeness of the lexicon it is based on. Unknown words in the lexicon will by default have no polarity and thus if too many unknown words exist within a document, results will tend towards zero.

There was also no spell check included, meaning that misspelled words would also contribute to a lack of polarity. Reports and news agencies tend to use more of a neutral voice when reporting, which would again skew sentiment towards zero. Climate change as one topic may be too abstract and have a lot of news coverage. Topics such as ”pollution” and ”rising temperature” are neutral concepts and sentiment may be hidden or rather depend on context and semantics. Meaning in language is also often conveyed through context rather than simply individual words. A good example of this is irony and sarcasm, which are difficult even for deep learning methods to pick up on. Sentiment analysis is most commonly used in marketing for analysis of customer or business reviews (Pandya and Mehta 2020), thereby fixing the ”discourse space”, i.e. context, and removing it as a variable, providing generally better insight. Simple improvements to the current pipeline include 1) narrowing the dataset, using strategies mentioned in section 3.3 above, as well as testing other SA packages such as SentiWordNet (Baccianella, Esuli, and Sebastiani 2010). Option 2) would be to use different metrics, such those included in the pattern package, which alongside sentiment also calculates subjectivity and modality (with how much certainty a sentence is expressed). Lastly, machine learning methods could also be applied: a prominent SA technique is BERT (Bidirectional Encoder Representations from Transformers), which fully takes into account word order (Alaparthi and Mishra 2021).

5.2.1.5 Conceptual Limitations

That said, sentiment analysis as a metric of polarisation may need to be rethought as a whole. Sentiment (positive/negative) does not equate to ideological stance (pro/anti). Both a climate activist or climate denier can present their arguments using negative words. Polarity and polarisation, despite being etymologically similar, are different and thus a more careful distinction should be made. The assumption from section 3.5 must be reconsidered, as current results show little support for it. More substantial improvements would include implementations of different methods such as ML-based methods (e.g. emotion classification), or even stance detection (Luo, Card, and Jurafsky 2021; Mohammad et al. 2016) to investigate polarisation as a social phenomenon.

5.3 Future Work

The current methodology has provided ideas about the state of polarisation surrounding and what kind of topics and events play a role in climate change discourse. Moving forward, research should focus more on the interaction between polarizing topics, as societal polarization certainly does not take place along the climate dimension. This would need deeper analysis of the language using more advanced NLP techniques. The first step for future research would be to address the aforementioned limitations, and expand the methodology as explained in 3.3. Polarization cannot be captured by one metric, at least by sentiment polarity, which seems to be an ongoing problem in the field (Kubin and von Sikorski 2021).Thus, following the multi-modelling paradigm, the ML and NLP-field have more techniques to offer to supplement and expand the analysis, such as named entity recognition (NER) or social network analysis to identify key actors and organisations as well as geographic or cultural factors that might play a role. Moreover, instead of querying data in bulk, it may be wise to also understand the connections in terms of replies and retweets to better understand discourse. Together, this would form a basis to provide actionable advice to public institutions. Combined with network studies, it would be easier to understand and monitor those harboring more extreme stances towards climate change and climate action.

5.4 Policy Advice

In the current state, it appears that polarization is not as widespread as some studies may suggest. Topic modelling brings up major issues associated with climate change, such as emissions and environmental disasters, and does not reveal any terms often related to climate change denial. Sentiment analysis, although at first glance quite unnoteworthy due to a largely invariant neutral sentiment, nevertheless holds some implications and affirm that polarisation around climate change is not in a dire state. In fact, as previous studies have shown, most people are at least somewhat concerned with climate change. That said, climate change is still a worrisome political problem, as even though outright denial may be quite rare, there may be denial about whether the consequences of climate change matter, in addition to heavy disagreements about what actions to take. Additionally, sentiment analysis in English data sets detected different tweet behaviour between verified and non-verified users. Relating this to the research questions, there is a strong indication that different countries have different news environments that are mainly concerned with events which affect local people directly. English Twitter has the greatest volume and broadest discourse space, with big news stories being very visible in topic modelling and sentiment analysis. Peaks in sentiment occur from retweeting, most likely by influencers or prominent news sources and not necessarily as an exchange of viewpoints by users. Internal police data, seems to indicate that climate-related incidents are becoming more common. A large proportion of this activity comes from the Extinction Rebellion, however based on descriptions, these do not appear to be extraordinary security threats compared to other activist groups.

Although at present the situation may not seem urgent in terms of security in the Netherlands, let it be clear that the scientific consensus about the consequences is. As such the situation must be continuously reassessed, since could change at any moment. All the results, literature and present knowledge taken together; the resulting policy advice is two-fold.

On the short-term, it would be wise to further develop monitoring capabilities. Analyses have demonstrated that volume, topics, and sentiment can be used to piece together the most influential or most prominent events on social media. Tools could make use of historical archives social media to allow for real-time monitoring. A conceptual modular framework is presented in Figure 5.1. Central to the framework is the selection of indicators. The polarization metric (number of high-sentiment tweets) could offer a starting point here.

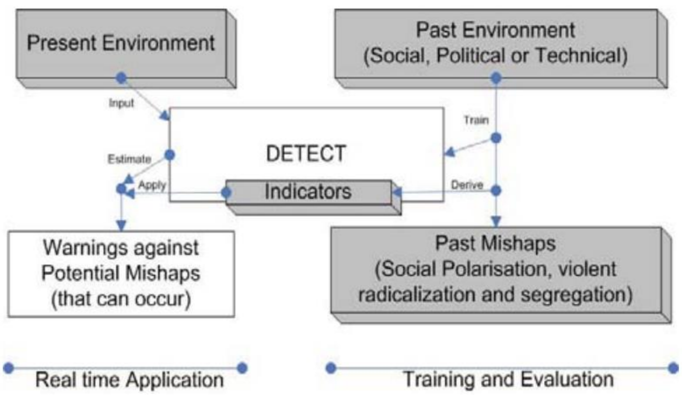


Figure 5.1. Polarization monitoring framework (Qureshi et al. 2011)

The security sector will surely play an important role in managing some consequences of climate change. Yet it is the perspective of the author that: ultimately, fighting polarization as solely a security issue is akin to treating the symptom, rather than the disease. On the longer term, it may be wise for the security sector to cooperate with other ministries as polarization does not only occur along the climate stance dimension. Polarization as noted by social scientists occurs along many social dimensions, which are ultimately what needs to be addressed. Moreover, the government can also adhere to depolarization principles, such as avoiding "us-versus-them" rhetoric or increasing transparency in decision-making (McCoy and Somer 2021).

5.5 Final Reflections

The truly global scale of climate change may make it the most complex scientific, political and social problem to exist. It is rigged with uncertainty and thus the analysis of the climate-conflict relation requires tacit understanding of how to deal with complexity, uncertainty, and contextuality. Systems thinking was crucial to make sense of how the various mechanisms of how climate brings about conflict potential. Many factors that lead to conflict are interdependent and thus contain feedbacks and non-linearities, which are key characteristics of EPA-related problems, requiring skills acquired throughout the study to formulate strategic policy advice.

From an academic perspective this thesis has made small steps in showing how polarization in society can be researched and analyzed. Moreover, it demonstrated what potential insights can be obtained by combining topic modelling and sentiment analysis. It has also explicated a number of conceptual and computational considerations that need to be taken into account, as we tackle this problem moving forward.

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7 Appendix

7.1 Figures

For full size figures used in this thesis:

https://github.com/EliasBach/THESIS/tree/main/Figures

7.2 Full Results

Full results found at:

https://github.com/EliasBach/THESIS/tree/main/Notebooks/Results

7.3 Code

Supplementary code used to gain results found at:

https://github.com/EliasBach/THESIS/tree/main/Notebooks

7.4 Background on Events

7.4.1 Global Climate Strike

Sparked by teenage campaigner Greta Thunberg's movement "Fridays for Future", millions of people across the many cities of the world rally for increased efforts for climate action. The week-long event was known as the "Global Week for Future", lasting from September 20th – 27th 2019 (BBC 2019).

7.4.2 July 2021 Floods in Western Europe

Following heavy rains lasting for several days around July 12th 2021 caused large flooding to occur along the rivers Rhine, Ahr, Ruhr, Mosel and Meuse. It was the heaviest flood in decades with an estimated damage of over €10 billion (BBC 2021).

7.4.3 Social Media Outcry following Remarks by Dutch Weatherman

Following several days of record-breaking temperatures, a prominent weather forecaster tweeted that these weather patterns were undeniably linked to climate change. This caused outcry among climate deniers (Metronieuws 2019).