

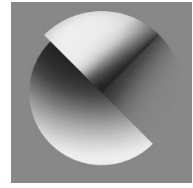
Viral climate imagery: examining popular climate visuals on Twitter

Isaac Bravo, Daniel Silva Luna, Stefanie Walter

Angaben zur Veröffentlichung / Publication details:

Bravo, Isaac, Daniel Silva Luna, and Stefanie Walter. 2025. "Viral climate imagery: examining popular climate visuals on Twitter." *Visual Communication*.
<https://doi.org/10.1177/14703572251320292>.

Viral climate imagery: examining popular climate visuals on Twitter

**ISAAC BRAVO**

Technical University of Munich, Germany

DANIEL SILVA LUNA

University of Antwerp, Belgium

University of Augsburg, Germany

STEFANIE WALTER 

Technical University of Munich, Germany

ABSTRACT

This study uses a multimodal approach, combining visual content analysis and textual analysis of tweet content to explore the virality of climate imagery on Twitter. Employing a combination of methods, including content analysis, latent class analysis, and automated text and sentiment analysis, the research the visuals, user information and public engagement of climate change related tweets shared between 2019 and 2022. The findings reveal a diverse array of viral visual content characterized by various formats, subjects and settings, identifying five frames related to celebrities, protests, politics and the visualizations and effects of climate change. These frames differ in terms of public engagement and sentiment expressed in user comments. Despite the democratic potential of online discourses, the study finds parallels with traditional media, including the underrepresentation of marginalized groups and themes such as adaptation and mitigation strategies. A lack of diversity is also evident in the users shaping viral visual climate change discourses on Twitter. Despite the platform's potential for diverse contributions, accounts from the US dominate, along with accounts by media and political entities with above-average followers.

KEYWORDS

climate change • images • social media • Twitter • virality

Visual Communication 2025

Vol. 0(0) 1–32



© The Author(s) 2025

Article reuse guidelines: sagepub.com/journals-permissions

DOI 10.1177/14703572251320292



INTRODUCTION

Social media have become increasingly crucial in shaping public discourse on climate change as it supersedes traditional media in how people learn about the topic and in how they consume and produce climate images (Pearce et al., 2019; Wang et al., 2018). The shift to social media is thought to democratize public discourse by providing a platform for a wider range of voices and perspectives, thus promoting more inclusive dialogue and diverse representations of climate change (Boulianne et al., 2020; Hopke and Paris, 2021). While there is a growing body of research on climate change visual communication, including studies on social media platforms, systematic large-sample analyses of visual representations of climate change remain relatively limited (O'Neill and Smith, 2014; Schäfer, 2020; Schäfer and Yan, 2023). To date, comprehensive studies that systematically engage with this topic are still scarce (DiFrancesco and Young, 2011; O'Neill, 2013; Smith and Joffe, 2009). Notably, most of these studies were conducted more than a decade ago, examining traditional news media outlets, with only a few recent examples exploring climate change images on social media (e.g. León et al., 2022; Mooseder et al., 2023).

This study examines the online visual representations of climate change through the lens of 'virality', a critical concept in social media logics that describes the rapid and widespread diffusion of content (Nahon and Hemsley, 2013). We analysed the 10 most viral climate change-related tweets with visual content of each month from 2019 to 2022 ($N = 662$). While centred on visual elements, our approach acknowledges the multimodal nature of social media communication by considering accompanying text and replies to tweets, providing context and enriching our understanding of the visual content.

By employing a variety of methods, we delineate the diverse attributes of viral climate change visuals on Twitter. Our findings reveal significant diversity in visual climate content on Twitter, characterized by a wide range of formats and content. However, we also uncover persistent continuities with traditional media, notably the overrepresentation of certain groups and themes (e.g. politicians, celebrities, consequences of climate change) and underrepresentation of others (e.g. Global South, farmers, adaptation and mitigation strategies). These results underscore that, while social media offer new avenues for representation, traditional media's dominant visual discourses continue to prevail, indicating that the potential for social media to democratize visual climate communication has yet to be fully realized.

CLIMATE CHANGE VISUALS AND THE ROLE OF SOCIAL MEDIA

Studies on climate change visuals have traditionally focused on recurrent images published in traditional news media outlets (DiFrancesco and Young, 2011; O'Neill, 2013; Smith and Joffe, 2009) and highlighted the prominence of politicians, celebrities, activists and protesters (Metag et al., 2016; O'Neill,

2013; Smith and Joffe, 2009). Common visual themes also include the causes and consequences of climate change, depicted through images of natural disasters and data visualizations like the ‘hockey stick’ graphs, and representations of solutions such as renewable energy technologies (DiFrancesco and Young, 2011; Hayes and O’Neill, 2021; Schäfer, 2020). These recurrent visual themes form what can be described as climate change’s visual discourses, an everyday visual lexicon that recurrently conveys dominant cultural narratives around the issue (O’Neill and Smith, 2014).

In contrast, climate change images on social media have been relatively unexplored (for exceptions, see León et al., 2022; Mooseder et al., 2023) despite the substantial impact of social media on shaping the climate change debate in recent years (Pearce et al., 2019; Wang et al., 2018). Social media disrupt traditional gatekeeping models employed by newspapers and television, introducing a diverse array of new actors into the creation, dissemination and framing of climate change narratives (Chen et al., 2022; Weitkamp et al., 2021). This has empowered new and diverse actors, exemplified by the rise of youth initiatives such as School Strike 4 Climate, which have gained prominence and shaped public opinion (Boulianne et al., 2020).

Social media platforms’ interactive nature democratizes access to climate-related information, sparking instant engagement and discussion, especially during significant events like climate summits or severe weather occurrences (Hopke and Hestres, 2018; Mooseder et al., 2023). However, the algorithmic curation and network structures on these platforms can also fragment dialogue, creating subcultures or echo chambers that may circulate disinformation (Brossard and Scheufele, 2022; Treen et al., 2020). Influencers play a crucial role in this ecosystem, leveraging their extensive reach and engaged audiences to significantly impact public opinion and discourse on climate change (Dekoninck and Schmuck, 2022). Moreover, social media’s affordances for engagement through mechanisms such as likes, shares and comments (Bucher and Helmond, 2018) have transformed how people interact with and disseminate climate-related content (León et al., 2022), potentially catalysing novel climate representations.

Consequently, the circulation of climate change images on social media is influenced not only by the content but also by the complex interplay of social actors and the unique characteristics of the platforms themselves. These dynamics are magnified by the digital environment’s speed in the creation, mutation and dissemination of images (Rose, 2016). Unlike traditional media, where distribution channels are more controlled, the vast majority of images on social media are transient, reaching only a limited audience. However, a few images will go ‘viral’, becoming touchstones in the online conversation on climate change (see Hawkins et al., 2019). The widespread visibility of these viral images grants them substantial influence over public perceptions of climate change, shaping the cultural landscape through which people interpret and experience the phenomenon (Nicholson-Cole, 2009).

UNDERSTANDING VIRAL IMAGES

The concept of virality describes the accelerated spread and expansive reach of information or content within and across digital platforms, often driven by user engagement, specifically liking and sharing, and its consequential effects on societal perceptions and discourses (Alhabash and McCalister, 2015; Denisova, 2020). This phenomenon encapsulates the logics of social media, characterized by network connectivity and data-driven visibility (Nahon and Hemsley, 2013; Van Dijck and Poell, 2013).

Research on virality in social media has examined the many characteristics of a post's content that explain their spread. Investigations have observed how denotative attributes of a post, such as the use of hashtags, hyperlinks and surface-level components of images, contribute to its virality (e.g. Nanath and Joy, 2023; Tellis et al., 2019). Additionally, connotative elements, such as emotional resonance and moral appeals, have been shown to significantly influence viral trends (e.g. Berger and Milkman, 2012). In the context of viral climate change imagery, we thus pose the question: *What are the visual characteristics of viral climate change images on Twitter (RQ1)?*

Furthermore, research has examined the influence of user attributes on engagement and virality, exploring explicit factors like occupation, age and geographic location, as well as implicit traits such as perceived trustworthiness and attractiveness (e.g. Han et al., 2020; Kamiński et al., 2021). The significant network effects generated by high-profile accounts and influencers, who possess large followings, can dramatically amplify the reach and impact of posts, typically outperforming content from lesser-known users (Goel et al., 2016). This leads us to the question: *What are the characteristics of the users posting viral climate change images on Twitter (RQ2)?*

CLIMATE VISUAL DISCOURSES

Climate visual discourses and their circulation are manifestations of particular cultural experiences (e.g. Born, 2019). Content creators, drawing upon their own cultural backgrounds, curate and share images in ways to evoke a preferred reading aligned with their worldview (see Hall, 1980). These visual discourses not only reflect creators' intentions but are also interpreted through the cultural and social lenses of the viewers. Depending on their backgrounds, viewers may affirm, question or contradict the worldviews conveyed, which impacts how they perceive and engage with the content (O'Neill et al., 2023).

The design and affordances of digital platforms provide distinct possibilities for this response. Features of these platforms, such as sharing, liking and commenting, provide users with opportunities to express their interpretations and actively engage with the visual discourses in a distinct manner (Bucher and Helmond, 2018). Importantly, the popularity of a discourse is not static but evolves over time. This temporal dynamic is influenced by societal changes and global events (Roxburg et al., 2019). Such shifts in visual

discourse popularity underscore the fluid nature of climate change narratives and their alignment with contemporary cultural and social contexts.

By identifying these visual discourses, their content, the people who post them and the ways in which they are engaged through the affordances of social media, we gain insights into the kaleidoscope of cultural experiences surrounding climate change visuals online. This analysis should not only capture static elements of these discourses but also acknowledge their dynamic nature, reflecting how societal changes and global events influence the popularity and prevalence of certain visual themes over time. This prompts us to address two more research questions: *What visual discourses are prevalent in viral climate change imagery on social media (RQ3)? How do these visual discourses vary in terms of their content features, the profiles of the contributors, the temporal dynamics of their popularity and the interaction affordances utilized (RQ4)?*

METHODOLOGY

Data and sample

Utilizing the ‘AcademicTwitter’ package in R (Barrie and Ho, 2021), we gathered data via the Twitter Academic API v2. This collection occurred before new access restrictions were implemented following Elon Musk’s acquisition of the platform. Our dataset specifically included tweets¹ from the period between 2019 to 2022 that contained any of the terms ‘climate change’, ‘climatechange’, or ‘#climatechange’. Each tweet in our selection was required to include at least one image or GIF.² To operationalize virality, we identified tweets that garnered the most engagement, specifically we selected the top 10 tweets for each month ranked by the highest combined totals of likes and retweets, indicators recognized in the literature as measures of virality (see Muñoz et al., 2022). Our final dataset consisted of 480 tweets with 662 images,³ shared by 351 unique users. We also collected the accompanying metadata from each tweet, including information about the users (e.g. followers), as well as engagement metrics (i.e. likes, replies, retweets). Additionally, we analysed 802,121 replies to these tweets to further understand the dynamics of public interaction with the viral content (see below for further details).

Standardized (image) content analysis

To systematically uncover the characteristics of viral climate images (RQ1), we first conducted a standardized content analysis. We developed a codebook based on established literature on climate imagery (e.g. DiFrancesco and Young, 2011, O’Neill, 2013; O’Neill et. al., 2023; Rebich-Hespanha et al., 2015), which included variables related to the image type, depictions of climate change causes and consequences, and the demographic representation (gender and ethnicity) of individuals depicted in the images. This codebook was refined through several pre-testing rounds, resulting in a finalized set of

13 variables. The images were coded using the open-access web application QCAMap (Fenzl and Mayring, 2017). The unit of analysis was the image; however, in a few cases where the image content was ambiguous the coders were able to draw on the tweet text to accurately classify the images.⁴ The coding team consisted of three coders who initially tested the reliability on a subset of the images ($n = 50$). The reliability scores for Krippendorff's Alpha ranged between 0.64 and 1.0, demonstrating a moderate to high level of agreement (Krippendorff, 2004) (see Appendix 1 for further details).

We further performed a content analysis of the profiles of users posting the images in order to understand the diversity of actors involved in spreading viral climate change visuals (RQ2). Two coders systematically categorized these profiles into seven actor types that have been identified by previous work on climate change networks on Twitter (Walter et al., 2019): Politics, Media, Celebrity, Science, Civil Society, Ordinary Citizen and Economy. Additionally, coders assessed the geographical location of each user, utilizing metadata for initial classification and conducting online searches for ambiguous cases. Discrepancies in coding were resolved through discussion. The reliability of this coding process was also assessed on a subset of the profiles ($n = 40$), with Krippendorff's Alpha scores of 0.91 for actor type and 0.92 for country of origin, both indicating high reliability (Krippendorff, 2004) (see Appendix 1 for further details).

Latent Class Analysis

We employed Latent Class Analysis (LCA) to identify prevalent visual discourses among the climate change images (RQ3), using the results from the standardized content analysis as input data. LCA is a statistical method suited for uncovering hidden groups or clusters in categorical data which, in our case, helps to reveal recurrent themes in the image dataset (Nylund-Gibson and Choi, 2018). For the LCA, certain variables from the content analysis were re-coded to streamline the process (detailed re-coding procedures are provided in Appendix 2). We used the PoLCA package in R (Linzer and Lewis, 2011) to run the LCA model.

Analysis of cluster characteristics

Upon identifying distinct clusters through LCA, we conducted a multi-faceted evaluation to uncover the nuances of each cluster (RQ4). This analysis utilized data from the initial content analysis and incorporated additional evaluative methods to assess content features, contributor profiles, temporal dynamics and interaction affordances. While our primary focus remained on visual content, we also analysed accompanying tweet text and replies to provide a more comprehensive context for the themes represented in each cluster. This holistic approach allowed us to capture the full complexity of climate change communication on Twitter.

1. **Content features:** We analysed the set of images within each cluster to identify prevalent topics and motifs. This was achieved by creating z-scores for each variable assessed in the content analysis, which were then visualized in a heatmap. This method provided a clear representation of predominant features and variations across clusters, facilitating a comparative analysis of their distinctive content characteristics. We further looked at other aspects of the content of the tweets in each cluster through text and sentiment analysis.
 - (a) *Text analysis:*⁵ To analyse the textual content accompanying the images in each cluster, we conducted an exploratory thematic analysis on the 5 percent most frequently occurring words in the tweets. Following Braun and Clarke's (2007) framework, we familiarized ourselves with the data, generated themes, reviewed and refined these collaboratively. The resulting themes, which highlighted the dominant narratives within each cluster, were visually represented through word clouds generated with the 'wordcloud' package in R (Fellows, 2018).
 - (b) *Sentiment analysis:* We also analysed the affective tones expressed in the replies to the tweets for each cluster. Following pre-processing,⁶ that resulted in a final sample of 802,121 replies, we conducted the analysis using the Vader lexicon via the 'vaderSentiment' library in Python (Hutto and Gilbert, 2014). Vader has been previously validated on climate change Tweets (Effrosynidis et al., 2022) and has shown better performance than other dictionary approaches (Rosenberg et al., 2023). To ensure its effectiveness for our specific context, we manually coded a random sample of 480 replies and compared the results with VADER's output, achieving an agreement rate of 85 percent. This analysis illuminated the predominant sentiments within the replies, providing insights into the affective undertones of the images in each cluster.
2. **Contributor profiles:** To assess the diversity of contributors across identified clusters, we analysed the profiles of users posting the images. This analysis utilized data on the types of actors (e.g. media representatives, celebrities, ordinary citizens), their geographic locations from the initial content analysis and follower counts, aggregated for each cluster. These factors were evaluated to understand the demographic diversity and social reach of the contributors within each cluster, thereby gaining insights into how different actor types and their geographic distribution contribute to the propagation of the climate change visual discourses.
3. **Temporal dynamics:** We assessed the posting frequency of images within each cluster throughout the study period to track temporal trends and changes in popularity. This analysis highlighted how the prominence of various visual discourses shifted over time, reflecting changes in public interest and the impact of significant global events.
4. **Interaction affordances:** Finally, we aggregated engagement metrics – including likes, replies, and retweets – for each cluster to capture the

type of user engagement with the images in each cluster. This assessment helped determine the reach and type of reaction to the visual discourses in each cluster.

RESULTS

Our analysis of viral climate change images on Twitter from 2019 to 2022 (N images = 662; N tweets = 480; N users = 351) revealed that photographs, including individual images and collages, were the dominant image type (60.7%), followed by screenshots (18.4%), data visualizations (6.5%) and posters (5.1%).⁷ Nearly half (49.2%) of the images portrayed human-made spaces (indoor spaces and urban areas), while natural settings were less common (19.2%).⁸

People featured in most images (62.2%), with politicians (16.9%) and celebrities (14.2%) being the most prominent. Protesters were visible in 8.5 percent of the images, with youth protests like Fridays for Future comprising about half (4.4%). Activist Greta Thunberg was present in 2.4 percent of all images, while scientists, farmers and Indigenous people had minimal representation ($\leq 2.0\%$). Gender and ethnic disparities were observed, with images predominantly featuring individuals with characteristics typically associated with males (46.8%)⁹ and white ethnicity (45.9%).¹⁰

Climate change causes were represented in 10.4 percent of images, while consequences were more prominent (26.1%), with extreme weather events making up 13.4 percent. Complex issues like economic consequences (0.5%) and human rights issues (0.2%) were rarely depicted. Mitigation and adaptation efforts were present in 10.0 percent of images, with climate-friendly technologies (4.1%) and reforestation/afforestation initiatives (2.6%) being the most common. Other sustainable practices, including sustainable farming, weather preparedness, sustainable transport and the 3R (reduce, reuse, recycle) movement were almost absent (all $\leq 1\%$). Animal representations were likewise scarce, with only 5.6 percent of the images featuring animals.

On average, the images received 6,413 retweets, 822 replies and 24,469 likes (Table 1). They were posted by 351 unique users with an average of 7,278,772 followers per image, suggesting a predominance of macro influencers (see Kay et al., 2020). About half of the images were shared by users from the US (49.3%), with the UK (10.4%) and India (8.0%) following far behind (Appendix 3). The images were mostly shared by politicians and political organizations (22.4%), ordinary citizens (18.3%), media-related accounts (15.0%) and celebrities (15.0%) (see Appendix 4).

Visual climate change discourses

The Latent Class Analysis (LCA) grouped our images into five clusters, helping us to identify distinct visual discourses around climate change that align with themes identified in the literature (DiFrancesco and Young, 2011;

Table 1. Images and their associated metadata by cluster.

| Cluster | Images per cluster (%) | Mean retweets per image | Mean replies per image | Mean likes per image | Mean followers per image |
|-------------------|------------------------|-------------------------|------------------------|----------------------|--------------------------|
| 1 Celebrities | 90 (13.6) | 6,915 | 498 | 27,215 | 1,851,902 |
| 2 Urban protest | 57 (8.6) | 5,667 | 852 | 27,535 | 4,385,609 |
| 3 Politicians | 133 (20.1) | 3,531 | 1,378 | 24,451 | 23,879,735 |
| 4 Visualizations | 151 (22.8) | 6,965 | 873 | 22,620 | 2,863,006 |
| 5 Effects of CC | 231 (34.9) | 7,700 | 587 | 23,864 | 3,435,400 |
| Total/mean | 662 | 6,413 | 822 | 24,470 | 7,278,772 |

León et al., 2022; O'Neill, 2013, O'Neill et. al., 2023; Rebisch-Hispanha et al., 2015).¹¹ These clusters vary considerably in size (Table 1, column 1). Figure 1 presents a heatmap illustrating the Z-scores for each cluster, delineating unique and common attributes across different levels of the variables. Below, we describe the features of each cluster, examine their salience over time (Figure 2), user engagement and follower counts (Table 1), users' geographic locations (Figure 3), types of users contributing to each cluster (Figure 4), word clouds derived from tweet texts (Figure 5) and the emotional valence of user replies (Figure 6).

Celebrities (cluster 1). This cluster, encompassing 13.6 percent of the images (Table 1), predominantly features indoor photos of celebrities associated with pop culture, with a higher share of non-white individuals (55.5%) (Figure 1). A sharp rise in these images occurred in 2020 during the COVID-19 pandemic (Figure 2), likely due to celebrities engaging more with social media during lockdowns. This cluster has the lowest share of images from US accounts (35.6%) and a large portion linked to South Korean accounts (34.4%) (Figure 3), underscoring the global impact of the K-Pop phenomenon. Celebrities posted the majority of these images (25.6%), followed by ordinary citizens (23.3%) and media-related individuals and organizations (22.2%) (Figure 4). The word cloud reflects themes of celebrities' and brands' roles ('bts_twt', 'blackpink', 'hyundai'), individual and collective participation ('awareness', 'earthday', 'help', 'world'), self-promotion ('selfie') and pandemic-related discussions ('home', 'stayhome', 'dark', 'darkselfiechallenge') (Figure 5). While the posts received the lowest number of replies (498) (Table 1), 91.7 percent have a positive valence (Figure 6).

Urban protests (cluster 2). This smallest cluster (8.6% of images, Table 1) features urban protests with a higher representation of women and white individuals (Figure 1), aligning with past research on the visual prominence of women in climate protests like Friday's for Future and Extinction Rebellion (Hayes and O'Neill, 2021). Protest images peaked in 2019, sharply declined during the pandemic years and modestly resurged in 2022,

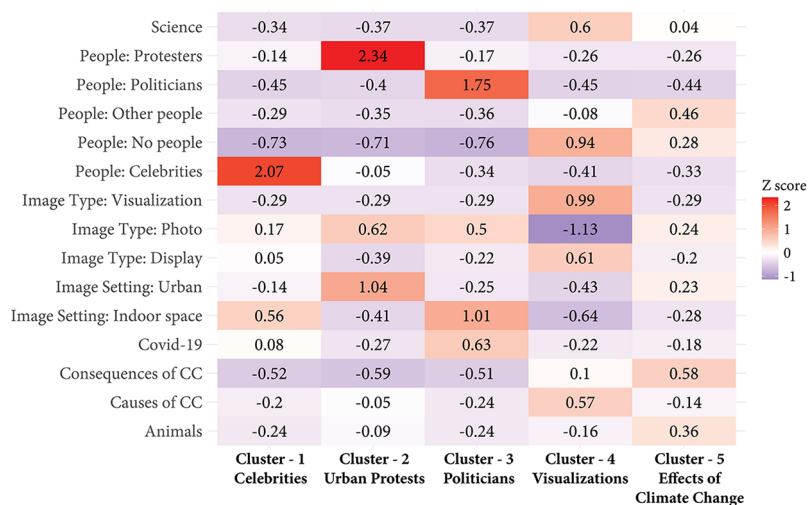


Figure 1. Heat map of Z scores of selected features per cluster.

Note: The Z-scores in the heatmap indicate how many standard deviations a cluster's mean value for an attribute is from the overall dataset's mean for that attribute, with positive values showing higher than average and negative values showing lower than average values. The heatmap for all the features can be found in Appendix 5.

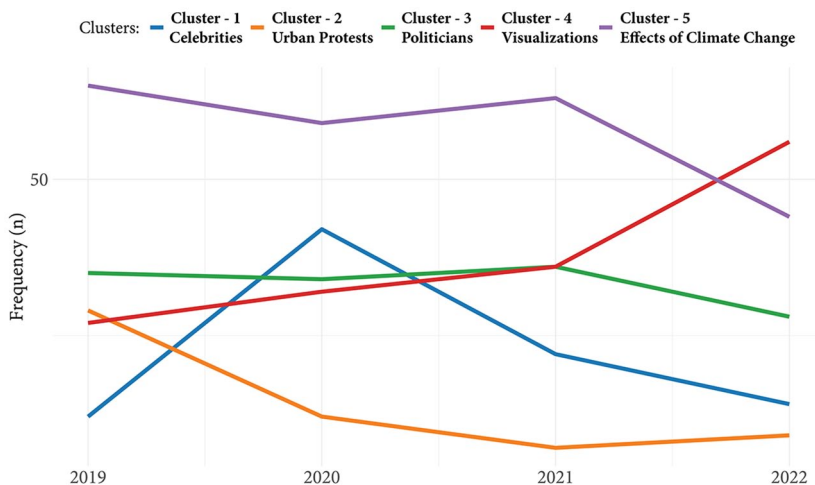


Figure 2. Prevalence of images by cluster across time (N = 662).

remaining below pre-pandemic levels (Figure 2). A substantial portion of users sharing these images originated from smaller nations (Figure 3), including Sweden (15.8%) and countries from the Global South like Cuba and Mongolia (7.0% each). Unlike other clusters, a considerable share of images was posted by individuals and organizations from civil society (31.6%) (Figure 4). The word cloud (Figure 5) underscores the urgent,

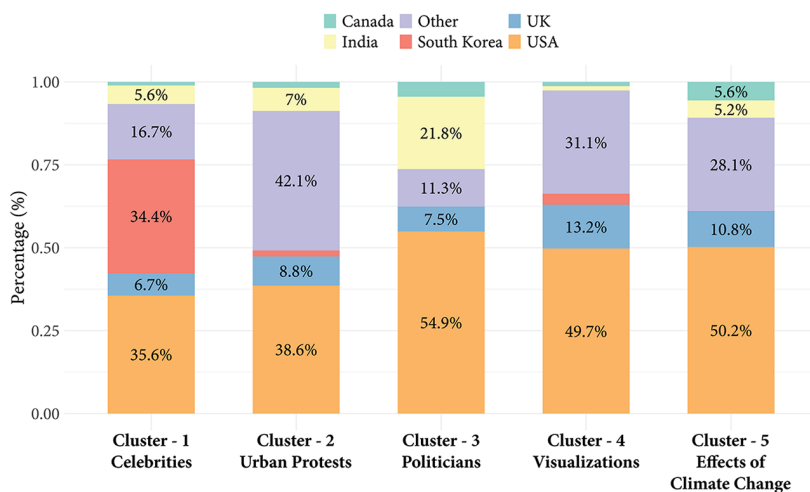


Figure 3. Proportion of images by geographic location of the users sending the tweet per cluster (N images = 662, N user = 351).

Note: The overall distribution of the geographic location can be found in Appendix 3.

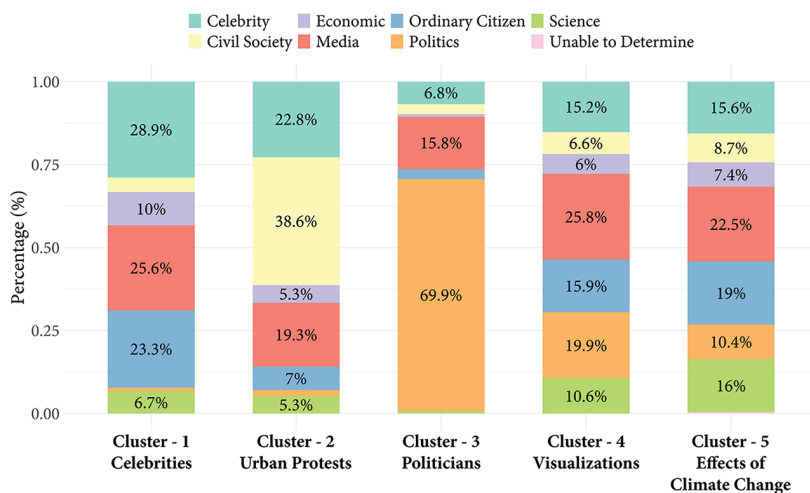


Figure 4. Proportion of images shared by actor type per cluster (N images = 662, N user = 351).

Note: The overall distribution of account types can be found in Appendix 4.

confrontational nature of activism and protest, suggesting calls for direct action ('activist', 'arrested', 'strike', 'climatestrike', 'fridaysforfuture'), urgency ('crisis', 'must'), and collective engagement ('people', 'us'). These images received the highest average number of likes (27,535) (Table 1), suggesting widespread support, but sentiment analysis revealed more negative (60.0%) than positive (40.0%) emotions in the replies (Figure 6).

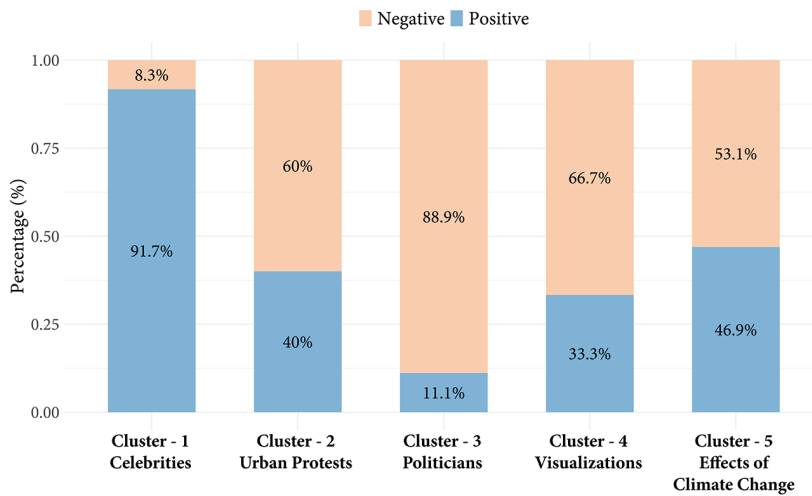


Figure 6. Distribution of sentiment in replies to images by cluster (N replies = 802,121, N images = 662).

previous three clusters (Figure 3). The types of accounts are mixed, with political and ordinary citizens having the highest share (19.9% each) (Figure 4). The thematic analysis based on the word cloud (Figure 5) highlights active engagement with climate science (‘emissions’, ‘science’, ‘heat’) and the causes of climate change (‘gas’, ‘fossil’, ‘oil’). Despite receiving the least likes (22,620), these images achieve virality through retweets (6,965) (Table 1), demonstrating users’ interest in sharing factual and scientific content and underscoring Twitter’s affordances as a tool for public science communication and environmental education. Two-thirds of the replies to tweets featuring these images tended to be negative (66.7%) (Figure 6).

Effects of climate change (cluster 5). The largest cluster, containing 34.9 percent of the images (Table 1), predominantly showcases the tangible consequences of climate change, covering a wide array of affected subjects such as nature, animals and ordinary individuals (Figure 1).¹² It consistently held the largest share among viral climate change images between 2019 and 2021, with 2022 being the only exception (Figure 2). Similar to clusters 3 and 4, half of these images originated from the US (51.5%) (Figure 3). Nearly a quarter (23.8%) were posted by ordinary citizens, with scientists and science organizations playing an important role compared to other clusters (13.0%) (Figure 4). Frequent words in the Tweet texts highlight the consequences of climate change (‘effects’, ‘emergency’, ‘forest’, ‘fire’, ‘health’, ‘pollution’) and emphasize widespread impacts on both the natural world and human life (‘earth’, ‘life’, ‘land’, ‘trees’, ‘water’, ‘weather’) (Figure 5). The primary driver of virality seems to be retweets, exceeding the average of other clusters (7,700) (Table 1) and indicating the public willingness to share the real-world impacts of climate change. Replies to images in this cluster showed a nearly equal share of negative (53.1%) and positive (46.9%) sentiment (Figure 6).

DISCUSSION

Our findings reveal a substantial diversity in viral climate visuals on Twitter, encompassing a wide range of formats and content. This diversity is exemplified by the three most retweeted climate images in our dataset, which feature strikingly different subjects and themes: a photo of a polar bear engaging in cannibalism in the wild, highlighting the ecological consequences of climate change (153,742 retweets, 2,239,746 likes); a visualization of extreme temperatures across the US during a polar vortex, emphasizing the scientific evidence and tangible impacts (95,873 retweets, 407,252 likes); and a photo of the K-pop sensation BTS in a hangar with a racing car (72,533 retweets, 142,314 likes), showcasing the intersection of celebrity culture and climate change awareness. This diversity is facilitated by social media's inherent openness, which allows users from various backgrounds to share their perspectives; dynamic network structures that enable rapid and widespread dissemination of content; and interactive features that encourage user engagement and participation (Van Dijck and Poell, 2013). These characteristics of social media platforms contribute to a broader range of climate change representations compared to traditional media, which is often constrained by editorial gatekeeping, reflecting elite institutional norms and ideologies, resulting in more homogeneous climate change imagery (O'Neill, 2013).

However, this seemingly democratic landscape has notable gaps in representation. Firstly, the focus on anthropocentric imagery overlooks non-human elements and manifests an ecologically myopic conceptualization of climate change. It neglects the broader ecological ramifications, non-human suffering, and the interconnectedness of human and natural systems (Almiron and Tafalla, 2019). Secondly, despite apparent diversity, key actors such as farmers, indigenous communities and grassroots leaders remain underrepresented, reflecting biases towards urban- and Western-centric perspectives, excluding those most affected by climate change (Belfer et al., 2017). This lack of representation can lead to an incomplete understanding of the disproportionate impacts of climate change on vulnerable communities and the valuable insights and solutions they can offer. Thirdly, complex issues, including human rights, economic impacts and responses, particularly those beyond market-driven technoscientific fixes, are largely absent. This omission of the multifaceted challenges of climate change hinders the development of a nuanced understanding needed for effective climate action (Moser, 2010). Without a comprehensive portrayal of climate change, public engagement and support for transformative solutions may be limited.

Our analysis revealed limitations in the diversity of users shaping viral visual climate change discourses on Twitter. Accounts from the US dominate, along with accounts by media and political entities with above-average followers. While this partly reflects Twitter's user demographics, with the US having the largest user base (Statista, 2024), the extent of this dominance

in climate change discourse is disproportionate in our sample (49.3%). This US-centric focus not only underscores their substantial influence but also raises concerns about a potentially skewed representation of climate change, marginalizing critical perspectives from other regions. For example, India, the country with the second most English speakers in the world only represented 8 percent of our sample. Additionally, prominence of media and political figures as key disseminators of these images suggests the persistence of traditional gatekeeping actors, albeit within the digital landscape of social media (Pearce et al., 2019).

These representational imbalances question the equity and epistemic diversity of climate change depiction on Twitter, challenging the democratic potential that a platform like this promised (e.g. Kirilenko and Stepchenkova, 2014). The skewed representation, evident in both image content and the actors sharing them, not only marginalizes non-Western and local perspectives but also reinforces existing socioeconomic hierarchies. By privileging the voices and experiences of those in positions of power and influence, this imbalance perpetuates the deficit of democratic participation in the visual landscape of climate change (e.g. Ruppel and Houston, 2023). As a result, the purported democratization of climate change communication in social media – Twitter in this case – appears partial at best, potentially perpetuating incomplete or misleading views of the issue. This finding highlights the need for further efforts to promote and amplify marginalized voices and perspectives in order to foster a more genuinely democratic and representative climate change conversation on social media.

While our investigation highlighted a diversity, albeit limited, in the content of viral climate change images, a more profound analytical layer was unveiled through cluster analysis. This method identified five common visual discourses coalescing around stable tropes, framing the climate narrative in specific ways: celebrities, protests, politicians, visualizations and effects of climate change. These clusters align with existing studies on visual climate themes in both traditional and digital media (Mooseder et al., 2023; O'Neill and Smith, 2014), suggesting that specific image types symbolize broader worldviews and resonate with audiences across different platforms.

The prominence of dominant worldviews, such as celebrity culture (cluster 1), political authority (cluster 3) and scientific knowledge (cluster 4), in the visual representation of climate change has substantial implications. While these discourses play an important role in raising awareness and shaping public opinion, their dominance may skew public understanding and engagement with climate issues. By prioritizing certain perspectives and narratives, these dominant discourses can potentially limit the depth and breadth of public discourse and awareness (Boykoff and Goodman, 2009).

Furthermore, the prevalence of mainstream perspectives can constrict the visual discourse space, leaving little room for alternative or transformative narratives. While we identified some alternative discourses, such as protests

and climate movements (cluster 2) and the portrayal of climate change effects (cluster 5), these face significant challenges in gaining traction and serving as a catalyst of change.

Protest and climate movement imagery, while offering a counterpoint to dominant perspectives, are often less visible and struggle to maintain a consistent presence (León et al., 2022; Mooseder et al., 2023). These alternative discourses are frequently small in scale and fluctuate significantly over time, being heavily dependent on current trends and events. As a result, their impact on the overall visual landscape of climate change communication can be limited.

Moreover, the portrayal of climate change effects, although prevalent, often manifests in passive forms of engagement. While these images raise awareness about the consequences of climate change, they lack the proactive commitment necessary for a more comprehensive and action-oriented narrative. To effectively address the climate crisis, visual communication must go beyond illustrating the problem through icons like polar bears, which often oversimplify the issue, and instead actively engage with systemic solutions and alternative futures that highlight the complex social and political dimensions of climate change (Born, 2019). This shift towards proactive and solutions-oriented visual communication is crucial for inspiring meaningful action and driving long-term change.

Our analysis calls for a critical reflection on the role of social media in shaping visual climate discourses. It encourages further research on how new communicative opportunities through social media can both strengthen dominant visual discourses and open up space for a truly diverse spectrum of voices and narratives in the climate discourse (see Carvalho, 2019). Future studies should explore the potential of social media in fostering inclusive and transformative climate communication and identify strategies for amplifying marginalized perspectives and counter-narratives. By understanding and harnessing the potential of social media, we can work towards creating a more equitable and impactful visual landscape for climate change communication.

As we emphasize the importance of cultivating diverse, participatory and expansive visual climate discourses in social media, it becomes crucial to understand how the process of virality, involving its complex interplay of bottom-up, user-driven engagement patterns and top-down, algorithmically mediated forces (Nahon and Hemsley, 2013), might be constraining the space available for alternative voices and narratives.

Among the various bottom-up factors driving content virality, emotional processes stand out. The prevalent content types found in our analysis support the emotionally charged nature of viral images. By 'emotionally charged', we refer to content that is likely to provoke intense arousal in viewers, regardless of whether these reactions are positive or negative (Berger and Milkman, 2012). Photographs depicting humans and their environments, the most common image type in our sample, often evoke strong emotional

responses. These images enhance emotional engagement and shareability by being relatable and immediate, regardless of whether they elicit joy, anger or sadness (e.g. Bakhshi et al., 2014). Similarly, the prominence of influential figures like politicians and celebrities in viral images suggests the role of affective processes in people's engagement. These figures act as emotional amplifiers, provoking intense reactions across the spectrum of positive and negative emotions, as evidenced by our sentiment analysis of replies (also see Chapman et al., 2016). Protests, extreme weather events and even climate graphs, as seen in our visualizations cluster, are also known to evoke strong emotional reactions (Lehman et al., 2019; Schneider, 2012; Stamps and Mastro, 2020). Whether these reactions are of concern, hope, or outrage, the intensity of the emotional response appears to be the critical factor. This suggests that the viral climate images we observe generally elicit high levels of emotional arousal, contributing to people's engagement and behaviours that promote widespread diffusion, regardless of whether the overall sentiment is positive or negative.

However, the use of emotionally charged content to generate engagement and achieve virality may oversimplify complex issues like climate change (e.g. Ali et al., 2019; Brown et al., 2017). Sensationalizing content often involves exaggeration, hyping or selective presentation to maximize emotional impact, risking the simplification of narratives and, in the most extreme cases, trivializing the gravity of climate concerns. The incentive structure by social media algorithms, favouring emotionally loaded images, may skew discourses even more, side-lining nuanced or alternative viewpoints.

Moreover, social media platforms, governed by top-down, algorithmically mediated networks, inherently favour users with large followings (Goel et al., 2016), such as celebrities and politicians (Kamiński et al., 2021), along with media organizations and corporations. Our analysis underscores how top-down processes, exemplified by the dominance of politically affiliated, media and entertainment accounts with substantial followings in our sample, play a pivotal role in the virality of climate change images on social media. This algorithmic bias can result in a homogenized discourse where mainstream and popular opinions dominate, effectively side-lining alternative perspectives from individuals and entities with less social media influence (Nechushtai et al., 2023).

The predominance of accounts with large followings in shaping climate change visual narratives on social media places smaller entities, often representing alternative or less mainstream perspectives, in a challenging conundrum. While seeking to broaden the discourse with diverse and potentially crucial insights into the climate crisis, small accounts grapple with the daunting task of gaining visibility in a digital landscape skewed towards established influencers (Hindman, 2018). This may lead to a pressure to conform to prevailing narratives and styles popularized by influential accounts, potentially diluting unique or alternative perspectives. Such conformity can further diminish the impact

of alternative, counter-mainstream narratives, reinforcing the dominance of mainstream discourses in climate change visual communication.

Rather than fostering a diverse and democratic space for climate discourse, the interplay of bottom-up user engagement processes and top-down algorithmic amplification in virality may be contributing to the predominance of homogeneous mainstream discourses on social media (Chayka, 2024). These dynamics limit the scope for truly democratic representation and critical engagement with climate change issues from a broad range of perspectives.

Other issues related to virality such as echo chambers, the transient nature of viral content leading up to our modern infodemic, or the viral spread of misinformation and disinformation, among other things (e.g. Törnberg, 2018) can be studied in the context of visual climate communication. These dynamics illustrate a critical paradox at the heart of social media's role in climate change visual communication. While these platforms have the potential to diversify and democratize discourse (Helberger et al., 2018), the existing structures and patterns of engagement often reinforce existing power dynamics and narratives, potentially at the expense of more nuanced, diverse and representative perspectives.

CONCLUSION

This study set out to examine the content of viral climate change images, the characteristics of users who share those images, the dominant discourses that permeate the visual discourse of climate change on social media and the emotional reactions they elicit among social media users. Focusing on Twitter, we combined multiple data sources, including the most liked and retweeted tweets, their texts, images, metadata and user replies over a period of 4 years (2019–2022), using standardized (image) content analysis, text and sentiment analysis and Latent Class Analysis.

While our findings are specific to Twitter, which has undergone significant changes following its acquisition and rebranding as X, our study remains a valuable contribution to understanding the broader landscape of climate change visual communication on social media. The patterns and dynamics we observed, such as the prevalence of certain visual discourses, the influence of prominent actors and the emotional resonance of viral content are likely to be present, to varying degrees, across other social media platforms; by providing a detailed analysis of these dynamics on one of the most influential platforms during a critical period, our study offers valuable insights into the complex interplay of factors shaping the representation and discourse surrounding climate change in the digital sphere. Furthermore, our methodological approach combining multiple data sources and analytical techniques can serve as a model for future research examining the visual communication of climate change and other critical issues on social media platforms. Some of

our findings may be influenced by the English-language keyword sampling, which is a limitation of this study. Another limitation is the reliance on user-provided information and meta-data for characterizing Twitter accounts. The geographical locations and user types may not always be accurately represented as this information cannot be independently verified. Moreover, focusing exclusively on viral climate change images may also overlook subtler and more nuanced discourses in lower-engagement content. It is also worth noting that, since Twitter's rebranding to X, the platform's API access for academic purposes has been paywalled, significantly limiting researchers' ability to conduct large-scale social media analyses and raising concerns about the future accessibility of digital research data. Future studies on this platform may face challenges (Murtfeldt et al., 2024) and researchers may need to explore alternative methods or platforms for studying online visual climate change communication.

Despite these limitations, our analysis provides a foundation for future research. We encourage ongoing exploration of online visual representation of climate change across diverse media platforms, providing insights into evolving discourses and their impact on public views and behaviours.

ORCID ID

Stefanie Walter  <https://orcid.org/0000-0002-9304-3469>

DATA AVAILABILITY STATEMENT

Links to the tweets that are analyzed in this study can be found here: <https://osf.io/53bty/>.

NOTES

1. That means retweets were excluded.
2. In our dataset, we included 10 GIFs. Despite the format's capability for multiple frames, the GIFs in our study featured single-shot visuals where the sequence of frames did not vary significantly, effectively presenting an almost static visual akin to a standard image. This uniformity across frames ensures that their inclusion is consistent with the analysis of the other images in our study.
3. When a tweet featured more than one image, all images were included in the dataset.
4. For example, there were images of Korean celebrities (e.g. K-Pop singers) or US politicians (e.g. Members of Congress) that coders might be unfamiliar with due to their cultural background. In those instances, the tweet text was used for reference.
5. Prior to conducting the text analysis, we pre-processed the tweet texts to ensure data quality and relevance. This pre-processing included

the removal of stopwords, specific phrases directly related to our sampling criteria such as 'climate change', as well as URLs, single letters and numbers that do not contribute to thematic analysis. These steps were executed using the 'tidytext' package in R (Silge and Robinson, 2016).

6. Prior to sentiment analysis, non-English replies were identified and translated into English using the R packages *cld2* (Ooms, 2022), *cld3* (Ooms, 2023) and *textcat* (Hornik et al., 2023), followed by translation via *googleLanguageR* (Edmondson, 2020). The replies were then converted into lowercase text, removing punctuation, special characters and emojis, eliminating stop-words and applying lemmatization to standardize these for analysis.
7. Remaining image types include illustrations (4.1%), memes (2.6%) and infographics (1.4%). In 1.2 percent of the images, we were unable to clearly assign the image type.
8. A total of 24.3 percent of the images featured no setting, e.g. data visualizations.
9. In 11.7 percent of the images depicting people, we were unable to classify their gender.
10. In 12.1 percent of the images depicting people, we were unable to classify their ethnicity.
11. We identified an optimal five-cluster solution, as corroborated by several model fit indices, including the Bayesian Information Criterion (BIC) and the Consistent Akaike Information Criterion (CAIC) (see Appendix 5 for further details).
12. Coded as 'other people' in Figure 1.

REFERENCES

- Alhabash S and McAlister AR (2015) Redefining virality in less broad strokes: Predicting viral behavioral intentions from motivations and uses of Facebook and Twitter. *New Media & Society* 17(8): 1317–1339. DOI: 10.1177/1461444814523726.
- Ali K et al. (2019) Viruses going viral: Impact of fear-arousing sensationalist social media messages on user engagement. *Science Communication* 41(3): 314–338. DOI: 10.1177/1075547019846124.
- Almiron N and Tafalla M (2019) Rethinking the ethical challenge in the climate deadlock: Anthropocentrism, ideological denial and animal liberation. *Journal of Agricultural and Environmental Ethics* 32(2): 255–267. DOI: 10.1007/s10806-019-09772-5.
- Bakhshi S, Shamma DA and Gilbert E (2014) Faces engage us: Photos with faces attract more likes and comments on instagram. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 965–974. DOI: 10.1145/2556288.2557403.

- Barrie C and Ho JC (2021) *academicwitterR*: An R package to access the Twitter Academic Research Product Track v2 API endpoint. Software, *Journal of Open Source Software*. DOI: 10.5281/zenodo.4714637.
- Belfer E, Ford JD and Maillet M (2017) Representation of Indigenous peoples in climate change reporting. *Climatic Change* 145: 57–70. DOI: 10.1007/s10584-017-2076-z.
- Berger J and Milkman KL (2012) What makes online content viral? *Journal of Marketing Research*, 49(2): 192–205. DOI: 10.1509/jmr.10.0353.
- Born D (2019) Bearing witness? Polar bears as icons for climate change communication in National Geographic. *Environmental Communication* 13(5): 649–663. DOI: 10.1080/17524032.2018.1435557.
- Boulianne S, Lalancette M and Ilkiw D (2020) ‘School strike 4 climate’: Social media and the international youth protest on climate change. *Media and Communication* 8(2): 208–218. DOI: 10.17645/mac.v8i2.2768.
- Boykoff MT and Goodman MK (2009) Conspicuous redemption? Reflections on the promises and perils of the ‘celebritization’ of climate change. *Geoforum* 40(3): 395–406. DOI: 10.1016/j.geoforum.2008.04.006.
- Braun V and Clarke V (2006) Using thematic analysis in psychology. *Qualitative Research in Psychology* 3(2): 77–101. DOI: 10.1191/1478088706qp063oa.
- Brossard D and Scheufele DA (2022) The chronic growing pains of communicating science online. *Science* 375(6581): 613–614. DOI: 10.1126/science.abo0668.
- Brown DK et al. (2018) A new sensation? An international exploration of sensationalism and social media recommendations in online news publications. *Journalism* 19(11): 1497–1516. DOI: 10.1177/1464884916683549.
- Bucher T and Helmond A (2018) The affordances of social media platforms. In Burgess et al. (eds) *The SAGE Handbook of Social Media*. London: SAGE, 233–253. DOI: 10.4135/9781473984066.
- Carvalho A (2019) Media and climate justice: What space for alternative discourses? In: Bhavnani KK et al. (eds) *Climate Futures: Reimagining Global Climate Justice*. Exeter: Bloomsbury Publishing, 120–126. DOI: 10.5040/9781350219236.ch-014.
- Chapman DA et al. (2016) Climate visuals: A mixed methods investigation of public perceptions of climate images in three countries. *Global Environmental Change* 41: 172–182.
- Chayka K (2024) *Filterworld: How Algorithms Flattened Culture*. London: Blink Publishing.
- Chen K et al. (2022) How climate movement actors and news media frame climate change and strike: Evidence from analyzing Twitter and news media discourse from 2018 to 2021. *International Journal of Press/Politics* 28(2): 384–413.
- Dekoninck H and Schmuck D (2022) The mobilizing power of influencers for pro-environmental behavior intentions and political participation.

- Environmental Communication* 16(4): 458–472. DOI: 10.1080/17524032.2022.2027801.
- Denisova A (2020) How to define ‘viral’ for Media Studies? *Westminster Papers in Communication and Culture* 15(1). DOI: 10.16997/wpcc.375.
- DiFrancesco D and Young N (2011) Seeing climate change: The visual construction of global warming in Canadian national print media. *Cultural Geographies* 18(4): 517–536. DOI: 10.1177/1474474010382072.
- Edmondson M (2020) googleLanguageR: Call Google’s ‘Natural Language’ API, ‘Cloud Translation’ API, ‘Cloud Speech’ API and ‘Cloud Text-to-Speech’ API. R package version 0.3.0, <https://CRAN.R-project.org/package=googleLanguageR> (accessed 1 October 2024).
- Effrosynidis D et al. (2022) The climate change Twitter dataset. *Expert Systems with Applications* 204: 117541.
- Fellows I (2018) wordcloud: Word Clouds. R package version 2.6 <https://CRAN.R-project.org/package=wordcloud>
- Fenzl T and Mayring P (2017) QCAMap: Eine interaktive Webapplikation für qualitative Inhaltsanalyse. *Zeitschrift für Soziologie der Erziehung und Sozialisation ZSE* 37(3): 333–340.
- Goel S et al. (2016) The structural virality of online diffusion. *Management Science* 62(1): 180–196. DOI: 10.1287/mnsc.2015.2158.
- Hall S (1980) Encoding/decoding. In: Hall S et al. (eds) *Culture, Media, Language: Working Papers in Cultural Studies, 1972–79*. London: Routledge.
- Han Y, Lappas T and Sabnis G (2020) The importance of interactions between content characteristics and creator characteristics for studying virality in social media. *Information Systems Research* 31(2): 576–588. DOI: 10.1287/isre.2019.0903.
- Hawkins E, Fæhn T and Fuglestedt J (2019) The climate spiral demonstrates the power of sharing creative ideas. *Bulletin of the American Meteorological Society* 100(5): 753–756. DOI: 10.1175/BAMS-D-18-0228.1.
- Hayes S and O’Neill S (2021) The Greta effect: Visualising climate protest in UK media and the Getty images collections. *Global Environmental Change* 71: 102392. DOI: 10.1016/j.gloenvcha.2021.102392.
- Helberger N, Karppinen K and D’acunto L (2018) Exposure diversity as a design principle for recommender systems. *Information, Communication & Society* 21(2): 191–207.
- Hindman M (2018) *The Internet Trap: How the Digital Economy Builds Monopolies and Undermines Democracy*. Princeton, NJ: Princeton University Press.
- Hopke JE and Hestres LE (2018) Visualizing the Paris Climate talks on Twitter: Media and climate stakeholder visual social media during COP21. *Social Media + Society* 4(3). DOI: 10.1177/2056305118782687.
- Hopke JE and Paris L (2021) Environmental social movements and social media. In: Takahashi B et al. (eds) *The Handbook of International Trends in Environmental Communication*. New York, NY: Routledge, 357–372.

- Hornik K et al. (2023) textcat: N-Gram Based Text Categorization. R package version 1.0-8, <https://CRAN.R-project.org/package=textcat>
- Hutto CJ and Gilbert EE (2014) VADER: A parsimonious rule-based model for sentiment analysis of social media text. *Eighth International Conference on Weblogs and Social Media (ICWSM-14)*. Ann Arbor, MI, June. DOI: 10.1609/icwsm.v8i1.14550.
- Kamiński M, Szymańska C and Nowak JK (2021) Whose Tweets on COVID-19 gain the most attention: Celebrities, political, or scientific authorities? *Cyberpsychology, Behavior, and Social Networking* 24(2): 123–128. DOI: 10.1089/cyber.2020.0336.
- Kay S, Mulcahy R and Parkinson J (2020) When less is more: The impact of macro and micro social media influencers' disclosure. *Journal of Marketing Management* 36(3/4): 248–278. DOI: 10.1080/0267257X.2020.1718740.
- Kirilenko AP and Stepchenkova SO (2014) Public microblogging on climate change: One year of Twitter worldwide. *Global Environmental Change* 26: 171–182. DOI: 10.1016/j.gloenvcha.2014.02.008.
- Krippendorff K (2004) Reliability in content analysis: Some common misconceptions and recommendations. *Human Communication Research* 30(3): 411–433. DOI: 10.1111/j.1468-2958.2004.tb00738.x.
- Lehman B et al. (2019) Affective images of climate change. *Frontiers in Psychology* 10. DOI: 10.3389/fpsyg.2019.00960.
- León B, Negro S and Erviti MC (2022) Social engagement with climate change: Principles for effective visual representation on social media. *Climate Policy* 22(8): 976–992. DOI: 10.1080/14693062.2022.2077292.
- Linzer DA and Lewis JB (2011) PoLCA: An R package for polytomous variable latent class analysis. *Journal of Statistical Software* 1(10): 1–29. DOI: 10.18637/jss.v042.i10.
- Metag J et al. (2016) Perceptions of climate change imagery: Evoked salience and self-efficacy in Germany, Switzerland, and Austria. *Science Communication* 38(2): 197–227. DOI: 10.1177/1075547016635181.
- Mooseder A et al. (2023) (Social) media logics and visualizing climate change: 10 years of #climatechange images on Twitter. *Social Media + Society* 9(1). DOI: 10.1177/20563051231164310.
- Moser SC (2010) Communicating climate change: History, challenges, process and future directions. *Wiley Interdisciplinary Reviews: Climate Change* 1(1): 31–53. DOI: 10.1002/wcc.11.
- Muñoz MM, Rojas-de-Gracia MM and Navas-Sarasola C (2022) Measuring engagement on Twitter using a composite index: An application to social media influencers. *Journal of Informetrics* 16(4). DOI: 10.1016/j.joi.2022.101323.
- Murfeldt R et al. (2024) RIP Twitter API: A eulogy to its vast research contributions. *arXiv preprint arXiv:2404.07340*.
- Nahon K and Hemsley J (2013) *Going Viral*. Cambridge: Polity Press.

- Nanath K and Joy G (2023) Leveraging Twitter data to analyze the virality of Covid-19 tweets: A text mining approach. *Behaviour & Information Technology* 42(2): 196–214. DOI: 10.1080/0144929X.2021.1941259.
- Nechushtai E, Zamith R and Lewis SC (2023) More of the same? Homogenization in news recommendations when users search on Google, YouTube, Facebook, and Twitter. *Mass Communication and Society* 1–27. DOI: 10.1080/15205436.2023.2173609.
- Nicholson-Cole SA (2009) Promoting positive engagement with climate change through visual and iconic representations. *Science Communication* 30(3): 355–379. DOI: 10.1177/1075547008329201.
- Nylund-Gibson K and Choi AY (2018) Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science* 4(4): 440–461. DOI: 10.1037/tps0000176.
- Ooms J (2022) cld2: Google's Compact Language Detector 2. R package version 1.2.4, <https://CRAN.R-project.org/package=cld>
- Ooms J (2023) cld3: Google's Compact Language Detector 3. R package version 1.6.0, <https://CRAN.R-project.org/package=cld3>
- O'Neill S et al. (2023) Visual portrayals of fun in the sun misrepresent heatwave risks in European newspapers. *Geographical Journal* 189: 90–103. DOI: 10.1111/geoj.12487.
- O'Neill SJ (2013) Image matters: Climate change imagery in US, UK and Australian newspapers. *Geoforum* 49: 10–19. DOI: 10.1016/j.geoforum.2013.04.030.
- O'Neill SJ and Smith N (2014) Climate change and visual imagery. *Wiley Interdisciplinary Reviews: Climate Change* 5(1): 73–87. DOI: 10.1002/wcc.249.
- Pearce W et al. (2019) The social media life of climate change: Platforms, publics, and future imaginaries. *Wiley Interdisciplinary Reviews: Climate Change* 10(2). DOI: 10.1002/wcc.569.
- Rebich-Hespanha S et al. (2015) Image themes and frames in US print news stories about climate change. *Environmental Communication* 9(4): 491–519. DOI: 10.1080/17524032.2014.983534.
- Rose G (2016) Rethinking the geographies of cultural 'objects' through digital technologies: Interface, network and friction. *Progress in Human Geography* 40(3): 334–351. DOI: 10.1177/0309132515580493.
- Rosenberg E et al. (2023) Sentiment analysis on Twitter data towards climate action. *Results in Engineering* 19: 101287.
- Roxburg N et al. (2019) Characterising climate change discourse on social media during extreme weather events. *Global Environmental Change*, 54: 50–60. DOI: 10.1016/j.gloenvcha.2018.11.004.
- Ruppel OC and Houston LJH (2023) The human right to public participation in environmental decision-making: Some legal reflections. *Environmental Policy and Law* 53(1/2): 125–138. DOI: 10.3233/EPL-239001.

- Schäfer MS (2020) Introduction to visualizing climate change. In: Holmes DC and Richardson LM (eds) *Research Handbook on Communicating Climate Change*. Cheltenham: Edward Elgar Publishing, 127–130. DOI: 10.4337/9781789900408.00022
- Schäfer MS and Yan X (2023) News and social media imagery of climate change: Analyzing the role and impact of visuals in public communication. In: Schäfer MS and Yan X (eds) *Climate, Science and Society*, ch. 8. London: Routledge, 66–73.
- Schneider B (2012) Climate model simulation visualization from a visual studies perspective. *Wiley Interdisciplinary Reviews: Climate Change* 3(2): 185–193. DOI: <https://doi.org/10.1002/wcc.162>.
- Silge J and Robinson D (2016) tidytext: Text mining and analysis using tidy data principles in R. *Journal of Open Source Software* 1(3): 37. DOI: 10.21105/joss.00037.
- Smith NW and Joffe H (2009) Climate change in the British press: The role of the visual. *Journal of Risk Research* 12(5): 647–663. DOI: 10.1080/13669870802586512.
- Stamps D and Mastro D (2020) The problem with protests: Emotional effects of race-related news media. *Journalism & Mass Communication Quarterly* 97(3): 617–643. DOI: 10.1177/1077699019891433.
- Statista (2024) Distribution of Twitter traffic by country. Available at: <https://www.statista.com/statistics/261402/distribution-of-twitter-traffic-by-country/> (accessed 1 October 2024).
- Tellis GJ et al. (2019) What drives virality (sharing) of online digital content? The critical role of information, emotion, and brand prominence. *Journal of Marketing* 83(4): 1–20. DOI: 10.1177/0022242919841034
- Törnberg P (2018) Echo chambers and viral misinformation: Modeling fake news as complex contagion. *PLoS one* 13(9), e0203958. DOI: 10.1371/journal.pone.0203958.
- Treen KMDI, Williams HT and O’Neill SJ (2020) Online misinformation about climate change. *Wiley Interdisciplinary Reviews: Climate Change* 11(5). DOI: 10.1002/wcc.665.
- Van Dijck J and Poell T (2013) Understanding social media logic. *Media and Communication* 1(1): 2–14. DOI: 10.17645/mac.v1i1.70.
- Wang S et al. (2018) Public engagement with climate imagery in a changing digital landscape. *Wiley Interdisciplinary Reviews: Climate Change* 9(2). DOI: 10.1002/wcc.509.
- Walter S, Lörcher I and Brüggemann M (2019) Scientific networks on Twitter: Analyzing scientists’ interactions in the climate change debate. *Public Understanding of Science* 28(6): 696–712. DOI: 10.1177/0963662519844131.
- Weitkamp E et al. (2021) Exploring the digital media ecology: Insights from a study of healthy diets and climate change communication on digital

and social media. *Journal of Science Communication* 20(3): A02. DOI: 10.22323/2.20030202.

BIOGRAPHICAL NOTES

ISAAC BRAVO is a Doctoral Candidate and Research Associate with the ClimateVision project at the Technical University of Munich. His research interests are in climate change communication and computational social science, as well as text and visual analysis.

Address: Technical University of Munich, Richard-Wagner-Str. 1, Munich 80333, Germany. [email: Isaac.Bravo@tum.de]

DANIEL SILVA LUNA holds a PhD in Science Communication from the University of Otago, Aotearoa/New Zealand. His current work as a postdoctoral researcher focuses on the representations of climate change in the media, the uses of artificial intelligence in science communication, and the role of emotions in shaping public engagement with science.

Address: University of Antwerp, Antwerp, Flanders, Belgium. [email: daniel.silvaluna@uantwerpen.be]

STEFANIE WALTER is an Assistant Professor in Science and Crisis Communication at the Technical University of Munich's Department of Science, Technology and Society at the School of Social Science and Technology. Her research interests are in climate change, crisis and political communication, as well as in computational social science and text analysis.

Address: Technical University of Munich, Richard-Wagner-Str. 1, Munich 80333, Germany. [email: Stefanie.Walter@tum.de]

Appendix 1. Intercoder reliability test results.

Reliability results for user category coding.

| Kappa | Krippendorff |
|-------|--------------|
| 0.91 | 0.91 |

Reliability results for country category coding.

| Kappa | Krippendorff |
|-------|--------------|
| 0.90 | 0.92 |

Reliability results for image coding.

| Variable name | Kappa | Krippendorff |
|--|-------|--------------|
| V1 – Image type | 0.71 | 0.70 |
| V2 – Setting | 0.81 | 0.81 |
| V3 – Animals | 0.83 | 0.83 |
| V4 – Representation of science | 0.64 | 0.64 |
| V5 – Causes of climate change | 1.00 | 1.00 |
| V6 – Consequences of climate change | 0.90 | 0.90 |
| V7 – Human activity | 0.88 | 0.83 |
| V8 – Adaptation and mitigation efforts | 0.84 | 0.84 |
| V9 – Pop culture reference | 0.81 | 0.82 |
| V10 – Covid-19 reference | 0.71 | 0.71 |
| V11 – People | 0.76 | 0.76 |
| V12 – Perceived gender composition | 0.86 | 0.86 |
| V13 – Perceived gender composition | 0.81 | 0.82 |

Appendix 2. Content analysis variables and their re-coded versions for analysis.

To maintain consistency and accuracy in the process, coders were instructed to provide only one response per image, even in cases where an image could potentially be coded to multiple categories. In such instances, the coders were asked to focus on the dominant category. After multiple practice sessions, each coder received one-third of the codebook and coded independently. Throughout the coding process, we noted certain images that required further disambiguation due to their complex or ambiguous nature. These images were later discussed among the authors to reach a consensus on the most appropriate coding, a process that helped ensure the reliability of the results. During analysis and reporting we simplified some of the codes.

| Variable name | Categories | Re-coded version for analysis |
|---------------|--|--|
| Image type | <ul style="list-style-type: none"> • Photo – single photo • Photo – collage • Illustration • Data visualization • Infographic • Screenshot • Meme • Posters/event invitations • Other/unable to determine | <ul style="list-style-type: none"> • Photo¹⁶ • Illustration¹⁷ • Visualization¹⁵ • Display¹⁸ • Other/unable to determine |
| Setting | <ul style="list-style-type: none"> • Nature – ocean, coastal, water • Nature – desert • Nature – forest/jungle • Nature – Arctic and Antarctic snow and ice • Nature – other (e.g. lakes, tundra, mountains) • Agricultural/rural • Urban – residential/commercial • Urban – industrial • Indoor space • Outer space • Other • No setting represented • Unable to determine | <ul style="list-style-type: none"> • Nature • Urban • Indoor space • No setting • Other/unable to determine |
| Animals | <ul style="list-style-type: none"> • Domestic – companion • Domestic – farming/work • Wild – mammal – marine mammal • Wild – mammal – polar bear • Wild – mammal – other • Non-mammalian marine animals • Wild – bird • Wild – insects • Wild – other (e.g. amphibians, reptiles) • Many different animal species • Other/unable to determine • No animals | <ul style="list-style-type: none"> • Yes • No |

(Continued)

Appendix 2. (Continued)

| Variable name | Categories | Re-coded version for analysis |
|---|---|--|
| Representation of science ¹⁹ | <ul style="list-style-type: none"> • Yes • No • Unable to determine | <ul style="list-style-type: none"> • Yes • No |
| Causes of climate change | <ul style="list-style-type: none"> • Yes • No • Unable to determine | <ul style="list-style-type: none"> • Yes • No |
| Consequences of climate change | <ul style="list-style-type: none"> • Floods • Droughts • Wildfires • Temperature rise • Other extreme weather events • Melting ice • Sea level rise • Human rights • Economic consequences • Biodiversity loss • Covid & general health • Other • No consequences represented • Unable to determine | <ul style="list-style-type: none"> • Yes • No |
| Engagement activities | <ul style="list-style-type: none"> • Politics – climate summit • Politics – other politics • Protest – youth protest • Protest – other protest • No engagement • Unable to determine | <ul style="list-style-type: none"> • Politics • Protest • No engagement |
| Adaptation and mitigation efforts | <ul style="list-style-type: none"> • Sustainable farming and livestock production • Promoting sustainable transport • 3R behaviours (reduce, reuse, recycle) • Reforestation and afforestation • Climate-friendly innovation • Extreme weather preparedness • Other • No climate action • Raising awareness • Unable to determine | <ul style="list-style-type: none"> • Yes • No |
| Pop culture reference | <ul style="list-style-type: none"> • Yes • No • Unable to determine | <ul style="list-style-type: none"> • Yes • No |

(Continued)

Appendix 2. (Continued)

| Variable name | Categories | Re-coded version for analysis |
|------------------------------|--|---|
| Covid-19 | <ul style="list-style-type: none"> • Yes • No • Unable to determine | <ul style="list-style-type: none"> • Yes • No • Unable to determine |
| People | <ul style="list-style-type: none"> • Politician • Protester/activist – Greta • Protester/activist – other • Celebrities • Scientists • Business people • Religious/civil leaders • Farmers • Indigenous people • Children • LGBTQ+ community • Other • No people • Unable to determine | <ul style="list-style-type: none"> • Politicians • Protester • Celebrities • Scientist • Children • Other • No people • Unable to determine |
| Perceived gender composition | <ul style="list-style-type: none"> • All female • Mainly female • Half female/half male • Mainly male • All male • Unable to determine • No people | <ul style="list-style-type: none"> • Female skewed • Male skewed • Half female/half male • No people |
| Perceived ethnic composition | <ul style="list-style-type: none"> • All white • Half white/half non-white • Mainly non-white • All non-white • Unable to determine • No people | <ul style="list-style-type: none"> • White skewed • Non-white skewed • Half white/half non-white • No people |

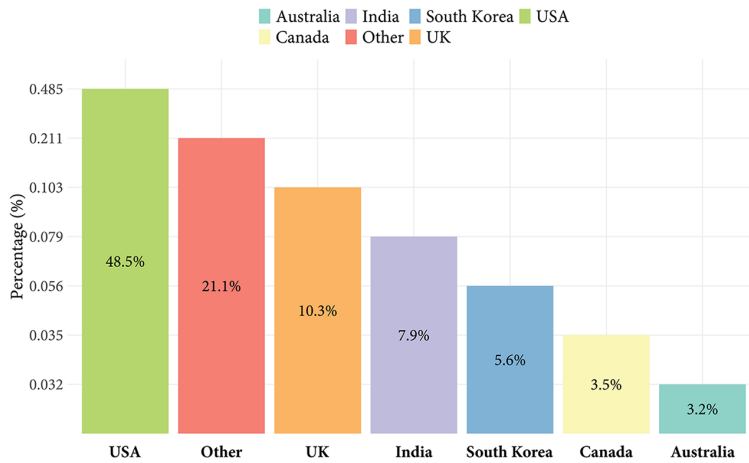
¹⁵Visualization: this combines data visualizations and infographics, representing all forms of data-driven visual content.

¹⁶Photo: this category includes both single photos and photo collages.

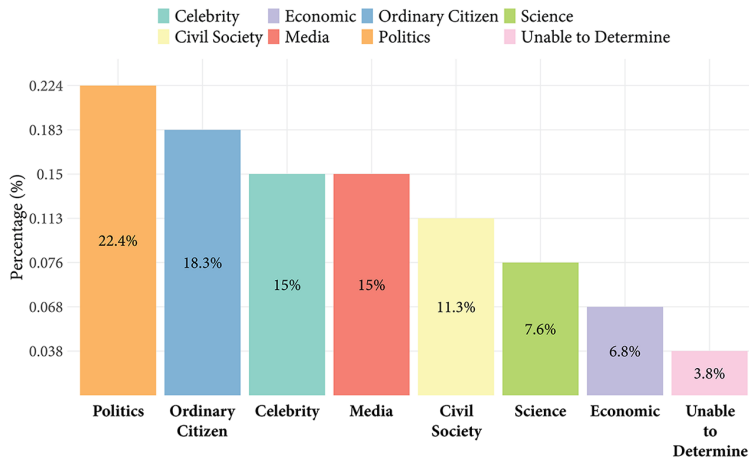
¹⁷Illustration: this category remains unchanged, representing hand-drawn or digitally created artistic images.

¹⁸Display: this new category encompasses memes, screenshots and posters, representing content that is often text-heavy or repurposed from other sources.

¹⁹‘Representation of science’ refers to representations of scientific processes, data, or institutions. Examples include climate change visualizations, infographics of climate data, or images of scientists in laboratory settings.



Appendix 3. Overall distribution of users by geographic location (N image = 662, N user = 351).



Appendix 4. Overall distribution of users by account type (N image = 662, N user = 351).

Appendix 5. Latent class analysis model fit indices and detailed heatmap.

| Number of classes | log-likelihood | resid. df | BIC | cAIC | likelihood-ratio |
|-------------------|----------------|-----------|-----------|-----------|------------------|
| 1 | -5072.081 | 637 | 10306.544 | 10331.544 | 3616.604 |
| 2 | -4572.765 | 611 | 9476.788 | 9527.78 | 2617.971 |
| 3 | -4335.371 | 585 | 9170.877 | 9247.877 | 2143.183 |
| 4 | -4163.636 | 559 | 8996.285 | 9099.285 | 1799.714 |
| 5 | -4044.876 | 533 | 8927.64 | 9056.64 | 1562.193 |
| 6 | -3977.8 | 507 | 8962.367 | 9117.367 | 1428.042 |

Note. BIC = Bayesian Information Criterion; cAIC = Consistent Akaike's Information Criterion; df = degrees of freedom.

As evident in this table, the five-class solution presented the lowest BIC (8927.64) and cAIC (9056.64) values without a substantial decrease in the log-likelihood from the six-class solution. The five-class solution was chosen as it provides a parsimonious model that adequately represents the data while preventing overfitting. Moreover, it provided meaningful classes based on previous literature, so that each class represented a distinct and interpretable subgroup within our sample.