Growing online attention and positive sentiments towards carbon dioxide removal

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Abstract

Scaling up CO2 removal is crucial to achieve net-zero targets and limit global warming. To engage with publics and ensure a social licence to deploy large-scale carbon dioxide removal (CDR), better understanding of public perceptions of these technologies is necessary. Here, we analyse attention and sentiments towards ten CDR methods using Twitter data from 2010 to 2022. Attention towards CDR has grown exponentially, particularly in recent years. Overall, the discourse on CDR has become more positive, except for BECCS. Conventional CDR methods are the most discussed and receive more positive sentiments. Various types of users engage with CDR on Twitter to different degrees: While users posting little about CDR pay more attention to methods with biological sinks, frequently engaged users focus more on novel CDR methods. Our results complement survey studies by showing how awareness grows and perceptions change over time.

Keywords: Social media, carbon dioxide removal, public perception

1 Introduction

All climate scenarios for keeping global warming to well below 2 °C warming rely on some form of carbon dioxide removal (CDR). While scale and deployment methods may vary, fast and significant scale-up of CDR to several giga-tonnes by mid-century is required to limit global warming to stay within the Paris climate goals [74, 75]. However, public perception of and support for new innovations has a strong influence on the political and economic feasibility of their widespread adoption [4, 9, 45, 59].

It is now widely acknowledged that public attitudes will be crucial for the effective and ethical development and deployment of novel technologies, including CDR. The general public play many important roles, including determining policy mandates, paying for deployment via taxes, creating 'demand pull' for new innovations, acting as advocates or in direct opposition, and acting as direct stakeholders in local siting decisions [27, 59].

Many CDR methods are not widely known to the majority of members of the public, with knowledge and awareness of CDR remaining persistently low in survey studies [23, 74]. Therefore, public perceptions of these methods are in a formative phase and still subject to change [68]. Here, we complement the literature on public perceptions of CDR with a crucial, yet underutilised, methodology, by analysing discourses on the social media platform Twitter.

Social media platforms provide an open space for various actors to share or shape their positions [29] and which facilitates, defines, and amplifies debates [55]. They can be crucial conduits where public information and perceptions of novel technologies becomes shared, with risk issues becoming potentially amplified or attenuated in the process [43]. Hence, it is particularly important to analyse policy-relevant discourses that might be picked up by news outlets or opinion leaders and thus impact debates beyond social media.

Here, we consider how different CDR methods are perceived by Twitter users, as it will influence the prospects of scaling them up [7, 26, 59, 85]. We go beyond existing studies of this type to present a detailed analysis of the types of users posting about CDR on Twitter, to understand how reflective they might be of the wider public, and thus wider public debates.

Research on the public perceptions of CDR usually draws on quantitative data from representative surveys or choice experiments as well as qualitative data from focus groups, interviews or deliberative workshops. The vast majority of existing research on public perceptions of CDR is using survey methods [6, 10, 14, 18–22, 25, 26, 34, 38, 44, 47, 69, 78, 82, 84, 86], with a majority of studies on countries in Western Europe and North America [74]. The regions where public perceptions on CDR are studied least are often those where mitigation pathways suggest to scale-up the deployment of CDR the most [13, 77]. Therefore there is a need to incorporate methods which can provide a more global picture of CDR perceptions. Studies find low levels of awareness and knowledge of most CDR methods in representative samples of the studied populations [7, 11, 15, 17, 26, 31, 41, 62, 77]. Factors such as trust in government, science and companies, beliefs about tampering with nature, and perceived trade-offs with other climate mitigation approaches are important determinants for people's initial reactions to CDR [63]. Deliberative studies find that attitudes toward novel CDR techniques can be cautious, conditional, and often ambivalent [7, 24, 26, 80]. Amongst other things, some publics may be concerned that it only presents a provisional solution for high continued emissions [11, 51, 52, 63]. However, evidence also shows that campaigns which try to improve 'acceptance' by improving public awareness of understanding (the so-called *information deficit* approach) can be ineffective and sometimes counterproductive [61, 71].

Research on public perceptions should utilise a wide variety of methods to keep up with the rapid development of CDR [42]. Analysing historic social media data provides a complementary line of evidence to established social science methods in three ways: It allows retrospective analysis of existing data for almost any topic; it alleviates the challenge of studying the perception of technologies that are largely unknown to the public as individuals are sharing their non-elicited opinion; and it provides a higher temporal resolution than repeated large-scale surveys. Social media content is generated by people who are already aware of CDR and have a minimum level of prior knowledge on the topic and originated from a non-elicited motivation to publicly share a statement. We argue this kind of analysis can be particularly useful to gather early signals on how awareness and perception grow or later evolve. Especially for new and emerging technologies that are not yet well known among the broader population, there is typically already a large number of statements by people with a general awareness that can be analysed in a timely fashion [1, 15].

Each line of evidence comes with their own benefits and limitations. Surveys and other deliberative methods offer researchers greater control over how and from whom evidence is collected at a particular point in time. But low public awareness of many CDR methods can lead to methodological challenges. For example, there is a risk of *framing effects* as a result of the way a question is presented or introductory information on the topic that participants received to base their response on. Data-driven analyses of social media content, on the other hand, allow researchers to track attention to a topic and sentiment towards it continuously over time, adjust research questions, and keep analyses updated. One of the main limitations is that the analysis is based on opinions from an essentially self-selecting group who may comprise a higher proportion of experts and those with a potentially vested interest in the topic. Therefore, we go beyond existing studies to empirically interrogate the proportion of users who fall into this category. The choice of platform will also influence the results, and is thus influenced by factors such as data availability. As such, we argue that social media analysis can provide a useful complement to other social science methods [30], rather than a replacement [81].

In this paper, we analyse past trends of debates around ten CDR methods on Twitter since 2010 and extend prior work [58] by comparing results for different user groups, including more recent data, and by scrutinising temporal developments. We pose the following research questions: What can we learn from social media data about perceptions of CDR? How do awareness and attitudes—as expressed by users online—change over time?And which types of users engage in CDR debates on social media? We use comprehensive keyword extraction based on expert inputs to retrieve posts about ten key CDR methods identified in the literature [54] and analyse them using machine-learning models for sentiment analysis. In this way, we provide novel insights, such as comparative tracking of attention and sentiment to CDR methods over time; showing that many users posting on CDR are not 'professional CDR communicators' or frequent tweeters, thus providing evidence in response to persistent concerns about Twitter analyses being strongly influenced by private interests; and linking findings from perception studies based on focus groups and questionnaires with high-resolution data from Twitter to illustrate how different lines of evidence integrate to form a more detailed understanding of public perceptions.

2 Results

Our analysis is based on 569,103 English-language tweets by 197,061 users that were retrieved using 54 method-specific queries [58] in the academic Twitter search API for ten CDR methods: *Conventional CDR* including soil carbon sequestration, ecosystem restoration, afforestation/reforestation, and blue carbon, as well as *novel CDR methods* including direct air capture (DAC, including DACCS), enhanced weathering, ocean fertilisation, ocean alkalinisation, biochar, and bioenergy with carbon capture and storage (BECCS). We also include a set of queries on general terminology related to greenhouse gas removal (GGR general) to capture the

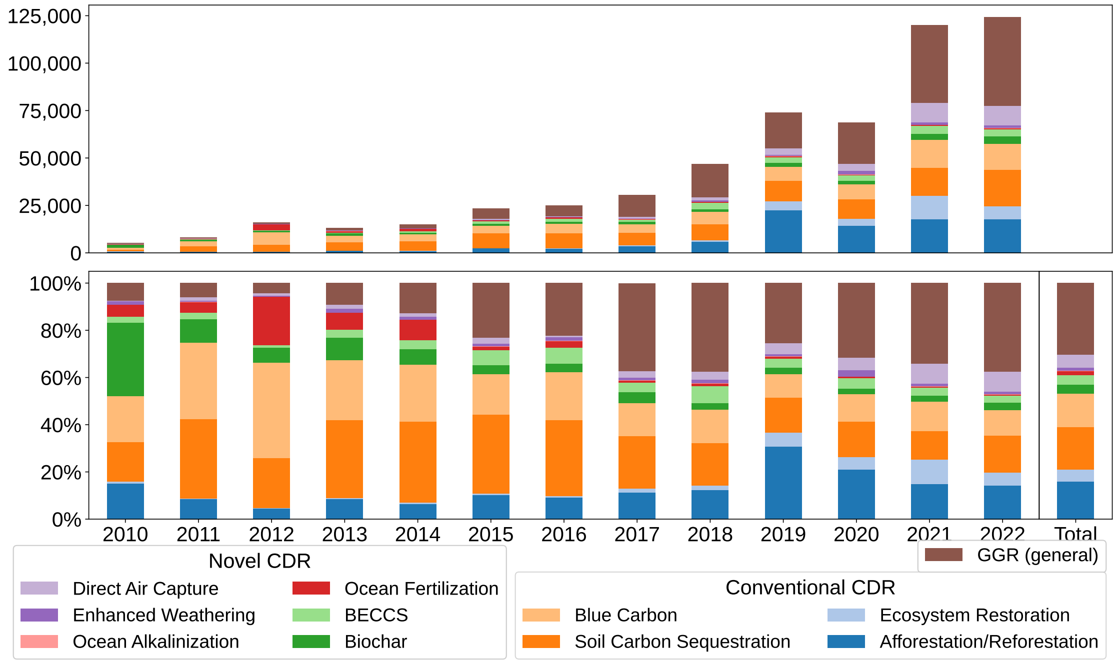


Figure 1: Tweet counts per CDR method per year. *Top panel:* Absolute tweet counts; *Bottom panel:* Share of tweets per year and overall.

changing prevalent terms over time [65] and some communities prefering to use GGR as it refers a wider range of negative emission technologies. Throughout this article, we will refer to this set of queries as 'general GGR' to clearly distinguish it from the method-specific queries. Overall, our corpus of CDR tweets is small in comparison to the millions of tweets that directly mention 'climate change' [33].

Attention to CDR has grown exponentially, mainly driven by conventional CDR and general GGR topics. The overall growth is shown in Figure 1 by the annual number of tweets per CDR method and the respective proportion. The CDR method mentioned in a tweet is determined based on the query that tweet was retrieved by. Attention to CDR was relatively low with less than 25k tweets per year until 2016, from where it grew to over 120k tweets annually, corresponding to a median annual growth rate of 32% (with standard deviation of 0.36). This growth is largely driven by a strong increase in tweets using general terms related to negative emissions. This is faster than the growth of tweets on climate change (28% annual growth on average) and even all English-language tweets on the platform (17%) [66].

We observe accelerating growth in attention towards CDR in recent years. In 2018 the annual growth in CDR tweets was 49%, and in 2019 59%. In 2020, the number of tweets slightly declines with the onset COVID-19 pandemic, similar to the wider climate-related discourse on Twitter [35, 39, 48, 64, 66, 72, 73]. In 2021, attention to CDR even grows by 76%, which is 62% of the pre-pandemic peak levels in 2019. Numbers remain at that level in 2022.

The vast majority of tweets (55% of all tweets; 77% excluding the GGR category) covers conventional CDR methods. Novel CDR methods, which are less developed, are only mentioned in 17% of all tweets (23% excluding GGR). Carbon capture and sequestration (CCS) is often

Table 1: Number of tweets by users with 1–2 (infrequent), 3–50 (moderate), and more than 50 (frequent) tweets in our corpus. In parentheses, we show the deviation of the share of tweets per user group per technology from the share of tweets per user group overall ('Total' row). Numbers may not sum to the total shown, as tweet may cover more than one CDR method. CCS and Methane removal only shown for comparison.

CDR Method	Infrequent	Moderate	Frequent	All
GGR (general)	52,783 (−2%)	73,661 (−2%)	46,767 (+3%)	178,939 (32%)
Direct Air Capture	6,354 (−11%)	13,996 (+1%)	11,059 (+11%)	32,087 (6%)
Enhanced Weathering	1,530 (−11%)	2,778 (−6%)	3,092 (+18%)	7,514 (1%)
Ocean Alkalinisation	127 (−15%)	331 (−2%)	340 (+19%)	807 (0%)
Ocean Fertilisation	4,489 (+10%)	4,732 (0%)	1,350 (−11%)	11,071 (2%)
Biochar	4,755 (−10%)	9,639 (+1%)	7,416 (+10%)	22,170 (4%)
BECCS	3,247 (−17%)	9,517 (−2%)	10,159 (+20%)	23,227 (4%)
Blue Carbon	24,518 (−2%)	39,414 (+4%)	17,373 (−3%)	85,207 (15%)
Soil Carbon Sequestration	26,420 (−6%)	51,178 (+6%)	25,825 (+1%)	106,022 (19%)
Ecosystem Restoration	12,531 (+11%)	12,324 (−2%)	4,411 (−8%)	29,887 (5%)
Afforestation/Reforestation	43,054 (+15%)	35,187 (−5%)	13,000 (−9%)	93,805 (16%)
Total	176,527 (31%)	243,240 (43%)	132,260 (23%)	569,103
CCS	*43,062 (−10%)*	*90,035 (+1%)*	*65,209 (+9%)*	*204,155*
Methane Removal	*2,124 (+17%)*	*1,866 (0%)*	*284 (−17%)*	*4,391*
Total (incl. CCS&MR)	*219,837 (29%)*	*329,312 (43%)*	*191,735 (25%)*	*763,800*

confused with or mistaken for CDR, hence we do not include it in our analysis. For comparison, we retrieved 204,155 tweets, which would make up 14–30% of annual tweets in the extended corpus, and included respective numbers in Table 1.

The shift in attention provides evidence for the emergence of CDR as a substantive discourse in climate change mitigation. Throughout the beginning of the last decade, the overwhelming number of CDR tweets were technology-specific. The general discussion on GGR only emerged later and has become the largest individual discourse after 2017 (with the exception of 2019). This rapid growth of tweets referring to general GGR concepts, such as 'carbon dioxide removal', 'greenhouse gas removal', or 'negative emissions' coincides with growing recognition of the role for CDR in climate policy. It is important to note, that the growth of tweets on general GGR is on top of CDR-method-specific tweets.

The attention trends towards individual CDR methods vary substantively and is dominated by conventional CDR. 2019 has seen a stark increase in attention to afforestation/reforestation (30% of annual tweets) and ecosystem restoration (5–10%). The small proportion of tweets on novel CDR are mainly comprised of direct air capture with 5% of all tweets in the observed time-frame, whereas the proportion was strongest in recent years (up to 8%). BECCS and biochar, which together make up about 10% of all CDR tweets, are the second most mentioned novel CDR methods. Ocean fertilisation only briefly received any notable attention around 2012 (3,318 tweets, 20% of tweets in 2012), but fell to very low levels after 2014 (540 tweets annually on average, 0–3% of annual tweets).

Moderate and frequent users pay more attention to novel CDR methods than infrequent users, who focus more on biological sequestration methods. We assign users to one of three groups based on their respective total number of CDR tweets in our corpus. We perform a comparative analysis of different user groups, for which we split the dataset into tweets by *infrequent users* who only tweet once or twice about CDR, *moderate users* with up to 50 tweets on CDR, and *frequent users* with more than 50 tweets in our corpus. This allows us to distinguish patterns driven by users that are very interested in or familiar with the topic—possibly even over an extended period of time—and those that may be driven by external factors. These external factors may be news articles or announcements that prompted a large set of users to tweet about CDR once or twice.

The top 1% of users, frequent users with more than 50 CDR tweets, account for 23% of all tweets, moderate users for 43%, and infrequent users for the remaining 31% of CDR tweets (see Table 1 for tweet counts or Tables S3 and S4 in the supplemental material for user counts). We use the deviation of the proportion of tweets per CDR method by each user group from this baseline distribution as a measure of prevalent awareness and interest.

The number of tweets by infrequent users is well above the average for conventional CDR methods, in particular afforestation/reforestation (+15% above baseline; 46% of tweets on afforestation/reforestation are posted by infrequent users), ecosystem restoration (+11%; 42%), and ocean fertilisation (+10%; 41%). The number of tweets on blue carbon and general GGR are almost at baseline level (-2%; 29% each). The share of tweets by moderate users is very close to the baseline for all CDR methods. The proportion is highest for soil carbon sequestration (+6%; 48%) and blue carbon (+4%; 46%), and lowest for enhanced weathering (-6%; 37%) and afforestation/reforestation (-5%; 36%), showing no clear trend to favouring conventional or novel CDR. Frequent users, on the other hand, clearly dominate the conversation on novel CDR methods, most notably BECCS (+20%; 44%), enhanced weathering (18%; 41%), DAC (+11%; 34%), and biochar (+10%, 33%). They are slightly under-represented on the most popular conventional CDR methods, namely afforestation/reforestation (-9%; 14%) and ecosystem restoration (-8%; 15%).

These observations align with findings in survey studies that show higher awareness amongst participants of afforestation and restoration projects for carbon removal than for BECCS, enhanced weathering, or DAC [12, 16, 74]. Interestingly, these methods are those with the highest proportion of tweets by frequent users: BECCS (44% of BECCS tweets are from frequent users), enhanced weathering (41%), direct air capture (43%), and biochar (33%) and are amongst those that receive the lowest attention overall (less than 15% of all tweets). This suggests that the small group of frequent users are the main drivers behind the attention towards lesser known CDR methods. Similarly, better known CDR methods are picked up by a wider audience as exhibited by higher share of tweets by infrequent users and highest shares of infrequent users for these methods.

Conventional CDR methods are generally perceived more positively and ocean fertilisation the most negative. We automatically classify the sentiment, i.e. the tonality, of each tweet using pre-trained transformer models to count how often a CDR method is mentioned in a predominantly positive or negative context. We validated the sentiment classification by comparing several state-of-the-art pre-trained models and a dictionary-based approach to each other and with a manually annotated set of 400 CDR tweets (see methods). For most CDR methods and tweets with general GGR keywords the share of positive sentiments is larger than the share of negative sentiment, with the exception of ocean fertilisation, where negative sentiments prevail. The latter exception could be due to discussion over the effectiveness and negative side effects of ocean iron fertilisation after controversial field experiments [24, 49]. Conventional CDR methods that are generally better known are mentioned most frequently in positive contexts, most notably afforestation/reforestation (37%, 12p.p. above average) and ecosystem restoration

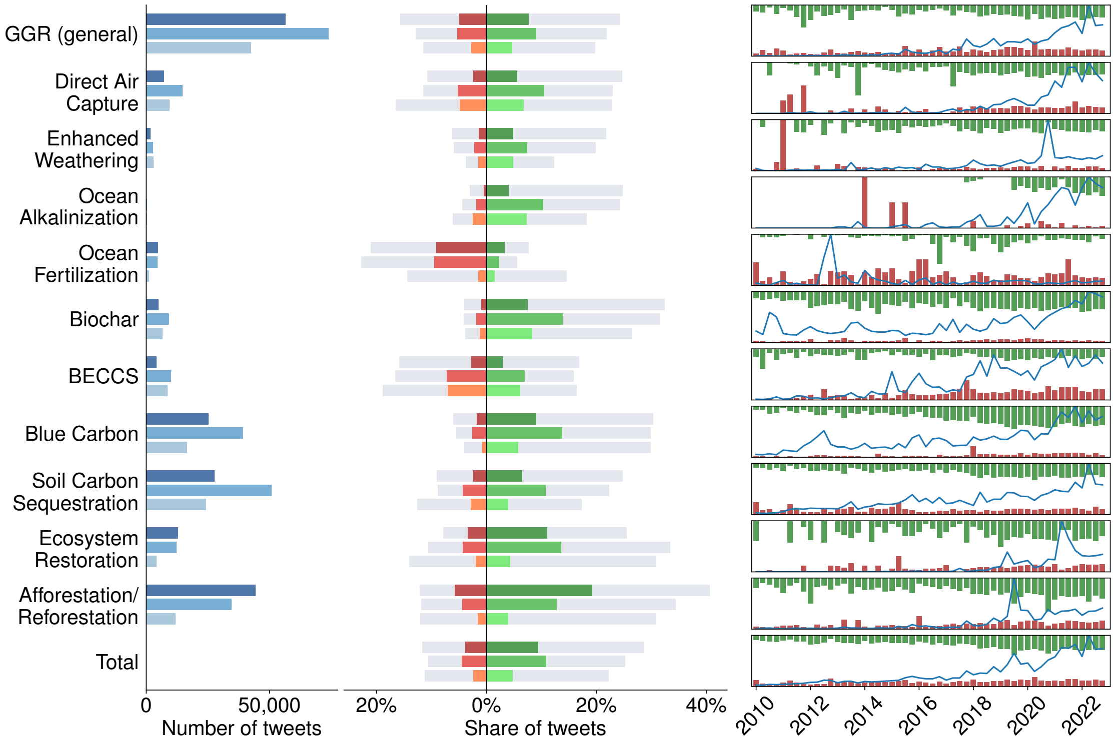


Figure 2: Sentiment in CDR tweets. *Left panel:* Number of tweets per CDR method and user panel, each triplet of bars refers to tweets by infrequent users (1–2 CDR tweets per user, darkest), moderate users (3–50 CDR tweets), and frequent users (over 50 CDR tweets, lightest). Bars for 'Total' omitted for readability. *Middle panel:* Share of tweets with mainly negative (red shades, growing to the left) or positive (green shades, growing to the right) sentiment. Proportion is relative to the total number of tweets per method. Grey shade indicates the respective proportion relative to the number of tweets per method per user panel. *Right panel:* Share of tweets with mainly positive (green bars from the top) and negative (red bars from the bottom) sentiment over time (quarterly resolution, proportion relative to total number of tweets per method per quarter). White space in between reflects neutral tweets or missing data. Blue line plot shows the absolute number of tweets per method per quarter.

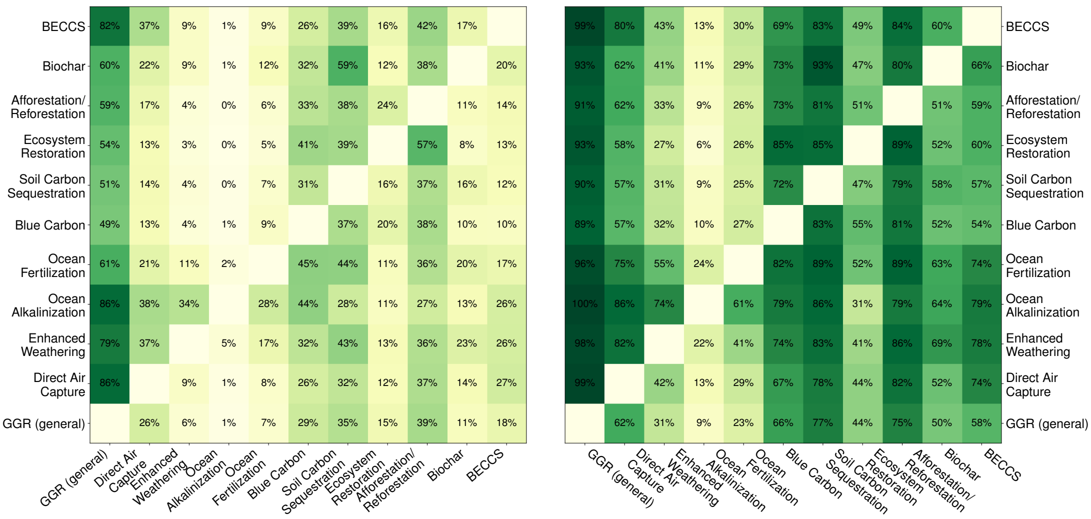
(29%). Biochar, blue carbon, and enhanced weathering are overall perceived most positively, because they have both high shares of positive tweets and the lowest shares of negative tweets. For novel CDR methods like BECCS and DACCS, the share of negative mentions is higher, but still larger than the share of positive sentiments. Overall, 24.9% of all tweets have a positive sentiment and only 10.7% are classified with a negative sentiment.

Frequent users tend to communicate more neutrally than moderate and infrequent users. Figure 2 shows the share of tweets with positive and negative sentiments by user group. Infrequent users have the least number of neutral tweets with respect to their sentiment (60%), followed by moderate users (64%), and frequent users (67%). These differences are mainly due to varying shares of tweets with a positive sentiment, as the proportion of tweets with a negative sentiment are very similar for all groups (around 11%). This pattern holds true for many CDR methods. However, infrequent users tend to tweet most positively about biological sequestration methods such as afforestation/reforestation and ecosystem restoration. Biochar, blue carbon, and enhanced weathering are overall perceived most positively (highest shares of positive tweets with lowest shares of negative tweets). Ocean fertilisation is the only CDR method where frequent users have a higher share of positive and notably lower share of negative tweets than the rest. This is similar for enhanced weathering, except there frequent users have the lowest share of positive and negative tweets. These users that tweet most often about CDR appear to be more sceptical about direct air capture (16% of tweets by frequent users are negative, compared to about 11% for the others), soil carbon sequestration (12.6% vs. 9%), and BECCS (19% vs. 16%) than infrequent and moderate users, as their share of negative tweets is notably higher for each respective method. Ecosystem restoration presents the strongest differences in sentiments between all groups. Moderate users have the highest share of positive tweets (33%, 14% overall) and infrequent users the lowest share of positive tweets (26%, 11% overall). At the same time, frequent users have the highest share of negative tweets (13%, 2% overall) and infrequent users the lowest share (8%, 3% overall).

The share of positive tweets increases over time for most CDR methods, except for BECCS. On average, the number of tweets grows by a factor of 1.32 (median) each year. This growth factor does not deviate much year-to-year (standard deviation 0.36), but we observe highest growth factor leading into 2018 and 2019 with a temporary decline in 2020. Overall, the median growth factor of tweets with negative sentiment (1.49) is slightly higher than for positive (1.46), while the absolute number of negative tweets remains lower (there are 62,162 with negative and 143,530 tweets with positive sentiment). The growth factor for neutral tweets is slightly lower for infrequent users (1.25) than for moderate users (1.28) and frequent users (1.27). Across all groups, the number of tweets with negative or positive sentiment grows faster, on average, than for neutral tweets, but with a higher standard deviation (mean deviation for positive: 0.76, neutral: 0.43, negative: 0.71). The number of tweets with a positive sentiment by infrequent users and moderate users grows faster than for negative tweets (1.34 for positive vs. 1.32 for negative and 1.56 vs. 1.32). For frequent users, this trend is reversed (1.30 vs. 1.38).

As mentioned earlier, this still results in the same proportion of negative tweets (11–12% for all groups, grey bars in Figure 2). The strong peak in attention to ocean fertilisation in 2012, was mainly driven by infrequent and moderate users and remains at a low level for all groups ever since. For all groups and CDR methods, the proportion of neutral tweets shrinks over time, suggesting that the public debate (on Twitter at least) may be becoming more emotional. We consider tweets on a method to become more polarised when the growth factor of tweets with positive or negative sentiment exceeds that of neutral tweets. Biochar and blue carbon are becoming more polarised across all user groups. For frequent users, soil carbon sequestration is also becoming more polarised. For infrequent and moderate users, afforestation/reforestation, BECCS, and GGR (general) show the same trend, and for moderate users additionally enhanced weathering. Overall, the net sentiment—the difference in daily shares of positive and negative tweets—is slowly growing at an average rate of 0.02% per day, except for tweets on BECCS (-0.01%).

Tweets by the top 1% of users have double the impact than those from users with only one or two tweets on CDR. Infrequent users (78% of all users), on average, posted 1.15 tweets, of which each, received 4.6 likes, was retweeted 0.4 times, and replied to 1.5 times. Moderate users (20% of all users) posted 6.1 tweets, and each tweet received 7.2 likes, was retweeted 0.5 times, and replied to 2.4 times on average. Tweets by frequent users (1% of all users), posted 101.1 tweets, where each on average received 10.5 likes, were retweeted 0.7 times



(a) Users with 3–50 tweets (B)

(b) Users with >50 tweets (C)

Figure 3: Overlap of users with tweets on multiple CDR methods. Underlying absolute overlaps are symmetric (per pair of technologies, the number of users with at least one tweet on each technology), the shown relative overlap is normalised by the number of users per row (number of users per technology).

and replied to 4 times. This shows that frequent users not only post more often, but each tweet received more likes, replies, and retweets than moderate users and double the amount than for tweets by infrequent users. Although infrequent users posted 31% of all tweets in the corpus, they only received 19% of all likes, 23% of replies, and 18% of retweets. Moderate and frequent users received more than double the absolute amount of likes and retweets. While moderate users posted 43% of all tweets, they received 43% of all likes and replies and 41% of all retweets. Frequent users posted 23% of all tweets and received 36% of all likes, 32% of replies, and 39% of retweets. This clearly shows, that posts by these users reach more people and are over-proportionally valued. For more details, see Table 1 or the appendix (Table S3 and Table S7).

In order to get a better understanding of the user groups, we selected a random sample of 100 users from each group (300 in total) and had two annotators label those as firms, business people, communications, NGO, policy, private, or science based on the user name, handle and description (see Methods for further details). We find that a majority of users can be attributed to a specific category (74% of infrequent, 83% of moderate, and 87% of frequent users). The largest category are private accounts (17% overall), followed by communications (13%), NGOs (13%), business people (12%), firms (11%) and science (11%). The share for these categories per user group is very similar. Only 4% of users were categorised as policy-related. The share of private accounts decreases with increased number of tweets (20% of infrequent users, 17% of moderate, and 13% of frequent users), for businesses and business people, shares only very slightly decrease. Conversely, the proportion of frequent users categorised as NGOs (6%, 16%, 18%), science (8%, 10%, 15%), and communications (11%, 14%, 15%) grows with tweet frequency. This finding suggests that frequent user accounts are more often run by experts or (semi-)professional communicators.

The most common overlap in user attention are biochar and soil carbon sequestration as well as ecosystem restoration and afforestation/reforestation. We found that Twitter users that regularly tweet about CDR are interested in several topics. In order to analyse user attention across multiple methods, we count the number of tweets by users that tweet on each pair of CDR methods. These overlaps, normalised by the number of tweets on the method per row are shown in Figure 3. As frequent users post more tweets than moderate users, the topical overlap is generally higher overall. Tweets on GGR in general have the highest overlap with all other topics, which is to be expected. This is followed by soil carbon sequestration, afforestation/reforestation, and blue carbon. To an extent, this effect can be attributed by the generally higher number of tweets on these CDR methods. Furthermore, tweets may refer to more than one CDR method and thus influence the aggregate counts. We account for these biases (see appendix for further details) and still observe a pronounced overlaps between several methods: There is a strong overlap in attention between ocean fertilisation, ocean alkalinisation, and enhanced weathering. These methods are similar in the sense that natural processes are artificially accelerated. Pronounced overlaps between BECCS and DAC as well as enhanced weathering and biochar reveal interest in a set of technologies for capturing CO_2 from airstreams or long-term storage on land.

3 Discussion

In this paper, we present an analysis of tweets on CDR and their sentiments as metrics for attention toward ten specific CDR methods and toward CDR in general. This is one means of understanding public mood toward these methods, and complements existing literature on perceptions of CDR which mostly uses other forms of data. Beyond providing insights into public perceptions, social media analyses capture and summarise the wide spectrum of arguments and opinions on a particular topic. Especially for novel topics such CDR, it is important to be aware of this spectrum as it can influence political debates in the future. Social media platforms provide an open space for various actors to share or shape their positions on potentially controversial topics [29]. This facilitates, defines, and amplifies (policy-relevant) debates [55], which are eventually picked up by news outlets and decision makers. Public perceptions research on novel innovations, including but not limited to CDR, comes with challenges. In the following, we discuss how our approach complements existing public perception research. We also discuss advantages and limitations of both social media analysis and other social science approaches to tackle these challenges.

We find that attention to CDR on Twitter has increased strongly, driven mainly by conventional CDR methods and general CDR. We also see that users tweeting more frequently about CDR tend to focus more on novel CDR methods, whereas infrequent users tweet more about conventional CDR methods. Frequent users are more often (semi-)professional communicators with a higher impact, measured by how many likes, retweets, and replies their tweets receive. However, counter to our expectations, a significant proportion of tweets came from infrequent users. Most of the methods are tweeted about more often in a positive than in a negative context, with increasing tendency over time. Frequent users communicate more neutrally.

We see from the results that sentiment toward nearly all CDR methods, and CDR in general, is trending positively as awareness and engagement grows. This is an important insight because it suggests that public discourse is evolving gradually in a generally favourable way toward most CDR methods—important for understanding whether there is broad 'social licence' to support policy-making in support of these techniques. That said, there are two exceptions to this trend. First, ocean fertilisation sentiment remains strongly negative over time, suggesting that great caution should be taken when considering whether to support it in policy [24]. Second, BECCS appears to be controversial and potentially polarising, with a gradual increase in negativity over the past 5 or so years and now equal shares of positive and negative sentiment. Thus BECCS proposals would likely benefit from additional context-specific research in the relevant locality, before decisions requiring public buy-in are made. Thus, timely tracking of these debates can help identifying early signals on how perceptions evolve. This can inform public engagement to ensure the rapid and socially accepted scale-up of climate solutions, such as novel CDR technologies.

Aligning existing public perception literature with our analysis. Our analysis shows that social media analysis offers a complementary line of evidence to other social science methods that measure public perceptions of CDR methods, such as surveys, focus groups, or expert interviews. In the following, we compare our results to findings in this literature.

Studies of public perceptions have found that participants exhibit a preference towards CDR methods perceived as more 'natural', yet definitions of what constitutes as 'natural' are often vague. Respondents generally prefer familiar land-based methods (afforestation/reforestation in particular) over others [31, 37, 41, 79, 83, 85]. This is reflected in our data, where the largest number of tweets are on afforestation/reforestation, soil carbon sequestration, and blue carbon, which also confirms findings from other Twitter-based studies [28, 58]. Conversely, ocean-based CDR methods, ocean fertilisation in particular, are often perceived as most risky [1, 5, 41] due to their perceived uncontrollability and irreversibility [8, 24]. This effect is expressed in our analysis by ocean fertilisation being the method with the highest share of tweets with a negative sentiment. However, frequent users, when compared to infrequent and moderate users, pay less attention to ocean fertilisation, have a much lower proportion of negative tweets, and the highest share of positive tweets on that method. This suggests that frequent users evaluate the risks involved differently compared to others. Surveys and expert interviews find that domain experts in CDR are often ambivalent when asked for their stance on specific CDR methods [76]. Assuming that frequent users have more expertise about CDR and some correlation between stance and sentiment, our Twitter dataset allows for a similar conclusion. Even though it is almost impossible to control for their level of expertise on a particular topic or the context that led them to share their opinion or a piece of information, the analysis of social media data is particularly useful to gather early signals on how awareness grows and perceptions evolve.

Twitter data as an indicator for people's 'awareness of' CDR. Twitter data, as such a large and global dataset, can fill gaps in knowledge relating to people's awareness of CDR methods, since the survey literature is geographically and temporally patchy [17, 26]. Yet apart from some subtle differences, this global and longitudinal dataset broadly supports findings from existing national surveys. For example, we find more attention to more familiar land-based methods than novel methods [11, 41]. In addition, enhanced weathering receives the second-lowest attention, in line with survey studies which find that people are particularly unfamiliar with this and other novel CDR methods [15, 17, 26, 77]. That said, the analysis here was limited to English-language tweets, thus the similarity in findings may simply reflect the longstanding bias in public perceptions surveys to Western industrialised nations.

Interestingly, we do not observe strong variations in attention between different user groups, which may run counter to expectations, since we might expect the high number of 'don't know' responses in surveys to be reflected by a lower number of tweets on that method by infrequent users; yet we find that the distribution across user groups is fairly even.

Perceptions of topics with low prior knowledge. A key challenge for public perceptions research is the low awareness of many specific CDR methods and the need for scaling up CDR deployment to reach the Paris climate targets. For our social media analysis, this is manifested in a low number of tweets. For example, there are only few tweets on ocean alkalinisation, which caused some metrics to deviate more strongly. In surveys or interviews, low levels of awareness mean that participants often hear about CDR methods for the very first time when being asked. This may lead to framing effects: the answers that participants give can depend on how a technology was described to them by the survey. Careful study design tries to control for or minimise these effects and methods to un-frame public engagement have been explored [6, 60].

31% of tweets in our dataset come from users that only tweet once or twice.

Thus our results suggest that social media data does not just capture perceptions of experts, advocates or other interested parties, but also reflects the views of those who might have less day-to-day involvement with CDR, and can therefore be expected to have less prior knowledge. For example, their tweet may have been provoked by some external factor, such as a news article. It is an open research question how familiarity might relate to user's sentiments and how different user groups shape the overall results.

Given the ubiquity of data analysis frameworks, it is very important to critically reflect whether a particular method is actually applicable in a way that allows robust and significant findings. Especially automated annotations using pre-trained machine learning models have to be verified on the dataset at hand. We manually annotated 400 tweets and compared several state-of-the-art pre-trained models and a dictionary-based model. Using these labels for validation, we selected the model from which we used the labels. We also found only a fair agreement between annotators, indicating how challenging this task is even for humans.

Understanding 'who' is surveyed. When comparing results across studies and approaches, it is important to consider the context and who's voice is actually included. In particular, there is no fixed definition of *the public* or who *interested parties* are. Social media constitutes one forum of public debate and can thus be seen as one of many publics. While it is very different from representative samples of a general population, both may be equally important for shaping future public perceptions on CDR, as public debates will influence opinions in the general population about the yet not very well known technologies. People also communicate differently depending on whether they are in a *professional* or *civic* role, which might change over time [27].

Surveys, experiments, and other deliberative approaches for elicited information operate within an artificial environment, allowing researchers to control and analyse the context. Usually, they aim to gather opinions from a representative sample of a general population, for example using recruitment quotas, and demographic variables to learn about explanatory factors for differences in the sample. At the same time, however, there is a clear trade-off between breadth and depth, with deliberative and discursive studies usually limited to fewer than 100 participants with low geographic dispersion, whereas survey studies can achieve sample sizes in the 1,000s, but are often limited by resources to a defined geographic area (for instance, one or more countries) [74].

Our Twitter analysis, on the other hand, is based on almost 200 thousand users, of which 40 thousand tweet regularly about CDR and over 1,000 posted more than 50 tweets on CDR in the observed time-frame. However, our approach leads to little control over whose voice is considered: The query strategy only includes English-language keywords and was only gathering data from Twitter (as opposed to multiple social media platforms). In this way, the underlying data will be biased toward countries with a larger proportion of English speakers, and toward the minority of the global population who use Twitter to more often publicly share their thoughts publicly on Twitter [2, 50, 53]. The data available through the academic Twitter API does not include demographic information—aside from self-reported geographic location of the users and tweets—to reliably quantify potential biases in that respect. Finally, it is worth noting that there is no way of conclusively validating whether the tweets analysed all came from real human beings. A recognised issue with Twitter analysis is the potential prevalence of bots (automated agents), which could skew the data [32, 36]. We attempted to control for this by excluding tweets from exceptionally high-volume posters (see Methods and Appendix B). However, this issue again highlights that Twitter data should not be used as a straightforward proxy for public sentiment, but instead as a complementary method, for instance to flag emerging controversies so that more in-depth, targeted research can then be conducted.

Tracking perceptions over time. Repeating large-scale surveys or organising focus groups to track perceptions over time would be a very time-consuming and costly endeavour. In many cases, these factors are prohibitive for tracking changes in perception over time with (frequent) updates. To our knowledge, only one large-scale survey on CDR (BECCS, DAC, enhanced weathering) from 2012 [86] was repeated in 2018 [15]. Our analysis shows similar trends (see Figure 1, Table S5), where attention to these three CDR methods is growing overall, but proportionally less than the other CDR technologies in our analysis.

The advantage of social media studies is, that such analyses can be repeated cost-effectively to track the development of discussions. Furthermore, they can also be conducted retrospectively and at relatively fine-grained resolution. In this way, the temporal granularity of social media data means that it can act as a sort of 'early warning' system for emerging controversies. A caveat though is reliable access to data. Unfortunately, there are now uncertainties over the continued use of Twitter as a longitudinal indicator, since changes to the platform in 2023 resulted in a substantial shift in the user base thus a discontinuity. It remains to be seen how recent restrictions to access data on Reddit and Twitter will allow for continued research based on social media data [46]. Even if full access for researchers would still be possible, the community may change and thus make it challenging to compare data from different time-frames.

Towards using multiple complementing lines of evidence for public perception research. Given their different strengths and limitations, social media data and other social science approaches to study perceptions of CDR can complement and inform one another. Twitter data can provide longitudinal insights, which most other techniques cannot do, because repeating surveys and deliberative methods tends to be too costly and logistically complex. Surveys and focus group results have already been used in mixed-methods study designs for triangulating and complementing results [26]. Social media analyses could be integrated with established social science methods in similar ways: Surveys could be used as a way to inform the design of or calibrate social media analyses. For example, some survey results may open further questions that cannot be answered using the collected data. From this starting point, social media data could then be used to fill knowledge gaps by either collecting historical trends up to the point of the study or add details and context to selected aspects. Similarly, findings from a social media study could be used inform the study design of a survey ahead of time. Another scenario to link approaches is to use social media data as a source for tracking trends at a higher resolution and perform conventional surveys to control for potential biases. There are similar potentials for enhancing public perception research in qualitative studies. For example, comments on surveys or statements from focus groups could be matched to posts on social media. There, responses or the context in which respective posts appear in may provide additional details and aspects. The number of views, votes, or replies to a particular statement might also inform researchers about whether the comment by a single respondent in a survey is supported by a wider audience. As these ideas for reciprocal stimulation show, future work can integrate these methodological approaches in different ways to further our knowledge about public perceptions of CDR.

4 Methods

In this work, we analyse a large set of 570k tweets on ten carbon dioxide removal (CDR) methods and greenhouse gas removal (GGR) in general. We further enrich the tweets with sentiment scores and categorise users by their characteristics. Finally, we compare the findings from our in-depth analysis with results of published survey studies.

Data procurement. The corpus of 569,103 tweets by 197,061 users was compiled by querying the Twitter academic full-archive search API (v2) on January 16, 2023 with 54 queries (see Section A and Table S1 in the appendix) These queries are derived from a prior study on geoengineering on Twitter [58], and are based on a comprehensive set of keywords from the CDR literature [54, 75] as well as feedback from experts. We appended `-is:retweet lang:en` to each query, so that results are limited to 'original' English-language tweets only.

The queries are grouped into ten CDR method categories and a category for general greenhouse gas removal terms. Each tweet is automatically annotated with the method category of the respective query. Most tweets (517,063; 91%) responded to queries from only one category, 43,485 (7.6%) to two categories, and 5,654 (1.1%) to more than two categories. Although the first tweet on Twitter was posted on March 21, 2006, we did not match any CDR tweets before February 9, 2007; until the end of 2009, 7,066 tweets on CDR were posted. In light of the low relevance of the topic in the early years of the platform, we limit our analyses and reporting to the time period 2010 to 2022.

CDR method categorisation. We use the method-specific queries to tag tweets. Based on the query a tweet was retrieved by, the respective CDR method (or the general GGR category) is assigned. Note, that a tweet may have been retrieved by more than one query, even across different methods. In aggregations, we count only distinct tweets (by their Twitter ID) per method, but the same tweet might be counted for multiple methods.

User groups. Following our initial exploration of the corpus, we noticed several users who posted an exceptional amount of tweets, which are often even very similar. Based on a closer analysis of the distribution of the average number of tweets sent by a user per day and manually validating random samples, we determined this to be spam-like behaviour. Therefore, we exclude 17,076 tweets (3% of the corpus) by 2,646 users (1.3%) who, on average, posted more than 100 tweets per day (see appendix for more detail).

Further, we categorise users based on their number of tweets in our corpus. This allows us to attribute findings to users that only posted one or two tweets on CDR in the entire 13 year time-frame ('infrequent users', n=153k, 78%), tweet several times about CDR (3–50 tweets 'moderate users', n=40k, 20%), and 'frequent users' who tweet very actively (more than 50 tweets, n=1308, 1%).

The lower bound is based on the average number of tweets per user (2.89) across the entire corpus, so that the first group contains all below-average users. The upper bound is based on the 99th percentile of tweet counts per user to capture the top 1% of users who tweet on CDR.

Sentiment classification. We use sentiment scores, which refers the tonality of a written text, as a proxy of how well a given CDR method is perceived. Many studies based on social media data use the NRC lexicon [56, 57] to compute scores based on the existence of keywords in the text. In this study, we rely on two state-of-the-art and more robust classifiers [3, 40], that are pre-trained on large and widely used datasets [67, 70]. These transformer-based classifiers are trained on tweets, even a subset of climate-related tweets, and other short texts. These classifiers are shown to perform very well on test data.

To verify the applicability of the pre-trained classifiers in our domain, we had three annotators label the sentiment (positive, negative, neutral) of 400 randomly selected tweets. Our inter-rater agreement (Fleiss' kappa) was $\kappa = 0.40$, which is only a slight to fair agreement. Given the large divergence in human annotations and results of both classifiers performing producing much more similar labels than human annotators, we decided to only report on the results of the classifier by Cardiff NLP [40] with results of the other classifier being essentially the same.

Manual user category annotation. In order to better understand who the users are, two annotators independently annotated 300 randomly sampled users, 100 from each user group. Each annotator was asked to assign each user based on their profile to one (or two) of the following categories: *firms* (official company and business association accounts), *business people* (individual users with central roles in corporations, advisors, self-employed or business owners), *communications* (news portals, journalists, and bloggers), *NGO* (official NGO accounts and proponents of social movements), *policy* (government accounts, officials, politicians and policy advisors), *science* (educational or research institutions, lecturers, students, and scientists), *private* (users that predominantly introduce themselves as private persons), and *other/unclear* (does not fit any other category or unclear or no description). In edge cases, annotators were allowed to add a secondary category. Inter-annotator agreement was moderate with a Cohen's kappa score of 0.54. When also counting matches with the secondary category agreement was substantial with a Cohen's kappa score of 0.67. For the final shares reported in the paper, the annotators resolved disagreements in a joint discussion.

Systematic literature search. We carried out a systematic search of existing public perception research of CDR in the English-language academic databases Scopus and Web of Science. We found 39 papers on 'public perceptions', 'attitudes', or 'opinions' on CDR published before 2023 [74]. Articles on related technologies, such as CCS, bioenergy (without CCS), forestry, and ecosystem restoration, were only included if they specifically discuss those in the context of removing carbon as defined in this paper. The most common methods for assessing public perception of CDR include surveys, questionnaires, focus groups, interviews, and deliberative workshops. Articles solely relating to expert perceptions were not included.

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Author contributions

Methodology, data procurement, formal analysis, visualisations, writing (original draft): T.R.; Twitter query development, user categorisation: F.M.-H.; Literature review: E.C.; Funding acquisition, supervision: J.C.M.; Conceptualisation, writing, review, and editing: all authors

Competing interests

All authors declare no financial or non-financial competing interests.

Data availability

The Twitter corpus compiled for this publication is (in part) available on Zenodo and can be accessed via this link: https://doi.org/10.5281/zenodo.10418701. Please note, that Twitter's terms of service do not permit sharing the full corpus, so the dataset is restricted to respective unique identifiers that can be used to hydrate the dataset using the Twitter API and our technology and sentiment annotations.

Code availability

The code to retrieve, classify, and otherwise enrich the data and to produce the tables and figures in this article is available on GitHub and can be accessed via this link: https://gitlab.pik-potsdam.de/mcc-apsis/twitter/twitter-geoeng.

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Appendix

A Twitter search queries and technology categorisation

The corpus of 763,800 tweets by 235,025 users was compiled by querying the Twitter academic full-archive search API (v2) on January 16, 2023 with the 43 queries listed in Table S1 (continues in S1). We appended `-is:retweet lang:en` to each query, so that results are limited to 'original' English-language tweets only. The queries are grouped into 10 technology categories and a category for general greenhouse gas removal terms. Each tweet is automatically annotated with the technology category of the respective query. Most tweets (679,286; 88.9%) responded to queries from only one category, 74,278 (9.7%) to two categories, and 10,236 (1.3%) to more than two categories.

This paper focuses on carbon dioxide removal. However, we also compare some results to closely related topics such as removal of the second most dominant greenhouse gas, namely methane removal, as well as CCS, which is often wrongly portrayed or perceived as a negative emission technology. Our corpus contains 204,155 tweets on CCS and 4,391 tweets on methane removal. Unless stated otherwise, we always refer to the remaining 569,103 tweets.

Although the first tweet on Twitter was posted on March 21, 2006, we did not match any tweets before Feburary 9, 2007; until the end of 2009, 7,066 tweets (0.9%) were sent. In light of the low relevance of the topic in the early years of the platform, we limit our analyses to 2010–2022.

B Additional dataset statistics

During our initial analysis we found accounts that post a large volume of tweets within a relatively short time-frame. Following manual inspection of some of these accounts, we determined this to be spam-like behaviour and exclude tweets by those from our analysis. Using the distribution of the number of tweets by a user, the number of tweets in our corpus by that user, and the average number of tweets per day (measured since first tweet until December 31, 2022), we determined 100 tweets per day to be the upper bound for inclusion. In this way, we exclude 2,961 (1.26%) out of 235,025 users with more than 100 tweets per day, which amounts to 17,076 (3.00%) of the 569,103 tweets in our corpus. We assign each remaining user to one of three categories: *infrequent users* with below average number of tweets (one or two tweets in our corpus), *moderate users* with above average number of tweets (3 to 50 tweets in our corpus), and *frequent users* with more than 50 tweets in our corpus. These ranges are determined based on dataset statistics as summarised in Tables 1, S3, and S4. In particular, the lower bound of moderate users is based on the average number of tweets per user (2.89) and the upper bound so that around 40% of tweets fall in that category. Overall, the remaining tweets are almost balanced across infrequent and frequent users (31% to 23%). While the proportion of tweets by infrequent users stays within the range of 37–48% across all technologies, there are strong deviations in the share of tweets by infrequent users (14–46%) and frequent users (12–44%). Enhanced weathering, ocean alkalinity enhancement, and BECCS are the most popular topics amongst frequent users (41–44%), closely followed by direct air capture and biochar (33–34%). Conversely, afforestation/reforestation, ecosystem restoration, and ocean fertilisation have the highest share of tweets by infrequent users (41–46%). This observation aligns with survey-based public perception research, which shows a higher awareness of afforestation and restoration for CDR than for BECCS, enhanced weathering, or DAC [12, 16, 74]. Methods that are less known, tend to be mentioned more often by frequent users, while better known CDR methods are picked up by a wider audience

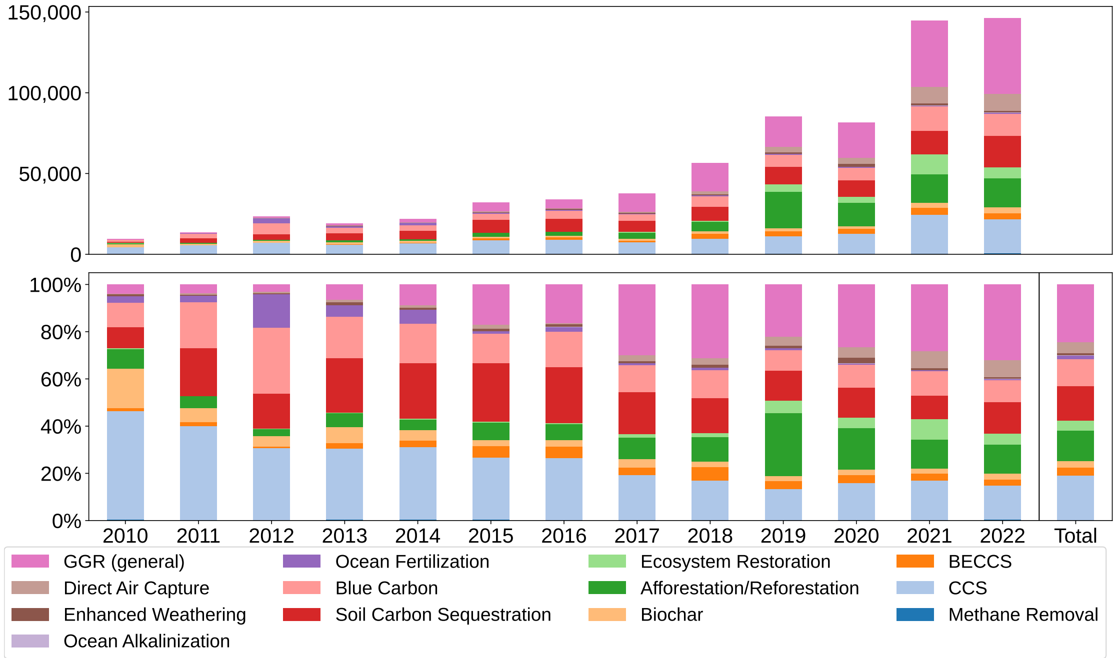


Figure S1: Tweet counts per CDR method per year. *Top panel:* Absolute tweet counts; *Bottom panel:* Share of tweets per year and overall. Analogous to Figure 1 but including tweets on CCS.

as exhibited by a higher share of tweets by infrequent users with only one or two tweets on CDR within the entire observed period. Corresponding to Figure 1, Figure S1 plots the absolute number and share of tweets per CDR method per year. For a more precise assessment, Table S5 lists all relevant numbers for these figures. The temporal derivative of that in the form of annual growth factor of the number of tweets per CDR method is shown in Table S6.

C User technology overlaps

The annotation of which CDR method is mentioned in a tweet is based on the query a tweet corresponds to. Tweets may match to multiple queries as multiple CDR methods are mentioned. Figure S2 shows the absolute number of tweets per pair of CDR methods as well as the proportion of that absolute number to the total number of tweets on that CDR method. This shows that general GGR terms are often used in the context of BECCS (16% of tweets mentioning BECCS also respond to GGR in general), DAC (14%), ocean alcalinisation (12%), enhanced weathering (9%), and biochar (7%). Other co-mentioned methods are 5% of BECCS tweets also mention DAC, 6% of biochar tweets also mention soil carbon sequestration, and 5% of ocean alkalinisation tweets also mention enhanced weathering. Given the similarities between those CDR methods, these co-mentions are to be expected. Other overlaps are negligible.

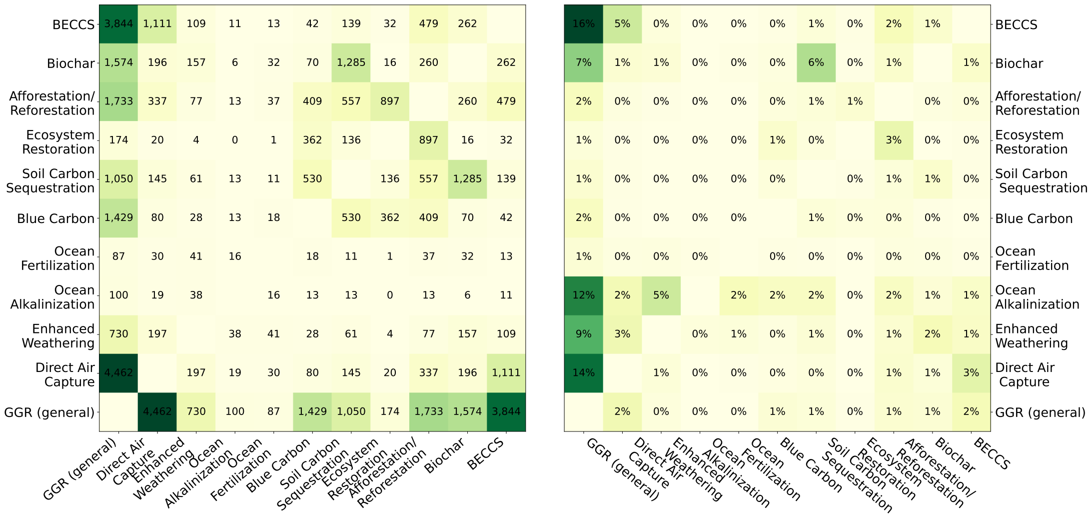
Shares in Figure 3 are given by $s_{ij} = u_{ij}/\hat{u}_i$, where $\hat{u}_i$ is the number of users with at least one tweet on method i and u_{ij} the number of users with at least one tweet on each method i and j. The distributions in this figure, however, naturally correlate strongly with the number of users with tweets per CDR method and the aforementioned co-mention of CDR methods. The distribution of the overlaps between methods is very similar across infrequent and frequent users, although the higher number of tweets per user in the right panel naturally leads to higher overlap shares.

Given these potential shortcomings, we propose an alternative approach to discuss overlapping attention to different CDR methods. Figure S3 shows the number of users with tweets on multiple CDR methods per pair of CDR methods in the lower triangular matrix. These numbers are the basis for the shares in Figure 3. In the upper triangular matrix of Figure S3, we show the deviation ($log_{10}(u_{ij}/e_{ij})$) from the expected overlap (e_{ij}), which is defined as

$$e_{ij} = \log_{10}\left(e'_{ij}\frac{\|u\|}{\|e'\|}\right), \text{ where}$$
$$e'_{ij} = \frac{\hat{u}_i\hat{u}_j}{\hat{U}} + \frac{m_{ij}}{(\tau_i/\hat{u}_i + \tau_j/\hat{u}_j)/2},$$

where $\hat{U}$ is the number of unique users, $\hat{u}_i$ is the number of users with at least one tweet on method i, τ_i is the number of tweets on method i, m_{ij} is the number of tweets mentioning method i and j (see Figure S2a), $\|u\| = \sum_i \sum_j u_{ij}$, and $\|e'\| = \sum_i \sum_j e'_{ij}$. Intuitively, this is the product of probabilities for seeing a user tweet on a particular CDR method based on the proportion of users per method to the number of users. Multiplying this joint probability by the total number of users gives an expected value, which we adjust by the multi-coding bias and the average number of tweets per user. The interim expected value e'_{ij} is slightly under-estimating and hence proportionally adjusted. A score of $e_{ij} = 0$ represents no deviation from the expected overlap, $e_{ij} > 0$ indicates that the overlap is stronger than expected, and $e_{ij} < 0$ lower than expected. A score of ± 0.3 means that the actual value is about double (or half) of the expected value.

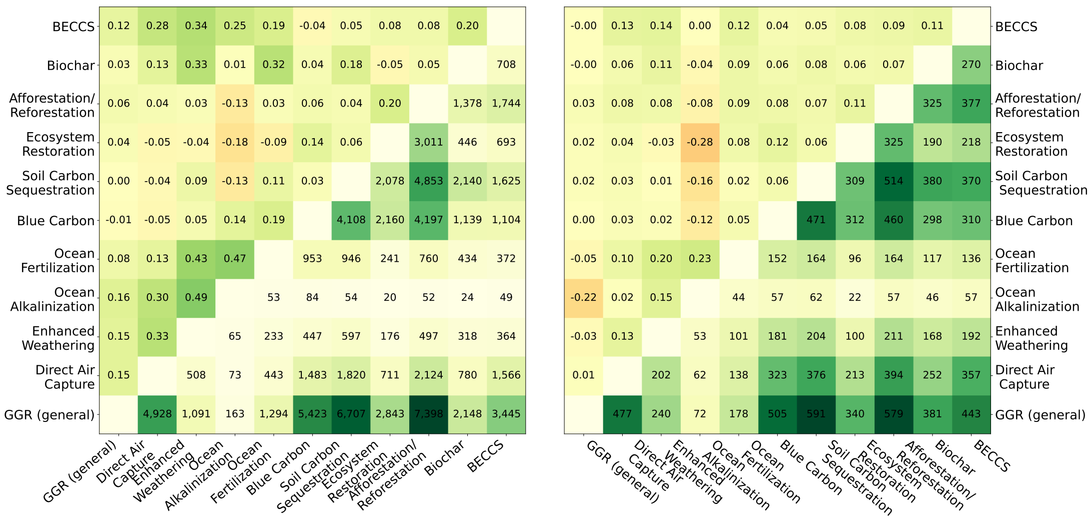
The scores in Figure S3 are symmetric, which allows us to show the deviation score and the actual absolute number of overlapping interests in one matrix for each user group. The deviations from the expected overlap in CDR method interests are mostly similar for moderate and frequent users. The overlap of interests on ocean alkalinisation with other CDR methods is mostly under-estimated, which is likely an artefact of the overall low number of tweets mentioning that method. For moderate users $\|u\| = 166,142$ and $\|e'\| = 162,097$ resulting in an adjustment quotient of around 1.025. For frequent users $\|u\| = 27,270$ and $\|e'\| = 23,470$ resulting in an adjustment quotient of around 1.162. The adjustment scores suggest that the expected overlaps are very close to the overall number of users with overlapping interest, however, even though the estimate is better for moderate users, some method overlaps were slightly under-estimated. For both user groups, BECCS has a stronger overlap with almost all other methods than expected, mainly with DAC, enhanced weathering, ocean fertilisation, and biochar. Biochar shows more overlaps than expected with enhanced weathering, ocean fertilisation, and DAC. The overlap of ecosystem restoration with ocean fertilisation, DAC, and enhanced weathering is lower than expected for moderate users, but the overlap with blue carbon is above expectation for both user groups.



(a) Absolute number of tweets

(b) Share of tweets

Figure S2: Number of tweets that mention multiple CDR methods for each pair of methods. Row-wise normalisation in the right panel is based on the total number of all tweets mentioning that method.



(a) Users with 3–50 tweets

(b) Users with >50 tweets

Figure S3: Number of users with tweets on each pair of CDR methods (lower triangle) and deviation from expected number of tweets (upper triangle).

Table S1: Queries used to retrieve tweets via the academic full-archive search API

Technology	QID	Query
Ocean Fertilisation	c_20	"ocean fertilization" OR "ocean fertilisation"
	c_21	"iron fertilization" OR "iron fertilisation"
	c_22	(fertilization OR fertilisation) (phytoplankton OR algae) (climate OR carbon OR co2)
	c_50	"iron seeding" (climate OR co2 OR carbon)
Ocean Alkalinisation	c_23	"ocean liming" -from:spangletoes
	c_49	"ocean alkalinity enhancement"
	c_57	"ocean alkalinization" OR "ocean alkalinisation"
Enhanced Weathering	c_24	"enhanced weathering" -from:spangletoes
	c_25	(olivine OR basalt OR silicate) (co2 OR emission OR emissions)
	c_26	olivine weathering
	c_51	(basalt OR silicate) weathering (co2 OR carbon OR enhanced)
Biochar	c_27	(biochar OR bio-char) (co2 OR carbon OR climate OR emission OR sequestration OR "greenhouse gas")
Afforestation/ Reforestation	c_29	afforestation (climate OR co2 OR emission OR emissions OR "greenhouse gas" OR ghg OR carbon)
	c_30	reforestation (climate OR co2 OR emission OR emissions OR "greenhouse gas" OR ghg OR carbon)
	c_31	tree planting climate
Ecosystem Restoration	c_32	(re-wilding OR rewilding) (climate OR carbon OR CO2 OR "greenhouse gas" OR GHG)
	c_56	("ecosystem restoration" OR "restore ecosystem") (climate OR carbon OR CO2 OR "greenhouse gas" OR GHG)
Soil Carbon Sequestration	c_33	soil sequestration (co2 OR carbon)
	c_36	"soil carbon"
	c_37	"carbon farming"
BECCS	c_38	BECCS (co2 OR carbon OR climate OR ccs OR biomass OR emission OR emissions)
	c_39	biomass ("carbon capture" OR "capture carbon" OR "co2 capture" OR "capture CO2" OR ccs)
	c_40	bioenergy ("carbon capture" OR "capture carbon" OR "co2 capture" OR "capture CO2" OR ccs)
(Methane Removal)	c_18	"methane direct air capture"
	c_19	"methane capture"
	c_54	methane removing atmosphere
(CCS)	c_10	"co2 sequestration" storage
	c_11	"carbon sequestration" storage
	c_12	"carbon dioxide sequestration"
	c_13	"carbon capture" storage
	c_14	"carbon storage" capture
	c_15	"carbon dioxide capture" storage
	c_16	"carbon dioxide storage" capture
	c_17	CCS (climate OR carbon OR co2)
Blue Carbon	c_41	seagrass (carbon OR co2)
	c_42	macroalgae (carbon OR co2)
	c_43	mangrove (carbon OR co2)
	c_52	kelp (carbon OR co2)
	c_53	(wetland OR wetlands OR marsh OR marshes OR peatland OR peatlands OR peat OR bog OR bogs) (carbon OR co2) (restore OR restoration OR rehabilitation)
	c_44	"blue carbon"
Direct Air Capture	c_45	DAC (climate OR carbon OR co2 OR emission OR emissions)
	c_46	"direct air capture"
	c_47	("carbon capture" OR "co2 capture") ("ambient air" OR "direct air")
	c_48	DACCS (carbon OR co2 OR climate)
GGR (general)	c_09	"methane removal"
	c_01	"negative emissions"
	c_02	"negative emission"
	c_03	"carbon dioxide removal"
	c_04	"co2 removal" -submarine -"space station"
	c_05	"carbon removal"
	c_06	"greenhouse gas removal"
	c_07	"ghg removal"
	c_08	"carbon negative" (climate OR co2 OR emission OR "greenhouse gas" OR ghg)
	c_55	(remove OR removing OR removed) (carbon OR co2) atmosphere

Table S2: Number of tweets by users with 1–2 (Infrequent), 3–50 (Moderate), and more than 50 (Frequent) tweets in our corpus, and by excluded users (EX). Value in parentheses are the share of tweets per user group per technology. Numbers may not sum to the total shown, as tweet may cover more than one CDR method.

Technology	Infrequent	Moderate	Frequent	EX	All
GGR (general)	52,783 (29%)	73,661 (41%)	46,767 (26%)	5,728	178,939
Direct Air Capture	6,354 (20%)	13,996 (44%)	11,059 (34%)	678	32,087
Enhanced Weathering	1,530 (20%)	2,778 (37%)	3,092 (41%)	114	7,514
Ocean Alkalinisation	127 (16%)	331 (41%)	340 (42%)	9	807
Ocean Fertilisation	4,489 (41%)	4,732 (43%)	1,350 (12%)	500	11,071
Blue Carbon	24,518 (29%)	39,414 (46%)	17,373 (20%)	3,902	85,207
Soil Carbon Sequestration	26,420 (25%)	51,178 (48%)	25,825 (24%)	2,599	106,022
Ecosystem Restoration	12,531 (42%)	12,324 (41%)	4,411 (15%)	621	29,887
Afforestation/Reforestation	43,054 (46%)	35,187 (38%)	13,000 (14%)	2,564	93,805
Biochar	4,755 (21%)	9,639 (43%)	7,416 (33%)	360	22,170
BECCS	3,247 (14%)	9,517 (41%)	10,159 (44%)	304	23,227
Total	176,527 (31%)	243,240 (43%)	132,260 (23%)	17,076	569,103
CCS	43,062 (21%)	90,035 (44%)	65,209 (32%)	5,849	204,155
Methane Removal	2,124 (48%)	1,866 (42%)	284 (6%)	117	4,391
Total (incl. CCS&MR)	219,837 (29%)	329,312 (43%)	191,735 (25%)	22,916	763,800

Table S3: Number of users with 1–2 (Infrequent), 3–50 (Moderate), and more than 50 (Frequent) tweets in our corpus, and by excluded users (EX). Numbers may not sum to the total shown, as each tweet or user may cover more than one technology.

Technology	Infrequent	Moderate	Frequent	EX	All
GGR (general)	48,562 (67%)	21,790 (30%)	1,138 (2%)	1,283	72,773
Direct Air Capture	5,939 (45%)	6,319 (47%)	737 (6%)	342	13,337
Enhanced Weathering	1,432 (44%)	1,439 (44%)	313 (10%)	62	3,246
Ocean Alkalinisation	120 (30%)	185 (47%)	83 (21%)	8	396
Ocean Fertilisation	4,197 (59%)	2,383 (34%)	263 (4%)	230	7,073
Blue Carbon	21,936 (62%)	11,669 (33%)	736 (2%)	956	35,297
Soil Carbon Sequestration	23,487 (60%)	14,367 (36%)	865 (2%)	665	39,384
Ecosystem Restoration	11,401 (65%)	5,518 (31%)	453 (3%)	265	17,637
Afforestation/Reforestation	40,018 (72%)	13,696 (25%)	843 (2%)	834	55,391
Biochar	4,383 (49%)	3,904 (43%)	533 (6%)	173	8,993
BECCS	3,099 (36%)	4,687 (54%)	734 (8%)	166	8,686
Total	153,260 (78%)	39,847 (20%)	1,308 (1%)	2,646	197,061
CCS	38,312 (62%)	21,330 (35%)	1,097 (2%)	1,087	61,826
Methane Removal	2,004 (59%)	1,132 (34%)	152 (5%)	87	3,375
Total (incl. CCS&MR)	186,964 (80%)	43,769 (19%)	1,331 (1%)	2,961	235,025

Table S4: Average number of tweets per user with 1–2 (Infrequent), 3–50 (Moderate), and more than 50 (Frequent) tweets in our corpus, and by excluded users (EX).

Technology	Infrequent	Moderate	Frequent	EX	All
GGR (general)	1.09	3.38	41.10	4.46	2.46
Direct Air Capture	1.07	2.21	15.01	1.98	2.41
Enhanced Weathering	1.07	1.93	9.88	1.84	2.31
Ocean Alkalinisation	1.06	1.79	4.10	1.12	2.04
Ocean Fertilisation	1.07	1.99	5.13	2.17	1.57
Blue Carbon	1.12	3.38	23.60	4.08	2.41
Soil Carbon Sequestration	1.12	3.56	29.86	3.91	2.69
Ecosystem Restoration	1.10	2.23	9.74	2.34	1.69
Afforestation/Reforestation	1.08	2.57	15.42	3.07	1.69
Biochar	1.08	2.47	13.91	2.08	2.47
BECCS	1.05	2.03	13.84	1.83	2.67
Total	1.15	6.10	101.12	6.45	2.89
CCS	1.12	4.22	59.44	5.38	3.30
Methane Removal	1.06	1.65	1.87	1.34	1.30
Total (incl. CCS&MR)	1.18	7.52	144.05	7.74	3.25

Table S5: Number of tweets and proportions (in per-cent) per CDR method per year. This table corresponds to Figures 1 and S1.

Method	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
GGR (general)	386 (7%)	493 (6%)	711 (4%)	1,228 (9%)	1,918 (13%)	5,445 (23%)	5,537 (22%)	11,358 (37%)	17,595 (38%)	18,822 (25%)	21,677 (32%)	40,958 (34%)	46,801 (38%)
Direct Air Capture	9 (0%)	115 (1%)	167 (1%)	199 (1%)	201 (1%)	554 (2%)	187 (1%)	902 (3%)	1,606 (3%)	3,351 (5%)	3,501 (5%)	10,170 (8%)	10,435 (8%)
Enhanced Weathering	71 (1%)	45 (1%)	58 (0%)	234 (2%)	193 (1%)	272 (1%)	357 (1%)	310 (1%)	683 (1%)	740 (1%)	1,950 (3%)	1,249 (1%)	1,223 (1%)
Ocean Alkalinisation	0 (0%)	0 (0%)	0 (0%)	15 (0%)	1 (0%)	12 (0%)	17 (0%)	14 (0%)	43 (0%)	53 (0%)	115 (0%)	230 (0%)	298 (0%)
Ocean Fertilisation	265 (5%)	371 (5%)	3,318 (20%)	928 (7%)	1,321 (9%)	358 (2%)	710 (3%)	311 (1%)	562 (1%)	702 (1%)	415 (1%)	500 (0%)	570 (0%)
Blue Carbon	1,000 (19%)	2,674 (33%)	6,557 (41%)	3,367 (25%)	3,606 (24%)	4,006 (17%)	5,046 (20%)	4,311 (14%)	6,667 (14%)	7,410 (10%)	7,941 (12%)	14,873 (12%)	13,606 (11%)
Soil Carbon Sequestration	867 (17%)	2,761 (34%)	3,452 (21%)	4,388 (33%)	5,144 (34%)	7,881 (34%)	8,012 (32%)	6,778 (22%)	8,419 (18%)	10,918 (15%)	10,260 (15%)	14,557 (12%)	19,459 (16%)
Ecosystem Restoration	37 (1%)	17 (0%)	26 (0%)	48 (0%)	90 (1%)	144 (1%)	151 (1%)	508 (2%)	911 (2%)	4,484 (6%)	3,602 (5%)	12,426 (10%)	6,804 (5%)
Afforestation/ Reforestation	783 (15%)	696 (8%)	718 (4%)	1,138 (9%)	969 (6%)	2,375 (10%)	2,284 (9%)	3,438 (11%)	5,794 (12%)	22,662 (31%)	14,427 (21%)	17,816 (15%)	17,644 (14%)
Biochar	1,606 (31%)	800 (10%)	1,007 (6%)	1,284 (10%)	988 (7%)	862 (4%)	927 (4%)	1,357 (4%)	1,332 (3%)	1,943 (3%)	1,737 (3%)	3,030 (3%)	3,870 (3%)
BECCS	132 (3%)	241 (3%)	175 (1%)	451 (3%)	565 (4%)	1,529 (7%)	1,665 (7%)	1,224 (4%)	3,281 (7%)	2,879 (4%)	2,924 (4%)	4,149 (3%)	3,681 (3%)
Total	5,156	8,213	16,189	13,280	14,996	23,438	24,893	30,511	46,893	73,964	68,549	119,958	124,391
CCS	4,397	5,444	7,119	5,749	6,736	8,355	8,877	7,188	9,445	11,095	12,701	24,267	21,264

Table S6: Annual growth factor as the quotient of year-to-year tweet counts shown in Table S5.

Method	2010–2011	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2021–2022	median (std)
GGR (general)	1.26	1.45	1.74	1.61	2.83	1.02	2.00	1.53	1.07	1.16	1.91	1.17	1.49 (0.52)
Direct Air Capture	13.44	1.39	1.23	1.00	2.72	0.34	4.93	1.74	2.08	1.05	2.93	1.03	1.57 (3.56)
Enhanced Weathering	0.68	1.25	4.25	0.80	1.35	1.37	0.83	2.22	1.08	2.62	0.64	0.98	1.17 (1.06)
Ocean Alkalinisation	—	—	—	0.07	12.00	1.42	0.88	2.87	1.28	2.15	1.95	1.31	1.42 (3.59)
Ocean Fertilisation	1.39	9.02	0.29	1.42	0.26	2.02	0.43	1.83	1.31	0.55	1.21	1.17	1.26 (2.37)
Blue Carbon	2.70	2.44	0.52	1.11	1.19	1.38	0.74	1.48	1.10	1.07	1.89	0.93	1.15 (0.66)
Soil Carbon Sequestration	3.14	1.27	1.31	1.14	1.53	1.02	0.84	1.22	1.30	0.94	1.42	1.34	1.29 (0.59)
Ecosystem Restoration	0.44	1.59	1.96	1.74	1.63	1.03	3.43	1.73	4.96	0.80	3.46	0.55	1.68 (1.36)
Afforestation/ Reforestation	0.88	1.04	1.83	0.74	2.51	1.00	1.41	1.68	3.92	0.64	1.23	1.00	1.14 (0.93)
Biochar	0.49	1.27	1.29	0.77	0.87	1.11	1.42	0.98	1.47	0.88	1.75	1.29	1.19 (0.35)
BECCS	1.83	0.73	2.56	1.25	2.76	1.08	0.73	2.67	0.88	1.01	1.42	0.90	1.16 (0.77)
Total	1.60	1.98	0.84	1.12	1.57	1.10	1.15	1.49	1.59	0.92	1.76	1.05	1.32 (0.36)

Table S7: Average number of likes (♥), retweets (⇄), and replies (↩) per tweet.

Method	Infrequent			Moderate			Frequent			EX			All		
	♥	⇄	↩	♥	⇄	↩	♥	⇄	↩	♥	⇄	↩	♥	⇄	↩
GGR (general)	4.3	0.4	1.1	7.3	0.6	2.2	9.2	0.8	3.4	2.5	0.4	1.1	6.8	0.6	2.2
Direct Air Capture	5.6	0.6	1.0	4.6	0.6	1.3	7.2	0.9	2.4	1.9	0.3	0.8	5.6	0.7	1.6
Enhanced Weathering	3.8	0.4	0.7	4.1	0.5	1.3	2.7	0.4	0.9	0.5	0.1	0.2	3.4	0.4	1.0
Ocean Alkalinisation	3.3	0.2	6.3	6.9	0.5	3.4	5.1	0.6	2.5	0.3	0.1	6.1	5.5	0.5	3.5
Ocean Fertilisation	0.4	0.1	9.0	0.8	0.1	1.8	1.0	0.2	1.3	0.1	0.0	4.8	0.6	0.1	4.8
Blue Carbon	4.2	0.2	1.2	7.7	0.3	2.6	7.5	0.2	3.7	1.5	0.1	0.6	6.4	0.3	2.3
Soil Carbon Sequestration	3.3	0.3	1.1	4.6	0.3	1.7	3.3	0.3	1.6	0.5	0.1	0.5	3.8	0.3	1.5
Ecosystem Restoration	4.7	0.4	1.4	17.1	0.7	5.1	138.3	3.8	44.5	6.8	0.5	2.6	29.7	1.0	9.3
Afforestation/Reforestation	6.9	0.5	2.0	11.5	0.7	4.0	8.9	0.5	4.3	7.0	0.6	3.4	8.9	0.6	3.1
Biochar	1.6	0.2	0.4	2.4	0.2	0.7	1.9	0.2	0.7	0.6	0.1	0.4	2.0	0.2	0.6
BECCS	2.0	0.3	0.7	3.1	0.4	1.3	4.2	0.7	2.1	1.2	0.2	0.6	3.4	0.5	1.6
Total	4.6	0.4	1.5	7.2	0.5	2.4	10.5	0.7	4.0	2.6	0.3	1.4	7.1	0.5	2.5
CCS	2.2	0.3	0.8	4.8	0.5	1.9	3.6	0.5	1.9	1.3	0.2	0.7	3.8	0.4	1.6
Methane Removal	1.6	0.4	0.4	4.0	0.6	1.3	2.1	0.4	1.2	0.3	0.1	0.2	2.6	0.4	0.8
Total (incl. CCS&MR)	4.1	0.4	1.3	6.5	0.5	2.2	8.2	0.6	3.3	2.3	0.3	1.2	6.2	0.5	2.2