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Research Article

Amplifying the storm: Climate disinformation dynamics during natural disasters on right-wing extremist Telegram channels

Climate change amplifies natural disasters, posing an existential threat to our society. However, a digital storm is raging on right-wing extremist Telegram channels where climate disinformation works to delegitimize scientific consensus. Investigating the factors that amplify climate disinformation is as critical to combating it as understanding natural disasters and their drivers. We find that climate disinformation is consistently amplified through unregulated platforms and conspiracist sources. Strikingly, a substantial portion of this amplification reflects coordinated behavior, suggesting both an opportunistic nature and the potential involvement of actors seeking to control climate narratives.

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Research questions

- What sources and platforms are amplified to construct climate disinformation within extremist[2] Telegram channels?
- How do scale and likelihood of climate amplification compare to baseline extremist Telegram discourse?
- How much of extremist climate discourse signals coordinated amplification?

Essay summary

- To examine the amplification ecosystem of climate disinformation, we collected 586,189 messages and metadata from 116 active right-wing extremist Telegram channels during the period encompassing three major natural disasters: Hurricane Milton, Hurricane Helene, and the January 2025 California wildfires.

[1] *A publication of the Shorenstein Center on Media, Politics and Public Policy at Harvard University, John F. Kennedy School of Government.*
[2] Our definition of right-wing extremism aligns with five key features highlighted by Mudde (1995): nationalism, racism, xenophobia, anti-democracy, and the strong state.

- After classifying a climate and non-climate subsample, we extracted website links from both subsamples and found significant overlap,[3] suggesting climate discussion is embedded within the broader extremist ecosystem of self-referencing echo chambers, low-moderated platforms, conspiracy sources, and ideologically coherent media.
- Climate content tends to be forwarded more compared to baseline extremist Telegram discourse and follows an episodic pattern, with climate discussion and amplification peaking at the onset of natural disasters before returning to a minor baseline prevalence.
- The climate disinformation ecosystem demonstrates an alarming percentage of coordinated behavior that disseminates claims of weather modification and climate hoaxes.
- Our findings highlight the importance of monitoring interventions across all social media platforms, particularly during stated natural disaster windows, when information uncertainty and climate discourse are at their highest.

Implications

In 2017, Hurricane Harvey struck the coast of Texas, causing an estimated $67 billion in damages, displacing 30,000 people, and resulting in 70 fatalities (Frame et al., 2020; Jonkman et al., 2018; Merdjanoff et al., 2022). Alongside the disaster came a downpour of mis/disinformation on social media,[4] some with harmful consequences—notably, the narrative of "immigration status is checked at shelters" causing many undocumented people to avoid seeking assistance (Hunt et al., 2020).

The Hurricane Harvey case highlights a broader pattern in which social media platforms serve as actors in the dissemination of climate-related mis/disinformation and its associated consequences (Essien, 2025; Lewandowsky, 2021; Storani et al., 2025; Tomassi et al., 2025). While these instances of disaster-related rumors were observed on other mainstream platforms like Facebook, Telegram has become a critical new frontier for climate disinformation (Börgmann et al., 2025).

This is unsurprising given that the rise of Telegram coincides with the mass ban of right-wing extremist groups on mainstream social media, who then found refuge within the platform's affordances of limited content moderation, enabling users to spread hateful and fake messages (Urman & Katz, 2022). For instance, emotional narratives of weather modification and climate hoaxes are mobilized to sow distrust and fear on Telegram channels (Tucci et al., 2025).

Exploiting these affordances are disinformation actors looking to control narratives. On Telegram, identified curated content on topics ranging from the Russian-Ukrainian war, COVID-19, and climate conspiracies has been deposited within extremist channels that function as both echo chambers and mechanisms for mass broadcast (Börgmann et al., 2025; Dukach et al., 2025; Kireev et al., 2025; Herasimenka et al., 2023; Vergani et al., 2022; Walther & McCoy, 2021). This is especially consequential for extremist groups, who are more vulnerable to disinformation and actively aid its propagation (Baptista & Gradim, 2022; Herasimenka et al., 2023; Nikolov et al., 2021; Törnberg & Chueri, 2025).

When these dynamics converge, they create a perfect sociotechnical storm that hinders the ability to address climate change and its consequences (World Meteorological Organization, 2024). The stakes of these consequences have become increasingly apparent in the devastating impacts of disasters such as

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[3] Specifically, we extracted root domains, which are the main part of the website's address excluding any sub-addresses (e.g., youtube.com).

[4] We recognize the complexity of categorizing content within extremist Telegram channels due to overlaps between misinformation, disinformation, and climate conspiracism. Therefore, we use misinformation as a broad content-level descriptor of false information, disinformation when network-level patterns suggest deliberate amplification of false information, and climate conspiracism as an underlying ideological framework.

Hurricane Helene, Hurricane Milton, and the January 2025 California wildfires,[5] which together accounted for approximately $161 billion in damages, 221 direct fatalities, and an additional estimated 440 excess deaths[6] linked to the California wildfires (Amorim et al., 2025; Beven II et al., 2025; Hagen et al., 2026; LAEDC, 2025; Newman & Noy, 2023; Paglino et al., 2025). Further emphasizing the relevance of the natural disaster under study, harmful narratives on social media produced credible threats against first responders during Hurricane Helene (ISD, 2024), forcing operational changes, such as FEMA halting door-to-door outreach after threats, that posed a systemic risk to disaster-response capacity for the broader population (Selig, 2024).

This pattern demonstrates that disinformation repeatedly undermines disaster preparation and response. Therefore, we argue that addressing climate change and its consequences requires attention to the informational ecosystem, specifically mapping how right-wing extremists produce climate disinformation.[7] Within this context, we collected extremist Telegram data from 116 active channels (see Appendix A) from August 24, 2024, to March 3, 2025, to capture the disaster preparation, the event, and recovery from three major natural disasters: Hurricane Helene, Hurricane Milton, and the January 2025 California wildfires. This timeframe underscores the importance of analyzing discourse during periods in which uncertainty coincides with widespread destruction. Specifically, we examined the amplification of climate-related content through forwards, domain-sharing practices, and indicators of inauthentic behavior. Investigating amplification patterns is methodologically valuable because it reveals which actors and information are prioritized for circulation within fringe discursive ecosystems.

Firstly, we found that climate disinformation on Telegram is not constructed in isolation. By classifying and then analyzing climate and non-climate extremist discourse from the study's timeframe, we found significant overlap between upstream sources. The domain sources draw largely from Telegram itself, other low-to-moderate moderated platforms (X and Rumble), conspiracy platforms, and right-leaning news sources. This result corroborates existing literature on echo chamber dynamics and self-confirming behavior within extremist spaces on Telegram (Herasimenka et al., 2023; Urman & Katz, 2022; Walther & McCoy, 2021; Willaert et al., 2022). Critically, it also exposes a challenge in content moderation, as extremist communities do not source content from a single platform. Rather, content moderation needs broader intervention across platforms to curb the spread of climate disinformation, especially during natural disasters.

Secondly, we assessed the scale and propensity of amplification of climate-related content within the extremist network relative to baseline extremist discourse on Telegram. The results show an episodic trend in which climate discourse spikes around the events of each disaster, peaking at 9.38% of all extremist discourse on Telegram during the disaster windows of Hurricane Milton and Hurricane Helene. This spike in discourse coincides with amplification, as climate-related content shows an overall 40% higher likelihood of being forwarded compared to the baseline. These findings highlight climate as a relevant point of discussion in fringe communities and its potential for amplification.

Finally, building on previous research on inorganic behavior on Telegram, we demonstrate that the ecosystem contains an alarming percentage of coordinated messages primarily disseminating climate disinformation (Blas et al., 2025; Dukach et al., 2025; Herasimenka et al., 2023; Kireev et al., 2025).[8] On the lower bound, approximately 20.7% of all climate messages sampled were exact or near-exact

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[5] Discussion was predominantly focused on the Southern California wildfires.
[6] Excess mortality estimates were not reported for Hurricane Helene or Hurricane Milton.
[7] While individual intent cannot be definitively confirmed, our analysis focuses on network-level amplification patterns rather than individual intent. Because the observed coordination signals are more consistent with deliberate amplification, we interpret these findings through the lens of disinformation (Gigiletto et al., 2020).
[8] We use *coordinated* to describe observable patterns suggesting artificial network-level amplification without making stronger claims about actor intent or degree of robotic automation.

messages posted in different channels within 24 hours of each other, bypassing the forward feature built into Telegram. Regarding the upper bound, approximately 39.2% of sampled climate-related messages met the specified criteria, with some messages appearing across separate channels while both using and circumventing the forward feature. This upper bound likely reflects a mixture of coordinated and organic sharing.

Taken together, these three findings build a cumulative argument that climate disinformation on Telegram is embedded within a shared sociotechnical extremist infrastructure, opportunistically amplified during natural disasters, and exhibits patterns of coordination. We call on policymakers, academics, and science communicators to treat low-moderated platforms as a new frontier of climate disinformation, particularly following the migration of extremist communities from mainstream platforms (Urman & Katz, 2022). Combating this phenomenon cannot be reduced to single-platform moderation. We recommend that cross-platform detection of the coordinated infrastructure be established during declared natural disaster windows as a regulatory standard applied uniformly across all social platforms to preserve authentic rather than manufactured voices,[9] thereby elevating free expression.

Findings

Finding 1: Climate discussions in extremist channels reflect the same domain-sharing patterns as the broader extremist ecosystem.

After performing binary classification to separate climate and non-climate discussion from 586,189 total messages taken from 116 active right-wing extremist Telegram channels, a subsample of 13,173 climate and 573,016 non-climate messages was extracted. Telegram represents the highest forwarded domain across both climate and non-climate subsamples, comprising 261,797 and 4,243,124 forwards, respectively. This makes up 19.7% of the total 1,331,120 climate forwards and 11.1% of the total 39,382,749 non-climate forwards, making Telegram domain sharing a notable 10.8% of all root domain sources.

Figure 1 demonstrates this continual dominance of low-to-moderate platform amplification in both subsamples' ecosystems, with X (formerly Twitter) and Rumble, a self-proclaimed alternative platform that "continues to embrace 'cancel culture'," leading domain forwarding (Ghosh & Stocking, 2022; Özturan et al., 2025). This is followed directly by conspiracy-identified sources such as disclose-tv and amg-news, suggesting an overall conspiracy-leaning within climate disinformation (Van Zandt, 2022, 2025). The remaining domains represent a smaller share of amplified content and include right-leaning news sources such as The Post Millennial, as well as YouTube, which, despite being comparatively more moderated than Telegram, has been identified as a platform that conspiracy-oriented communities continue to use alongside low-moderation alternatives (Zeng & Schäfer, 2021).

Despite broad structural similarity across subsamples, minor distributional differences warrant note. Bitchute, an alternative video platform, appears prominently in the climate subsample, likely reflecting the displacement of climate denial content following YouTube's targeted removal policies for climate misinformation (Zeng & Schäfer, 2021). Additionally, the presence of funding platforms such as GiveSendGo and PayPal in the climate subsample and captkylepatriots.store in the non-climate subsample suggests that both subsamples embed commercial monetization infrastructure alongside content distribution. Regardless of these differences, the overall similarity between domain distributions indicates

[9] Potential monitoring protocols may unintendedly exacerbate the production of conspiratorial narratives. Therefore, we call on further research to investigate appropriate implementation of this detection protocol.

that climate denial on Telegram is not operating through a distinct information ecosystem but is instead embedded within the broader extremist one.

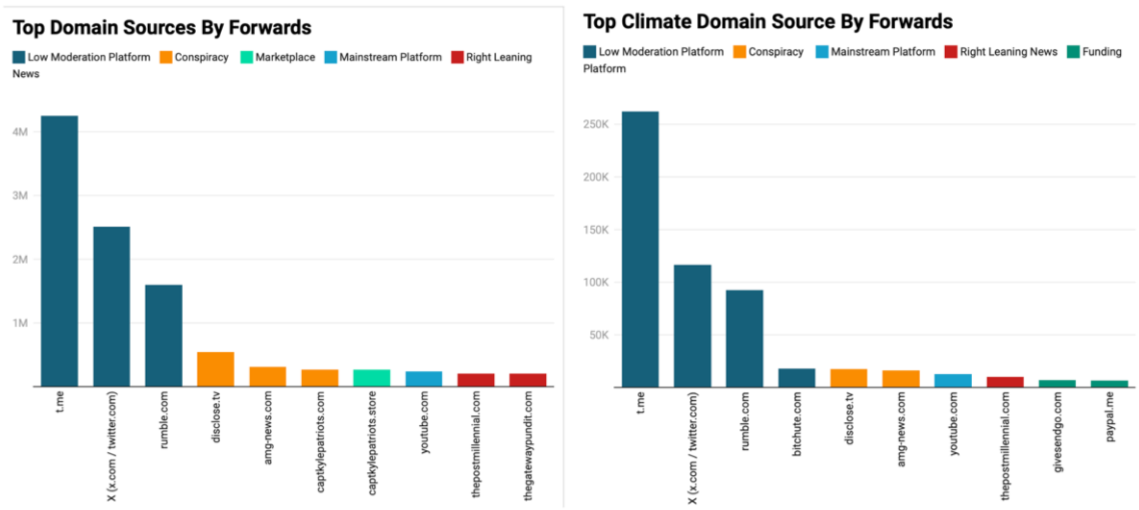

Figure 1. Graphics displaying the top forwarded domain roots within climate and non-climate extremist Telegram discussions, classified by domain type.

Finding 2: Climate discourse spikes during natural disasters and shows higher amplification within extremist Telegram channels.

To examine how climate discourse is mobilized within fringe-right Telegram communities, a weekly temporal analysis was conducted, tracking climate content as a proportion of total network discourse, allowing for the identification of periods of elevated climate engagement relative to total activity. Figure 2 demonstrates heightened episodic spikes during Hurricane Helene, Hurricane Milton, and the January 2025 California wildfires, followed by a sharp proportional decline from peak values to a baseline that rarely exceeds 2% of total network discourse during both pre-disaster and post-disaster recovery. This signals opportunistic engagement with climate-related issues rather than sustained ideological interest. Additionally, the hurricanes generated a combined peak of 9.38% of network discourse versus 3.85% for the California wildfires, possibly reflecting the political context of the November 2024 U.S. presidential election and subsequent inauguration on January 20, 2025.

Figure 3 further demonstrates the amplification of climate narratives through the affordance of forwards. Consistently, climate-related messages have a 40% higher forward rate than the baseline, with spikes also coinciding with the three natural disasters under study. This may further reinforce the opportunistic and amplifying potential of natural disasters, which corroborates existing research on fear as a driver of engagement and disinformation within right-wing extremist spaces (Hilberts et al., 2025; Törnberg & Chueri, 2025). Interestingly, the forwarding amplification spike observed in late August 2024 does not correspond to any identifiable major climate event, nor does it coincide with elevated climate discourse prevalence, suggesting that forwarding amplification within these networks is not exclusively driven by climate events themselves. This decoupling between amplification and discourse volume may reflect a high-engagement post or non-climate external event temporarily inflating forwarding activity, suggesting that climate content amplification in these communities can be mediated by factors beyond climate salience.

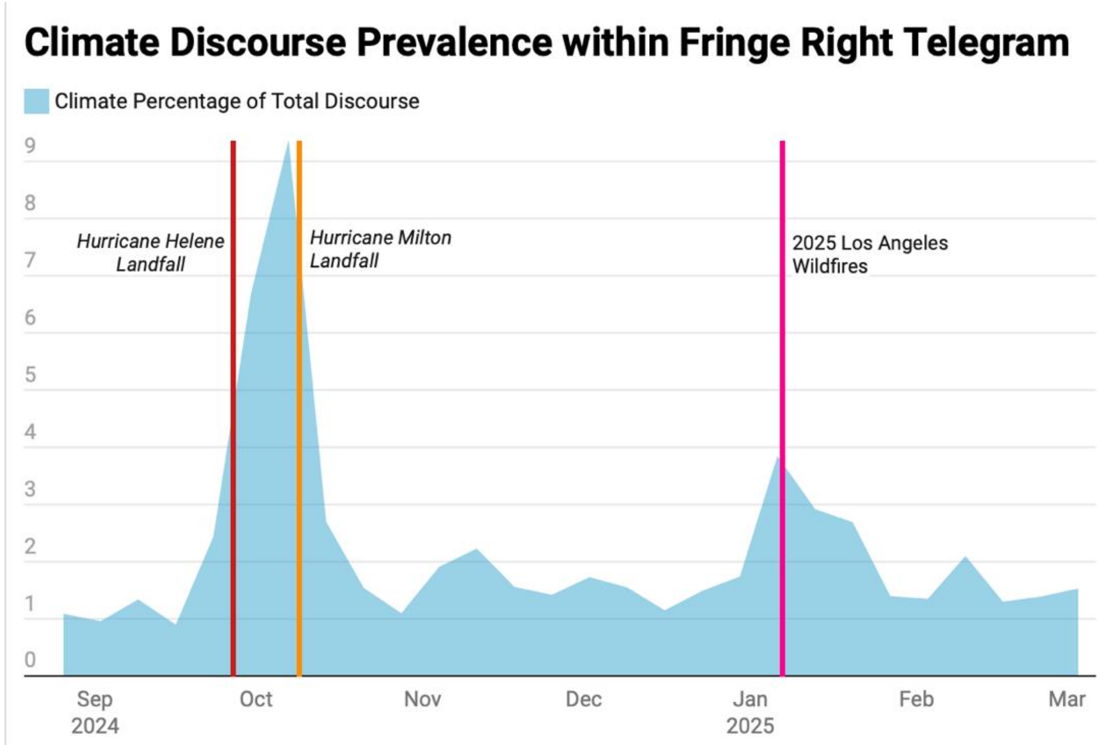

Figure 2. Weekly climate discourse prevalence within right-fringe Telegram. *Lines mark landfall dates for Helene (Sept. 26) and Milton (Oct. 9), and the date wildfires reached the LA metro area (Jan. 7). Early discourse increases for the wildfires likely reflect smaller precursor fires and emergency warnings.*

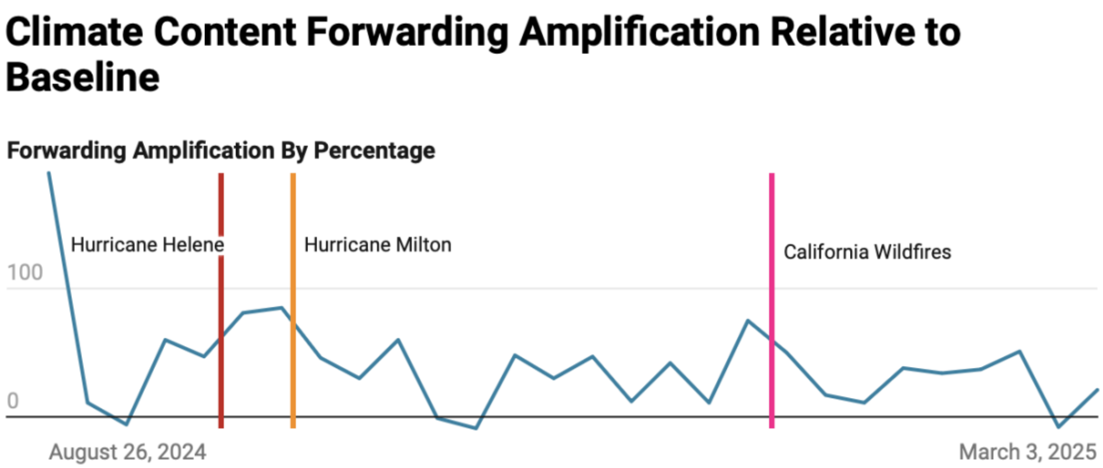

Figure 3. Weekly forwarding amplification of climate content relative to a baseline of extremist discourse. *0 indicates equal forwarding rates; positive values indicate climate content forwarded at a higher rate than extremist discourse, and negative values indicate a lower rate.*

Finding 3: Climate discussion within extremist Telegram channels has significant signals of coordinated behavior.

Extending research on coordinated activity on Telegram, this study argues that amplification also involves the coordinated sharing of content across channels that strategically bypass the platform's forward feature. From this perspective, measuring coordination may give further insights into why climate-related discussion is amplified and opportunistic within extremist ecosystems. In Figure 4, at the lower bound, 2,730 (20.7%) "pure coordinated" messages within the climate subsample had content that appeared in other channels within a 24-hour window and did not use the forward feature built into Telegram. Of those purely coordinated messages, 1,830 (67.0%) used a copy-and-paste method, suggesting a bot approach to amplification (see figure 5), compared to 900 near-duplicate messages. Mixed Messages, defined as content that appeared in other channels within a 24-hour window but also included at least one forwarded message, totaled 2,425 (18.5%), suggesting a mix of coordination and potential organic forwarding. Similarly, the mixed message group had 2,023 (83.0%) exact duplicates (see Figure 5). Taken together, this yields an upper bound of 5,165 (39.2%) messages, with 8,008 (60.8%) classified as organic.

Beyond the quantitative patterns of coordination, a qualitative examination of the coordinated messages revealed the substance of what was being amplified. Messages from the coordination group exhibited narratives characterized by climate change denial, allegations of "scientific fraud," blame of political opponents for neglecting natural disaster victims, and weather modification claims (see Appendix B). While this qualitative analysis is exploratory, given the study's scope, the narratives identified are illustrative of broader patterns amplified through coordination. These findings corroborate both the source domains being propagated and existing research on climate conspiracy narratives, further establishing right-wing extremist Telegram channels as a conduit for their spread.

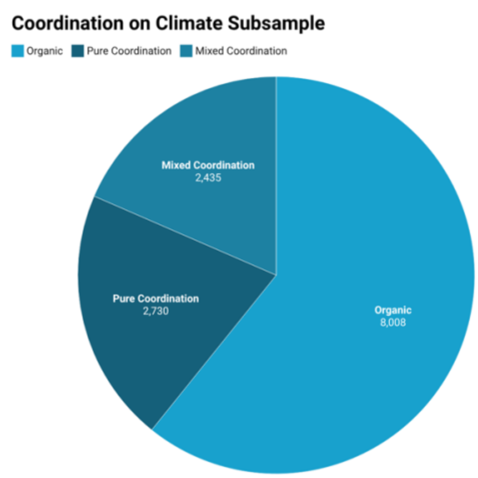

Figure 4. Share of pure and mixed coordination in the climate subsample.

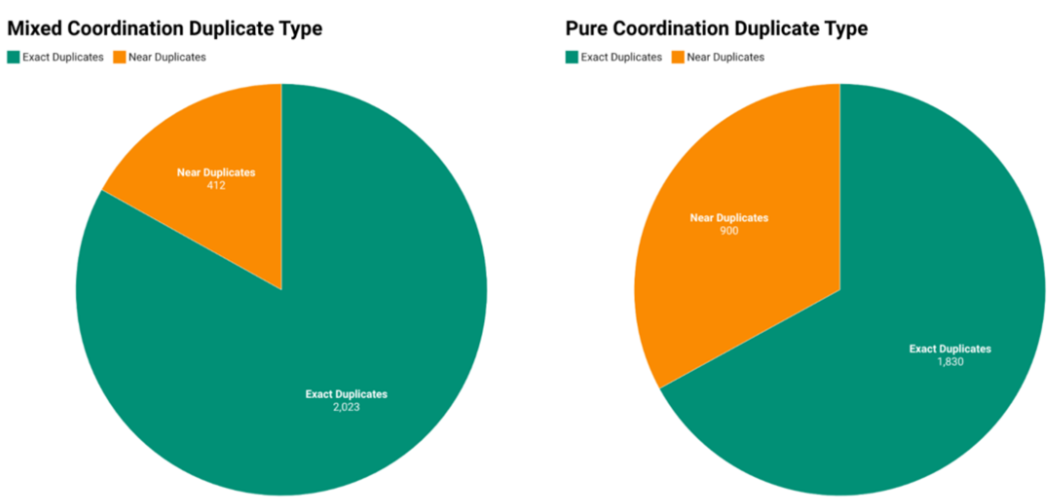

Figure 5. Graphics displaying the share of near and exact duplicates for both mixed and pure coordination groups.

Methods

Snowball sampling

This study employed a snowball sampling method (SSM) to gather data on American right-wing extremist Telegram channels, which has been established as an appropriate method for hard-to-reach social media populations (Dosek, 2021). An alias account was created to minimize suspicion, and all data were collected from public channels, anonymized, and managed in accordance with IRB-approved protocols (IRB #7051). SSM was initiated by joining eight channels using keywords associated with right-wing groups, with subsequent channels identified through shared source content and Telegram's algorithm-driven channel recommendations. While amassing the corpus, a bot extracted key metrics from all posts, including message content, views, channel ID, forwards, and data, and stored them in an encrypted database.

Dictionary classification

A custom dictionary method was employed to classify climate and non-climate messages via keyword matching (Silge & Robinson, 2017). Small variations in keyword spelling and pluralization were accounted for to ensure comprehensive capture of each term used within each message. This method is both empirically validated and consistent with Telegram's terms of service, which prohibit AI training on platform data (Macanovic & Przepiorka, 2024; Telegram, 2025). The dictionary was initially built upon an existing National Oceanic and Atmospheric Administration (NOAA) climate glossary to maintain alignment with established terminology and iteratively refined through manual validation of 200 randomly sampled messages per subsample (National Oceanic and Atmospheric Administration, 2023). Validity was determined by whether a message explicitly addressed a climate-related topic in some capacity, whether through engagement with a natural disaster or through comments about a weather-related organization such as the Federal Emergency Management Agency (FEMA).

As extremist communities often engage with climate topics conspiratorially, standard climate terminology requires refinement to accurately capture this discourse. During refinement, overly generic or politically adjacent terms generating false positives were removed from the dictionary, while climate-specific policy terminology was added to better capture the nuanced language of the discursive ecosystem under study. Classification performance of the initial round had a total F1 score of 0.678, while the final round yielded a notable increase with a final F1 score of 0.890, making it a robust method for binary classification. Further detailed classifier validation results are provided in Appendix C, with the full final dictionary in Appendix D and an omitted keyword list in Appendix E.

Amplification forward tracking

After the final climate and non-climate subsamples were curated, total messages and forwards were analyzed temporally by comparing the message-to-forward ratio of each subsample. The full temporal analysis spanned weekly intervals from the study period, providing a baseline measure of discourse volume and amplification.

Tracking content sharing by website

Root domains were extracted across each Telegram message present within the study's timeframe to identify upstream content sources and cross-platform contamination. Amplification was ranked by aggregating forward counts across domains. Prominent root domains such as Twitter/X were combined to match root domains with functionally equivalent sources.

Coordination detection

Building on established methods, we apply text-based coordinated detection techniques to the climate change subsample, using text similarity, bypassing Telegram's forward feature, and temporal proximity as a proxy for coordination (Blas et al., 2025; Giglietto et al., 2020). Exact duplicates were identified as identical messages appearing across at least two distinct channels. Near duplicates were identified using TF-IDF vectorization with cosine similarity computed across all cross-channel message pairs, flagging those with a score at or above 0.85. This threshold reflects a conservative detection approach that accounts for minor variations in messaging, such as minor misspellings, emoji deviations, and punctuation, while minimizing false positives. Flagged messages were then assessed against a 24-hour posting window and the presence or absence of Telegram's native forwarding feature to distinguish between organic, mixed, and coordinated transmission patterns.

Limitations

The classifier's 81% precision rate (see Appendix C) means approximately one in five climate messages may be false positives, potentially inflating prevalence estimates. The snowball sampling methodology excluded private channels, which limited generalizability across all extremist Telegram channels. Future quasi-experimental research would strengthen causal claims about the role natural disasters play in shaping climate disinformation. Such research would offer further insight into whether these events precede climate disinformation spikes or are associated with them. Finally, further investigation of the channels involved in cross-posting and coordinated activity could determine whether amplification dynamics are driven by a small number of highly active actors or are more broadly distributed across the network, informing methods for detecting coordinated behavior during crises.

Bibliography

Amorim, R., Villarini, G., Czajkowski, J., & Smith, J. (2025). Flooding from Hurricane Helene and associated impacts: A historical perspective. *Journal of Hydrology X, 27,* Article 100204. https://doi.org/10.1016/j.hydroa.2025.100204

Baptista, J. P., & Gradim, A. (2022). Who believes in fake news? Identification of political (a)symmetries. *Social Sciences, 11*(10), Article 460. https://doi.org/10.3390/socsci11100460

Beven, J. L., II, Alaka, L., & Fritz, C. (2025). *Tropical cyclone report: Hurricane Milton (AL142024)*. National Hurricane Center. https://www.nhc.noaa.gov/data/tcr/AL142024_Milton.pdf

Blas, L., Saraf, D., Salkar, T., et al. (2025). Large-scale detection of multilingual coordinated activity on Telegram. *npj Complexity, 2*, Article 33. https://doi.org/10.1038/s44260-025-00056-w

Börgmann, H., Hammer, D., Beyer, J., Ziock, J., Stegers, F., Keßling, P., & Münch, F. (2025, April 24). *Destructive discourses: The digital dissemination of climate misinformation and disinformation*. Institute for Strategic Dialogue Germany. https://isdgermany.org/destruktive-diskurse-digitale-verbreitung-von-klimabezogener-mis-und-desinformation-2/

Dosek, T. (2021). Snowball sampling and Facebook: How social media can help access hard-to-reach populations. *PS: Political Science and Politics, 54*(4), 651–655. https://doi.org/10.1017/S104909652100041X

Dukach, Y., Adam, I., & Furbish, M. (2025). *Digital occupation: Pro-Russian bot networks target Ukraine's occupied territories on Telegram*. Atlantic Council. https://www.atlanticcouncil.org/in-depth-research-reports/report/report-russian-bot-networks-occupied-ukraine/

Essien, E. O. (2025). Climate change disinformation on social media: A meta-synthesis on epistemic welfare in the post-truth era. *Social Sciences*, *14*(5), Article 304. https://doi.org/10.3390/socsci14050304

Frame, D. J., Wehner, M. F., Noy, I., Rosner, S., & Kopp, R. E. (2020). The economic costs of Hurricane Harvey attributable to climate change. *Climatic Change, 160*(2), 271–281. https://doi.org/10.1007/s10584-020-02692-8

Ghosh, S., & Stocking, G. (2022, December 21). *Key facts about rumble*. Pew Research Center. https://www.pewresearch.org/short-reads/2022/12/21/key-facts-about-rumble/

Giglietto, F., Righetti, N., Rossi, L., & Marino, G. (2020). It takes a village to manipulate the media: Coordinated link sharing behavior during 2018 and 2019 Italian elections. *Information, Communication & Society, 23*(6), 867–891. https://doi.org/10.1080/1369118X.2020.1739732

Hagen, A. B., Cangialosi, J. P., Chenard, M., Alaka, L., & Delgado, S. (2026). *Tropical cyclone report: Hurricane Helene (AL092024)*. National Hurricane Center. https://www.nhc.noaa.gov/data/tcr/AL092024_Helene.pdf

Herasimenka, A., Bright, J., Knuutila, A., & Howard, P. N. (2023). Misinformation and professional news on largely unmoderated platforms: The case of telegram. *Journal of Information Technology & Politics*, *20*(2), 198–212. https://doi.org/10.1080/19331681.2022.2076272

Hilberts, S., Govers, M., Petelos, E., & Evers, S. (2025). The impact of misinformation on social media in the context of natural disasters: Narrative review. *JMIR Infodemiology*, *5*, Article e70413. https://doi.org/10.2196/70413

Hunt, K., Wang, B., & Zhuang, J. (2020). Misinformation debunking and cross-platform information sharing through Twitter during Hurricanes Harvey and Irma: A case study on shelters and ID checks. *Natural Hazards*, *103*(1), 861–883. https://doi.org/10.1007/s11069-020-04016-6

Institute for Strategic Dialogue [ISD]. (2024, October 8). *Hurricane Helene brews up storm of online falsehoods and threats*. Institute for Strategic Dialogue. https://www.isdglobal.org/digital-dispatch/hurricane-helene-brews-up-storm-of-online-falsehoods-and-threats/

Jonkman, S. N., Godfroy, M., Sebastian, A., & Kolen, B. (2018). Loss of life due to Hurricane Harvey. *Natural Hazards and Earth System Sciences, 18*(4), 1073–1078. https://doi.org/10.5194/nhess-18-1073-2018

Kireev, K., Mykhno, Y., Troncoso, C., & Overdorf, R. (2025). Characterizing and detecting propaganda-spreading accounts on Telegram. In *Proceedings of the 34th USENIX Security Symposium*. USENIX Association. https://www.usenix.org/system/files/usenixsecurity25-kireev.pdf

Lewandowsky S. (2021). Climate change disinformation and how to combat it. *Annual Review of Public Health*, *42*, 1–21. https://doi.org/10.1146/annurev-publhealth-090419-102409

Los Angeles County Economic Development Corporation. (2025). *Impact of 2025 Los Angeles wildfires and comparative study*. https://laedc.org/wildfirereport/

Macanovic, A., & Przepiorka, W. (2024). A systematic evaluation of text mining methods for short texts: Mapping individuals' internal states from online posts. *Behavior Research Methods*, *56*(4), 2782–2803. https://doi.org/10.3758/s13428-024-02381-9

Merdjanoff, A. A., Abramson, D. M., Park, Y. S., & Piltch-Loeb, R. (2022). Disasters, displacement, and housing instability: Estimating time to stable housing 13 years after Hurricane Katrina. *Weather, Climate, and Society, 14*(3), 535–550. https://doi.org/10.1175/WCAS-D-21-0057.1

Mudde, C. (1995). Right-wing extremism analyzed: A comparative analysis of the ideologies of three alleged right-wing extremist parties (NPD, NDP, CP'86). *European Journal of Political Research*, *27*(2), 203–224. https://doi.org/10.1111/j.1475-6765.1995.tb00636.x

National Oceanic and Atmospheric Administration. (2023, September 11). *Weather glossary*. https://www.noaa.gov/jetstream/appendix/weather-glossary

Newman, R., & Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. *Nature Communications, 14*, Article 6103. https://doi.org/10.1038/s41467-023-41888-1

Nikolov, D., Flammini, A., & Menczer, F. (2021). Right and left, partisanship predicts (asymmetric) vulnerability to misinformation. *Harvard Kennedy School (HKS) Misinformation Review*, *1*(7). https://doi.org/10.37016/mr-2020-55

Özturan, B., Quintana-Mathé, A., Grinberg, N., Ognyanova, K., & Lazer, D. (2025). Declining information quality under new platform governance. *Harvard Kennedy School (HKS) Misinformation Review*, *6*(3). https://doi.org/10.37016/mr-2020-176

Paglino, E., Raquib, R. V., & Stokes, A. C. (2025). Excess deaths attributable to the Los Angeles wildfires from January 5 to February 1, 2025. *JAMA*, *334*(11), 1018–1019. https://doi.org/10.1001/jama.2025.10556

Selig, K. (2024, October 14). Meteorologists face harassment and death threats amid hurricane disinformation. *The New York Times*. https://www.nytimes.com/2024/10/14/us/meteorologists-threats-conspiracy-theories-hurricanes.html

Silge, J., & Robinson, D. (2017). *Text mining with R: A tidy approach.* O'Reilly Media. https://www.tidytextmining.com

Storani, S., Falkenberg, M., Quattrociocchi, W., Lodi, G., & Vicini, A. (2025). Relative engagement with sources of climate misinformation is growing across social media platforms. *Scientific Reports*, *15*(1), Article 18629. https://doi.org/10.1038/s41598-025-03082-9

Telegram. (2025). *Telegram channels*. https://telegram.org/tour/channels

Tomassi, A., Falegnami, A., & Romano, E. (2025). Disinformation in the digital age: Climate change, media dynamics, and strategies for resilience. *Publications*, *13*(2), Article 24. https://doi.org/10.3390/publications13020024

Törnberg, P., & Chueri, J. (2025). When do parties lie? Misinformation and radical-right populism across 26 countries. *The International Journal of Press/Politics*, *31*(2). https://doi.org/10.1177/19401612241311886

Tucci, G., Bastos, J. G., & Carneiro, B. (2025). *Contesting climate futures: Mapping misinformation narratives and networks on Telegram*. Digital Methods Initiative. https://www.digitalmethods.net/Dmi/SummerSchool2025ContestingClimateFutures

Urman, A., & Katz, S. (2022). What they do in the shadows: Examining the far-right networks on Telegram. *Information, Communication & Society, 25*(7), 904–923. https://doi.org/10.1080/1369118X.2020.1803946

Van Zandt, D. (2022, September 16). *Disclose TV*. Media Bias/Fact Check. https://mediabiasfactcheck.com/disclose-tv/

Van Zandt, D. (2025, January 3). *American Media Group (AMG-news.com)*. Media Bias/Fact Check. https://mediabiasfactcheck.com/amg-news/

Vergani, M., Martinez Arranz, A., Scrivens, R., & Orellana, L. (2022). Hate speech in a Telegram conspiracy channel during the first year of the COVID-19 pandemic. *Social Media + Society, 8*(4). https://doi.org/10.1177/20563051221138758

Vraga, E. K., & Bode, L. (2020). Defining misinformation and understanding its bounded nature: Using expertise and evidence for describing misinformation. *Political Communication*, *37*(1), 136–144. https://doi.org/10.1080/10584609.2020.1716500

Walther, S., & McCoy, A. (2021). US extremism on Telegram: Fueling disinformation, conspiracy theories, and accelerationism. *Perspectives on Terrorism, 15*(2), 100–124. https://www.jstor.org/stable/27007298

Willaert, T., Sessa, M. G., & Van Soest, J. (2022, November 14). *The disinformative ecosystem: Link-sharing practices on Telegram as evidence of cross-platform amplification* (EDMO BELUX Investigative Report). EU DisinfoLab. https://www.disinfo.eu/publications/the-disinformative-ecosystem-link-sharing-practices-on-telegram-as-evidence-of-cross-platform-amplification/

World Meteorological Organization. (2024). *State of the global climate 2023* (WMO-No. 1347). https://wmo.int/publication-series/state-of-global-climate/state-of-global-climate-2023

Zeng, J., & Schäfer, M. S. (2021). Conceptualizing “dark platforms”: Covid-19-related conspiracy theories on 8kun and Gab. *Digital Journalism*, *9*(9), 1208–1230. https://doi.org/10.1080/21670811.2021.1938165

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Competing interests
The authors declare no competing interests.

Ethics
All data were collected from public channels, anonymized, and managed in accordance with IRB-approved protocols (University of Virginia IRB #7051).

Data availability
All materials needed to replicate this study are available via the Harvard Dataverse:
https://doi.org/10.7910/DVN/ZDZ55T

Appendix A: List of extremist Telegram channels

The Telegram Group Tag is a username associated with every public channel, while subscribers represent the total number of users following each channel and receiving its content. Subscriber counts were collected during the study's timeframe, with an average of 71,403 subscribers per channel. This demonstrates the reach extremist content has within Telegram's ecosystem.

Table A1. *A list of all 116 right-wing extremist-defined Telegram channels used within the analysis.*

Telegram Channel	Subscribers
@real_DonaldJTrump	655,574
@TrumpJr	452,978
@disclosetv	381,318
@realKarlBonne	218,338
@PepeMatter	198,398
@qthestormrider777	192,074
@georgenews	187,352
@TrumpChannel	181,142
@LauraAbolichannel	175,720
@ResisttheMainstream	174,468
@CharlieKirk	170,418
@RealDonaldoTrumpo	169,532
@epochtimes	168,806
@rattletrap1776	166,922
@Santasurfing	157,817
@Jack_Posobiec	152,206
@FearlessReport	144,952
@ShadowofEzra	144,172
@bioclandestine	143,521
@VigilantFox	137,397
@TheStormHasArrived17	121,354
@GeneralMCNews	120,342
@TheConspiracyHole	113,702
@DanScavinoForce	107,211
@CaptKylePatriots	103,018
@insiderpaper	100,377

Telegram Channel	Subscribers
@QNewsOfficialTV	99,695
@WW3INFO	92,748
@NewsmaxTV	92,658
@stormypatriotjoe21	91,823
@candlesinthenight	91,717
@MJ_Innocent	90,446
@BREAKINGHEADLINES	90,203
@AMGNEWS2022	77,782
@mel_gibsonchannel	76,818
@police_frequency	75,905
@NTDnews	75,884
@ConservativeBrief	75,463
@RealHealthRanger	72,617
@redpillpharmacist	69,530
@Ezra_Cohen_Q	67,366
@tuckercarlsonchannel	66,654
@DonaldTrumpOffice	65,500
@stfn_news	64,758
@MrKidPool17	64,197
@PepeDeluxed	61,107
@PearFEED	58,130
@MarkRLevin	57,553
@NesaraGesaraSecrets	55,953
@White_Hats1	54,051
@Elon_Musk	50,730
@The17Letter	49,736
@Tironianae	48,057
@usa_news_trump	47,225
@QanonFighters	43,329
@ivanka_trump or @IvankaTrump47	42,251
@Trump45_47	39,378
@Tucker_Carlsoni	38,937

Telegram Channel	**Subscribers**
@Melania_Trump3	38,134
@WHGrampaChannel	37,470
@The_Storm3	36,906
@general_flynn or @GenFlun	36,891
@Qanon1	36,202
@qanonplus	35,760
@Cruz_Ted	35,473
@ishjay1960	34,906
@trump_donald	34,736
@FightingTheCommies	33,728
@Qanon0	32,923
@CharlieWardFriends	31,936
@LizHarrington	31,393
@John_Durham4	31,317
@President_Donald_Trump1	30,901
@QNEWSPATRIOTTTV	30,752
@Q_Anon8	30,240
@Shadow_Of_Ezra2	30,201
@dotconnectinganons	29,961
@Julian_Assange2	27,953
@LetsGoBrandon	27,738
@ThePostMillennial	26,407
@jfkawakening_q_17	26,213
@Trump_Offic	25,380
@John_kennedy3	24,656
@WhiteLivesMatterOfficial	21,761
@Q_Warriors	19,731
@inmagnaexcitatio	19,325
@QAnonMap	18,089
@FreeTheWillPatriots	17,345
@theamericantribune	16,806
@AmericaGreatAgainChat	13,722

Telegram Channel	Subscribers
@Qtip9	12,803
@JDVance1VP	11,951
@Truth_Social6	11,314
@Trump_Organization1	11,309
@TheGatewayPunditChat	10,772
@Conservative Network	10,705
@MissPATRIOTChelseaGirl	10,235
@Donald_Trumpa	10,138
@FundamentalChristianity	9,174
@Q17TrustThePlan	7,474
@The_17thLetter_Q	7,159
@fourwatches	7,104
@BasedRandPaul	6,601
@USProudPatriots	6,484
@MelzieKayeMind	5,842
@makegreatnow	5,029
@GretchenGM062616	4,559
@TGAMAGAzine	4,402
@kiwifarmschat	3,258
@MakeAmericaGreatAgainNow	3,077
@nationalistzulkarneyndivision3	2,629
@traceytray17	2,581
@bootsontheground1111	2,283
@hitlermediaarchive	1,530
@basedbible	1,086
@Qannon17	969

Appendix B: Example extremist climate messages

Table B1. *Each entry below represents a coordinated, defined message taken directly from an extremist Telegram channel.*

Narrative	Message #	Message Content
Climate Hoax	1	"Climate experts believe the next ice age is on its way." Leonard Nimoy, 1978: "Scientists are telling us... that the threat of an ice age is not as remote as they once thought." During the lifetime of our grandchildren, Arctic cold and perpetual snow could turn most of the inhabitable portions of our planet into a polar wilderness.
Climate Denial	2	Trump: "Nobody's more into the climate than I am, but this is a climate hoax... It's a hoax destroying our country." "You have a thing called weather, and you go up and you go down... The climate's always been changing." "The green technology isn't powerful enough."
Climate Denial	3	1960s – "Oil will run out in 10 years." 1970s – "A new Ice Age is coming in 10 years." 1980s – "Acid rain will destroy all crops in 10 years." 1990s – "The ozone layer will disappear in 10 years." 2000s – "The Arctic ice caps will be gone in 10 years." 2010s – "Global warming will cause irreversible damage in 10 years."
Scientific Fraud	4	"It scares me that scientific fraud is so easy to conduct... Anything that comes out of the UN should be dismissed." Geologist Prof. Ian Plimer on the UN's tampering of historical temperature data to fit the "climate crisis" narrative. "During the times of Jesus, it was warmer than now."
Scientific Fraud	5	"They're only interested in world government... controlling people, and they're not elected." Geologist Prof. Ian Plimer responds to the UN IPCC's claim that 2023 was the hottest year on record: "That's fraud." "I'm not surprised, coming from a UN organisation." "They have ignored the long-term geological record."
Scientific Fraud	6	Cue the "Climate Change" shills blaming the L.A. fires on fake science propaganda. Our climate is changing, but the prime driver are natural cosmic/Earth cycles (the Sun), not humans. Blaming humans allows more government control and more tax money to be taken from the human slaves.
Blame for Disaster Victims	7	Trump rips Sleepy Joe and Fundraising Kamala for not helping the victims of the hurricane.

Narrative	Message #	Message Content
Blame for Disaster Victims	8	The GREAT people of North Carolina are being stood up by Harris and Biden, who are giving almost all of the FEMA money to Illegal Migrants in what is now considered to be the WORST rescue operation in the history of the U.S. On top of that, Billions of Dollars is going to foreign countries!
Blame for Disaster Victims	9	FEMA EXPOSED: $700 Celebrity Payouts While Ordinary Americans Burn – Deep State Corruption Fuels Disaster Exploitation from Maui to Malibu! FEMA gives $700 loans to celebrities while ordinary Americans are left to burn! From Maui to Malibu, the Deep State's corruption fuels disaster exploitation.
Weather Modification	10	SkyNet 2.0 EXPOSED: Chemtrails, Directed Energy Weapons, and the Global Elite's Sinister Weather Control Agenda! The truth is out: the skies above us are no longer natural. They're battlegrounds in a war waged by global elites against humanity.
Weather Modification	11	Why doesn't California use cloud seeding to fight wildfires? Just make it rain when there's a red flag warning! Bingo!!! @TikTokNews45
Weather Modification	12	Florida Republican Lawmaker Introduces Legislation to BAN Weather Engineering Amid Rising Concerns Over Climate Manipulation.

Appendix C: Dictionary classifier validation results

A 95% confidence interval was analyzed using the Wilson score interval, as it is effective for values near 0 or 1. Furthermore, the Delta method was utilized as F1 is a non-linear function of precision and recall, making standard binomial confidence intervals not directly applicable. Round 1 used only the initial NOAA-derived dictionary (n=200). Round 2 reflects dictionary refinement following the removal of ambiguous terms, driving false positives. High recall across both rounds indicated a conservative tendency towards inclusion.

Table C1. *Summary of classifier validation results for both round 1 with the NOAA dictionary and round 2 after further curation of the custom dictionary.*

Metric	Method	Round 1 Estimate	Round 1 95% CI	Round 2 Estimate	Round 2 95% CI
Precision	Wilson score	51.5%	[44.6%, 58.3%]	81.0%	[75.0%, 85.8%]
Recall	Wilson score	99.0%	[94.8%, 99.8%]	98.8%	[95.7%, 99.7%]
F1 Score	Delta method	0.678	[0.618, 0.738]	0.890	[0.857, 0.924]

Appendix D: Full list of keywords

The following terms represent the final list of keywords used for the custom-made dictionary classifier. The terms initially came from the NOAA glossary and were refined after manual validation of the data.

Figure 6. *Dictionary of keywords/phrases used in the classifier.*

A		
Ablation	Abutment	Abutment seepage
Accessory cloud	Accuracy	Acid rain
Acre-foot	Active conservation storage	Active storage capacity
Adiabatic process	Advection	Advection fog
Aeration zone	Afterbay	Agglomerate
Air mass	Air mass thunderstorm	Air parcel
Air pressure	Air quality statement	Air stagnation
Air transportable mobile unit	Alberta clipper	Albedo
Alert flood warning system	Alluvium	Altimeter
Altitude	Anabranch	Anchor ice
Anchor ice dam	Anemometer	Aneroid barometer
Annual flood	Antecedent precipitation index	Anticipated convection
Anticyclone	Anticyclonic rotation	Anvil
Anvil crawler	Anvil dome	Anvil rollover
Apparent temperature	Aquiclude	Aquifer
Aquifuge	Arch dam	Arctic air
Arctic high	Arcus	Area forecast discussion
Area of influence	Area-capacity curve	Arroyo
Artesian well	Artificial control	Atmosphere
Atmospheric pressure	Atmospheric stability	Attenuation
Automated local evaluation in real time	Automatic weather observing system	Avalanche
Avalanche advisory	Aviation area forecast	
B		
Back scatter	Back-building thunderstorm	Back door cold front
Back-sheared anvil	Backflow	Backing

Backing winds	Backsight	Backwater curve
Backwater effect	Ball lightning	Bank storage
Bankfull stage	Barometer	Base flood
Base reflectivity	Baseflow	Basic fire weather services
Basin	Bathymetric chart	Beach erosion
Beam width	Beaver's tail	Bermuda high
Bimetallic thermometer	Blizzard	Blowing dust
Blowing snow	Bow echo	Braided stream
Breakup jam	Breezy	Bulk richardson number
C		
Capping inversion	Catchment area	Ceiling balloon
Ceilometer	Celsius	Channel routing
Channelization	Circulation cell	Cirrocumulus
Cirrostratus	Cirrus	Climate
Climate accord	Climate change	Cloud
Coalescence	Coastal flood statement	Coastal flood warning
Cold air advection	Cold front	Columnar ice
Composite hydrograph	Composite reflectivity	Confluence
Conservation storage	Convection	Convective available potential energy
Convective condensation level	Convective inhibition	Cooling degree day
Cooperative observer	Core punch	Coriolis effect
Creek	Crest	Critical depth
Critical flow	Cumulonimbus cloud	Cumulus cloud
D		
Dam failure	Debris cloud	Degree day
Dense fog	Density current	Depression storage
Derecho	Derived products	Design criteria
Detention basins	Detention storage	Dew point
Downburst	Downdraft	Drainage basin
Drifting snow	Drought	Dry adiabat
Dryline	Dual doppler	Duration curve

E		
Ebb current	Effluent stream	El nino
Elevation angle	Embankment	Energy helicity index
Enhanced fujita scale	Entrainment	Erosion
Estuary	Evaporation	Evapotranspiration
Excessive heat warning	Extratropical	Eye wall
F		
Fahrenheit	Fathom	Federal emergency management agency
Fema	Feeder bands	Fetch
Field capacity	Fire behavior	Fire danger
Flash flood	Flash flood statement	Flash flood warning
Flash flood watch	Flood plain	Flood stage
Flood warning	Flood watch	Fog
Forecast crest	Forward flank downdraft	Frazil ice
Freeze	Frontal inversion	Frost
Fuel moisture	Funnel cloud	
G		
Gage height	Gale warning	Gallery
Gate	Geostrophic wind	Glacier
Global warming	Gradient	Graupel
Gravity wave	Greenhouse	Ground fog
Ground water	Gust	Gyre
H		
Haarp	Hail	Haines index
Halos	Hanging ice dam	Haze
Headwaters	Heat advisory	Heat index
Heavy snow	Helicity	High frequency active auroral research program
High seas	High wind warning	Hodograph
Humidity	Hurricane	Hydrograph
Hydrology		

I		
Ice jam	Ice pellets	Ice shove
Ice storm	Impermeable	Inflow
Infrared satellite imagery	Interception	Intermittent stream
Inundation map	Isobar	Isotherm
J		
Jet max	Jet streak	Jet stream
Jetty	Jokulhlaup	Juvenile water
K		
Kelvin	Knot	
L		
Lake breeze	Lake effect snow warning	Laminar flow
Landspout	Lapse rate	Level of free convection
Levee	Lifted index	Lightning
Line echo wave pattern	Live fuel moisture	Low clouds
Low level jet	Low wind	
M		
Macroburst	Main stem	Major flooding
Marine small craft wind warning	Mass curve	Mesocyclone
Mesoscale	Mesoscale convective complex	Mesoscale discussions
Meteorology	Microburst	Moisture convergence
Monsoon	Mount weather	Mountain wave
Multi-cell thunderstorm	Multiple vortex tornado	
N		
National oceanic and atmospheric administration	National weather service	Nimbostratus
Nne flow	Noaa	Nor'easter
North atlantic oscillation	North pacific high	Nws
O		
Occluded front	Observed water level	Ocean current
Orographic lifting	Outflow boundary	Overcast
Overland flow		

P		
Parcel	Paris agreement	Partial pressure
Peak flow	Peatlands	Percolation
Persistent convection	Piedmont	Plume
Point forecast	Polar jet	Precipitation
Pressure gradient	Prevailing winds	Proximity warning
Q		
Q-vectors	Qpf discussion	Quasi-stationary
R		
Radar beam	Radar cross section	Radar reflectivity
Radial velocity	Radiation	Radiation fog
Rain	Rain shadow	Rain shield
Rapid deepening	Rating curve	Rawinsonde
Rear flank downdraft	Receiver	Recurrence interval
Red flag warning	Reflectivity	Refraction
Regulatory floodway	Relative humidity	Reservoir
Resolution	Response time	Retrogression
Return flow	Ridge	Rip current
River basin	River forecast center	River flood statement
River flood warning	River flooding	River gage
Roll cloud	Rope cloud	Routing
Runoff		
S		
Sacramento soil moisture accounting model	Safetynet	Saffir-simpson hurricane intensity scale
Saffir-simpson hurricane wind scale	Santa ana wind	Sea breeze
Sea level pressure	Sector visibility	Sediment storage capacity
Seepage	Seiche	Serial derecho
Severe storm	Severe supercell thunderstorm	Severe thunderstorm
Severe thunderstorm warning	Severe thunderstorm watch	Severe weather statement
Shear	Sheet flow	Shelf cloud
Shoaling	Shore ice	Short term forecast
Showalter index	Sidereal year	Sleet

Slight risk of severe thunderstorms	Small craft advisory	Snow
Snow advisory	Snow and blowing snow advisory	Snow depth
Snow flurries	Snow pack	Snow pellets
Snow pillow	Snow shower	Snow squalls
Snow water equivalent	Soil moisture	Southern oscillation
Space weather prediction center	Special fire weather	Spin-up
Squall line	Staff gage	State weather roundup
Station pressure	Stationary front	Steam fog
Steering winds	Stratocumulus	Stratosphere
Stratus	Stream gage	Streamflow
Sublimation	Subsidence	Subsidence inversion
Subtropical cyclone	Subtropical depression	Subtropical storm
Sunny	Supercell	Supercooled liquid water
Supersaturation	Surface based convection	Surface pressure
Surface runoff	Surface water	Sustained wind
Synoptic chart	Synoptic track	Syzygy
T		
Tail cloud	Tailwater height	Temperature
Terminal aerodrome forecast	Thermal highs	Thermal lows
Thermometer	Threshold runoff	Thunderstorm
Tilted storm	Time-height display	Toe drain
Toe of dam	Tornado	Tornado alley
Tornado warning	Tornado watch	Total totals
Towering cumulus	Trade winds	Transpiration
Transport wind	Transverse bands	Travel time
Tropical cyclone	Tropical depression	Tropical storm
Tropical storm warning	Tropical storm watch	Tropical wave
Tropical year	Tropopause	Troposphere
Trough	Tsunami	Turbidity
Turbulence	Twister	Typhoon

U		
Ultraviolet radiation	Unambiguous range	Undercurrent
Underflow	Unit hydrograph	Unstable air
Updraft	Upper level system	Upper-level disturbance
Upslope flow	Upslope fog	Upstream
Urban flash flood guidance	Urban flooding	Urban heat island
U.s. geological survey	Uv index	
V		
V notch	Vadose zone	Valley winds
Vapor pressure	Variable ceiling	Variable wind direction
Vault	Veering wind	Vertical wind shear
Vertically stacked system	Very windy	Virga
Virtual temperature	Visual flight rules	Volcanic ash
Volume scan	Vortex	Vorticity
W		
Wall cloud	Warm air advection	Warm core low
Warm front	Water supply outlook	Water table
Water vapor plume	Water vapor satellite imagery	Water year
Watercourse	Waterspout	Wave crest
Wave spectrum	Wave trough	Wavelength
Weather balloon	Weather forecast office	Weather synopsis
Wedge tornado	Weighing-type precipitation gage	Weir
Wetland	Whirlwind	Wildfire
Wind	Wind chill	Wind direction
Wind gust	Wind rose	Wind shear
Wind speed		
X		
X-rays		
Y		
Yellow snow		

Z		
Z/r relationship	Zero datum	Zonal flow
Zone forecast product	Zone of aeration	Zone of saturation
Zoned embankment dam	Zulu time	

Appendix E: Full list of omitted keywords

The following terms represent the final list of omitted keywords not used in the custom-made dictionary classifier. The terms initially came from the NOAA glossary and were removed after manual data validation. For instance, "Aurora" was removed due to its connection to a false allegation of immigrants eating pets that circulated among extremist discussions, the bank/band was removed due to its ties with cryptocurrency, and the rainbow was removed due to its association with the LGBTQ+ community, who consistently remain targeted on extremist Telegram. Most of the remaining words were omitted due to broad generalizability within extremist communication.

Figure 7. *Dictionary of omitted keywords.*

Arid	Aurora	Bank
Band	Bar	Broken
Breach	Break-up	Brunt
Ceiling	Channel	Dam
Echo	Eye	Fair
Flow	Flood	Gauge
Inversion	Lag	Pressure
QPT	Rainbow	Range
Seas	Shower	Stable
Surge	Swell	TAF
Trace	Track	Visibility
WAA	Wave	XBT
Cross-section	Divide	Diversion
Divergence	Discharge	ITCZ
Stage	Streamer	Infiltration
Advisory	Convergence	Algorithm
Tide		