Sentiment analysis of the Twitter response to Netflix's *Our Planet* documentary

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Abstract

The role of nature documentaries in shaping public attitudes and behaviour towards conservation and wildlife issues is unclear. We analysed the emotional content of over two million tweets related to *Our Planet*, a major nature documentary released on Netflix. We show that tweets were largely negative in sentiment at the time of release of the series. Further analyses revealed that this effect was primarily linked to the highly-skewed distributions of retweets and, in particular, to a single negatively-valenced and massively retweeted tweet (>150,000 retweets). We also compared the sentiment associated with species mentioned in

Our Planet and a set of control species, with similar features but not mentioned in the documentary. Species mentioned in *Our Planet* were associated with more negative sentiment than the control species, and this effect coincided with a short period following the airing of the series. Our results are consistent with a general negativity bias in cultural transmission, and document the difficulty of evoking positive sentiment, on social media and elsewhere, in response to environmental issues.

Introduction

Public perception and public opinion play important roles in wildlife conservation. Public pressure on politicians can instigate policy change (Phillis et al. 2013), while consumer choice can favour environmentally-friendly products or services (Nuno et al. 2018). In turn, public perception and public opinion may be shaped by the media portrayal of threats to species and the environment, particularly amongst urban dwellers with little direct access to nature (Aitchison, Aitchison, and Devas 2021; Silk et al. 2018; Nolan 2010; Dunn, Mills, and Veríssimo 2020; Fernández-Bellon and Kane 2020), an idea formalised in conservation science as the "extinction of experience" (Soga and Gaston 2016; Gaston and Soga 2020).

However, the role of traditional media such as television documentaries in shaping people's perception, opinion and behaviour is far from clear (Aitchison, Aitchison, and Devas 2021; Jones et al. 2019). For example, there is little evidence for popularly-assumed effects such as the reduction in plastic straw use in response to the television documentary *Blue Planet 2* (Dunn, Mills, and Veríssimo 2020). The Al Gore documentary film *An Inconvenient Truth* was shown to increase knowledge of global warming and intention to take action, but this intention did not reliably translate into action one month later (Nolan 2010). Television documentaries and films featuring wildlife may even undermine conservation messages, such as by portraying some species as dangerous (e.g. sharks) or abundant (e.g. wildebeest), and failing to show any human impact on the species and their habitats (Aitchison, Aitchison, and Devas 2021; Bradshaw, Brook, and McMahon 2007). Furthermore, the reach of traditional media such as television documentaries is often limited to specific countries and audiences, not all of whom may be able to enact the relevant change (J. H. Wright 2010).

New broadcast media such as subscription services Netflix, Amazon Prime and Disney+ might overcome some of these limitations. They are multi-national, allowing simultaneous broadcast in multiple countries. Given their subscription model, they are under less commercial pressure to sensationalise content in order to maximise viewership of specific programmes. They are also less restricted by impartiality rules compared to traditional broadcasters such as the BBC. This greater freedom from ratings-chasing and impartiality restrictions could potentially lead to more accurate portrayals of the negative human impact on wildlife and the environment (Aitchison, Aitchison, and Devas 2021).

Another recent development is the use of social media in conservation campaigns (Kidd et al. 2018; Wu et al. 2018). Traditional media such as television is one-way, broadcasting to a passive audience. Social media allows the audience to feed back immediately to the programme makers, to share salient content (e.g. film clips) and to discuss issues raised by the programme amongst themselves. This interactivity might increase engagement and more effectively shape viewers' opinions and behaviour.

Social media can also be an effective method to measure the public response to nature documentaries, wildlife campaigns and environmental issues in general (Burivalova, Butler, and Wilcove 2018; Kidd et al. 2018; Nanni et al. 2020), albeit with limitations such as disparities in internet access in different areas of the globe or documented gaps between online and offline behavior (J. Wright, Lennox, and Veríssimo 2020). More broadly, the emerging field of conservation culturomics (Ladle et al. 2016; Correia et al. 2021) uses quantitative analyses of digital texts, including social media, to assess public interest in conservation issues (see also (Di Minin, Tenkanen, and Toivonen 2015; Toivonen et al. 2019)). Such methods have been applied specifically to the effects of nature documentaries, such as the BBC's *Planet Earth 2* (Fernández-Bellon and Kane 2020).

Here we examine the social media response to Netflix's 2019 documentary series *Our Planet*, produced by Silverback Films in collaboration with the World Wildlife Fund. Historically, nature documentaries fall into one of two categories: hard-hitting documentaries with explicit environmental messages that typically reach a small audience (e.g. *An Inconvenient Truth*) or mass audience documentaries with little or no environmental message (e.g. *Blue Planet*). *Our Planet* aimed to bridge this gap by being a mass audience documentary with explicit environmental messaging throughout. This included explicit portrayal of the impact of humans on the environment, such as the detrimental effect of climate change on species' habitats, and calls to action, providing the public with constructive ways to change their behaviour to aid conservation efforts.

All episodes of *Our Planet* were released on Netflix simultaneously in multiple countries on 5th April 2019. It was narrated by Sir David Attenborough and supported by extensive and carefully-planned Twitter and other social media campaigns. The première was held in the Natural History Museum in London and was attended by public figures such as Prince (now

King) Charles and Prince William and the ex-footballer David Beckham. The documentary was accompanied by online material specifically dedicated to conservation issues, with pages on "What Can I Do?" or "Take Action" and several additional short movies intended to raise conservation awareness. By March 2021, Netflix reported that 100 million viewers had watched the series to date (Moore 2021).

We worked with Silverback Films who provided us with information on the documentary before broadcast (e.g. the topics and species featured in each episode) and who were interested in gauging reaction to the series on social media. We applied sentiment analysis to a large dataset of tweets related to *Our Planet* to test whether viewers responded with positive or negative sentiment, and whether any observed change lasted beyond the immediate release of the programme. Sentiment analysis uses a dictionary of words and symbols such as emoticons that have positive (e.g. "love", "good", "happy", smiling face emoticon) or negative (e.g. "angry", "frustrated", "sad", frowning face emoticon) valence to automatically score each tweet on a scale between -1 and +1, where -1 is fully negative and +1 fully positive (see Methods section).

We make no specific prediction regarding whether sentiment is positive or negative. On the one hand, several previous studies have shown a preference for negative sentiment in social media sharing (Schöne, Parkinson, and Goldenberg 2021; Bellovary, Young, and Goldenberg 2021) and "fake news" (Acerbi 2019a), while lab experiments have shown that people preferentially acquire and transmit negative information from and to others (Bebbington et al. 2017). Moreover, *Our Planet* contained explicitly negative content designed to elicit shock and anger. On the other hand, *Our Planet* also aimed to elicit positive emotions such as awe for the natural world as do other mass audience documentaries without an explicit environmental message.

We started by collecting tweets that included the #ourplanet hashtag. However, a limitation of only looking at tweets that explicitly mention *Our Planet* is that we do not have any baseline or comparison group. Perhaps all tweets, or all animal-related tweets, happened to become more positive in sentiment during this time period, and the release of *Our Planet* was entirely incidental. To address this limitation we also compared three sets of tweets from the same time period: (i) tweets mentioning control species not featured in *Our Planet* (e.g. porpoise), but, where possible, matched on various characteristics with species that were featured in *Our Planet* (e.g. dolphin); (ii) tweets mentioning species that were featured in *Our Planet* but which did not include the #ourplanet hashtag, and were likely unrelated to the Netflix show; and (iii) tweets mentioning species featured in *Our Planet* that also included the #ourplanet hashtag. Only the third group should show the effect of *Our Planet* on tweet sentiment, with the first two showing the sentiment of tweets covering similar topics (animals, conservation).

Given this and the aims above, we made the following specific predictions:

- H1. The sentiment of tweets containing the #ourplanet hashtag becomes more extreme (more positive or more negative) after the release of the series on 5th April 2019.
- H2. The sentiment of tweets that both feature species mentioned in *Our Planet* and contain the #ourplanet hashtag is more extreme than the sentiment of tweets that feature control species not featured in *Our Planet*, and of the sentiment of tweets mentioning *Our Planet* species that do not contain the #ourplanet hashtag.
- H3. Both these effects last beyond the immediate release date of *Our Planet* on 5th April 2019.

Methods

Data overview

All eight episodes of *Our Planet* were released simultaneously on Netflix on 5th April 2019. Automated tweet collection lasted nine weeks from 15th March 2019 to 17th May 2019. This allowed us to divide the data into three consecutive periods of three weeks each: pre-release, release, and post-release. Ethical approval for data collection was obtained beforehand from the University of Exeter College of Life and Environmental Sciences Penryn Research Ethics Committee (application eCORN001657, 13/12/2018). All tweets are publicly available and no personal information was collected beyond twitter username (which is often anonymous). We collected in real time, using the official Twitter API though the R library `rtweet` (Kearney 2019), tweets containing:

- the character string "Our Planet", case insensitive
- the hashtag #ourplanet, case insensitive
- the names of nine species prominently mentioned in *Our Planet*: dolphin, flamingo, wild dog, caribou, wolf, polar bear, wildebeest, elephant seal and walrus
- the names of nine "control" species: porpoise, macaw, dingo, mule deer, coyote, panda, waterbuck, snow leopard and lynx

The nine species mentioned in *Our Planet* were chosen in advance of data collection following discussion with Silverback Films. The nine control species were chosen to represent species not appearing prominently in *Our Planet*. Where possible we chose control species that had broadly similar characteristics as species featured in *Our Planet* (e.g. polar bear - panda, wild dog - dingo), although this was not possible in two cases (see Supporting Information Table S1, for the full matchings and explanations). Mentions of species were detected in the collected tweets by searching for the common name character string, plus slight variations, such as plural forms.

After filtering out tweets whose language was not English, we had a full dataset of n = 3,504,254 tweets, including retweets of the same tweets. For each tweet, we collected the full text, the date and time it was created, the number of followers of the author of the tweet, and, for retweets, the number of times the original tweet was retweeted at the time of collection.

The full dataset contained all mentions of the text "Our Planet" and case insensitive variants thereof, as well as the #ourplanet hashtag. However upon inspection of the tweet content it was apparent that many mentions of "Our Planet" did not refer to the Netflix documentary. We therefore narrowed the data to just the #ourplanet hashtag, which excluded irrelevant tweets.

The dataset used for the analysis (n = 2,137,635) was composed of n = 224,895 tweets with the hashtag #ourplanet or case insensitive variants thereof, e.g. #OurPlanet or #ourplanet; n = 1,158,704 tweets mentioning a species featured in *Our Planet*; and n = 934,435 tweets mentioning a control species not featured in *Our Planet*. Note that the sum of these three sample sizes does not equal the total sample size because these categories are not mutually exclusive, e.g. 169,240 tweets containing the #ourplanet hashtag also featured *Our Planet* species. There are n = 573,820 unique tweets obtained by removing all retweets of the same tweet.

We used the R package **vader** (Roehrick 2020) to perform a sentiment analysis of the tweets. Vader, short for Valence Aware Dictionary and sEntiment Reasoner, was chosen because it is especially suited for analysing short social media texts, performing well when analysing emoticons (such that emoticons contribute to the final sentiment score), slang/acronyms, and punctuation and capitalisations typical of social media posts (Hutto and Gilbert 2014). We used the Vader 'Compound' score, which sums, for each tweet, the valence of each word and provides a normalised score from -1 (extreme negative) to +1 (extreme positive). For examples of tweets classified as positive and negative in our analysis see Supporting Information Tables S2 and S3. 635 tweets could not be processed in the sentiment analysis and so were excluded from all analyses.

Distribution of tweets

We found a highly skewed pattern of retweets in the dataset. For all tweets (featuring the #ourplanet hashtag and/or any of the *Our Planet* or control species), the most-retweeted tweet was retweeted 157,068 times (tweet text: "rt XXXX: seal accidentally scares baby polar bear"; categorised as containing an *Our Planet* species - polar bear - but not containing the #ourplanet hashtag; sentiment score = -0.59; NB tweeter and retweeter usernames here and in our full dataset are anonymised as XXXX) and the second most-retweeted tweet was retweeted 155,062 times (tweet text: "the sad reality of climate change. the walrus with no ice or place to go. #walrus #ourplanet #climatechange #climate"; categorised as containing an *Our Planet* species - walrus - and also containing the #ourplanet hashtag; sentiment score = -0.65). These two tweets combined make up 14.6% of the data, and were each retweeted more than twice as many times as the third most-retweeted tweet.

For those tweets that featured the #ourplanet hashtag, the skew was much higher: the most-retweeted tweet was retweeted 155,062 times (the second-most-retweeted in the full dataset, see above), or 68.9% of the data. The next most-retweeted tweet was retweeted 2,370 times. Figure 1 shows this skew for both all tweets and hashtag tweets by plotting the logged tweet count.

This skewed distribution means that any analysis will be skewed by the small number of highly-retweeted tweets. Consequently, we ran analyses on both the full dataset, including retweets, and the unique tweet dataset, excluding retweets.

Analysis

We first checked the overall sentiment of the data, presenting basic descriptive statistics (mean, median and standard deviation) of the Vader compound score. We used intercept-only Bayesian regression models to detect deviations of the outcomes from zero (neutral sentiment). Following the model equation format of McElreath (2020b), the intercept-only regression model is specified as:

$$S \qquad \mathrm{al}(\mu \;\; \sigma)$$

$$\mathrm{al}(0 \quad 5)$$

$$\mathrm{al}(1)$$

where S_i is the sentiment score of tweet i, and μ and σ are the mean and standard deviation of the sentiment scores respectively, which have normally and exponentially distributed priors respectively.

To test H1 and H3 we ran Bayesian regression models with time as a predictor and emotion score as the outcome for tweets containing the #ourplanet hashtag. We analysed time in two ways, discrete and continuous. For the discrete time analysis we divided the dataset into three consecutive periods of three weeks each: pre-release, release, and post-release. This was used as an index variable in a linear Bayesian regression model with normally distributed priors (McElreath 2020b). For the continuous time measure we used days since data collection began (15th March 2019) scaled to start at zero. This was used as a continuous predictor in a Bayesian regression model, comparing linear, quadratic and cubic models using WAIC (McElreath 2020b). The discrete time model is specified as:

$$\text{l}(\mu \quad \sigma)$$

$$ME[i]$$

$$\text{al}(0 \quad 5) \qquad [1 \quad 3]$$

$$\text{al}(1)$$

where TIME$[i]$ is an index variable specifying in which of the three time periods tweet i was tweeted. The continuous time model is specified as:

$$\text{l}(\mu \quad \sigma)$$

$$\text{l}(0 \quad 5)$$

$$\text{l}(0,1)$$

$$\text{al}(1)$$

where T_i is the continuous time measure for tweet i.

To test H2 and H3, we used the same discrete and continuous time measures but we considered three different datasets: tweets that feature species mentioned in *Our Planet*; tweets that feature control species not featured in *Our Planet*; and tweets mentioning *Our Planet* species that do not contain the #ourplanet hashtag. As above, we used a Bayesian regression model with time (discrete or continuous) as a predictor and emotion score as the outcome.

As an unplanned extension of our main analysis, we tested the general effect of sentiment on retweet probability. A Poisson regression model was run with unique tweets as data points, the count of the number of retweets for that tweet as the outcome measure, and Vader compound score and user follow count as predictors. This model was specified as:

$$\text{on}(\lambda_i)$$

$$\log(\lambda_i)$$

$$\text{al}(0,3)$$

$$\text{al}(0,5)$$

$$\text{al}(0,5)$$

where R_i is retweet count, F_i is follower count, and S_i is the sentiment score for tweet i.

All analyses were run using the `rethinking` package version 2.13 (McElreath 2020a) and `cmdstanr` (Gabry and Češnovar 2022) in R version 4.1.3 (R Core Team 2022). We report 89% confidence intervals and compare models using WAIC rather than reporting p-values (McElreath 2020b). The data (with twitter usernames removed or anonymised) and analysis code are available at: https://osf.io/rv8ek/?view_only=b5990922269c40c686692e4a7aa1bc8a (anonymised repository for review)

Results

Overall sentiment of *Our Planet* tweets

For all tweets including retweets, the mean and median emotion score were both negative (mean = -0.40, median = -0.65, sd = 0.47). For unique tweets excluding retweets, the mean was slightly positive and the median was zero (mean = 0.12, median = 0.00, sd = 0.50). The distributions of both are shown in Figure 2. Intercept-only regression models reproduced these means and confirmed their deviation from zero (all tweets: mean = -0.40[-0.40,-0.39], sd = 0.47[0.47,0.47]; unique tweets: mean = 0.12[0.11,0.12], sd = 0.50[0.50,0.50]). The full data including retweets are heavily influenced by the most-retweeted tweet with an emotion score of -0.65, which can be seen in Figure 2. The data including only unique tweets show a hump at zero (neutral sentiment), a small hump around -0.5 (negative sentiment), and a larger hump around +0.6 (positive sentiment).

Sentiment over time

For the discrete time analysis, we compared the sentiment between three 3-week periods (pre-release, release and post-release) for tweets containing the #ourplanet hashtag. For all tweets including retweets, Figure 3A shows that at pre-release, sentiment was largely positive; at release, sentiment became strongly negative, although this was skewed by the highly-retweeted outlier tweet with a sentiment score of -0.65; and at post-release, sentiment becomes slightly positive but not as positive as pre-release.

For unique tweets excluding retweets, Figure 3B shows a similar pattern but less extreme: pre-release tweets are slightly positive, at release tweets become less positive (but not negative), and post-release tweets are more positive than at release. Regression analyses supported these patterns for all tweets (Table S4) and unique tweets (Table S5). In both cases pre-release was most positive, release was most negative, and post-release was more positive than release.

For the continuous time analysis, we ran regression models with time as a continuous measure starting at the beginning of the data collection period, comparing time as a linear, quadratic and cubic predictor. Model comparison showed that the cubic model best fit the data for both all hashtag tweets and unique hashtag tweets. The model estimates (posterior mean and posterior percentile intervals) are shown in Figure 3C and 3D for all tweets and unique tweets respectively. These confirm the positive sentiment at the start of the time period, the increasingly negative sentiment reaching a minimum after release, and the less negative sentiment at the end of the period. The relationship for all tweets (Figure 3C) is more extreme than that for the unique tweets (Figure 3D) due to the highly retweeted outlier in the former dataset.

Species comparison

Figure 4 shows that, for all tweets including retweets, control species show little change in sentiment over time, if anything becoming marginally more positive around the release of *Our Planet* (Figure 4A & 4D). *Our Planet* species with no #ourplanet hashtag become negative around the time of release then marginally positive at post-release (Figure 4B & 4E). *Our Planet* species with the #ourplanet hashtag show a more extreme pattern of becoming strongly negative at release (Figure 4C & 4F). This is likely due to the highly-retweeted outlier with an emotion score of -0.65. Unlike all hashtag tweets shown in Figure 3B, this negativity remained in the post-release period, albeit slightly more positive than at release.

Perhaps a more accurate picture not affected by the outlier can be seen in Figure 5, which shows the same analysis as Figure 4 but for unique tweets excluding retweets. Figure 5A and 5D show for discrete and continuous time respectively that control species showed no effect of the *Our Planet* release date on sentiment, as we would expect. Tweets were consistently neutral or very slightly positive. *Our Planet* species without the #ourplanet hashtag show a similar pattern but with a slight decrease in sentiment at release (Figure 5B and 5E). This may be due to tweets about *Our Planet* species that referred to the documentary without using the #ourplanet hashtag. *Our Planet* species with the #ourplanet hashtag, however, show a marked decline at release to become clearly negative overall (Figure 5C and 5F). Like for all tweets (Figure 4C), this negativity persisted to the post-release period, becoming only slightly more positive than at release. The patterns shown in Figures 4 and 5 were confirmed by Bayesian regression models as shown in Tables S6 and S7 respectively.

Retweet analysis

A further unplanned analysis was conducted on retweet count. This can be seen as a measure of tweet popularity, or a measure of the extent to which people wish to transmit a tweet to others. Model comparison showed that a full model with both tweeter follower count and tweet emotion score fit the data better than models with just one or neither predictor. This full model is shown in Table S8. Follower count had a reliably positive effect on retweet count ($\beta_{follower}$ = 1.26[1.26,1.26]). As one would expect, tweets from users with more followers are retweeted more. Emotion had a negative effect, with more negative sentiment tweets getting retweeted more, consistent with the analyses above ($\beta_{emotion}$ = -1.34[-1.35,-1.34]).

Further analysis, however, showed that the effect of emotion was driven by the highly-retweeted outlier shown in Figure 1B. Removing the most-retweeted tweet resulted in a small positive effect of emotion ($\beta_{emotion}$ = 0.06[0.05,0.06]). The effect of follower count remained positive and larger than emotion ($\beta_{follower}$ = 0.75[0.75,0.76]). This indicates that any effect of emotion on retweet count is largely driven by the outlier shown in Figure 1B.

Accepted Article

Discussion

Netflix's *Our Planet* was one of the first wildlife documentary series produced by an international subscription-service rather than a traditional television broadcaster. The producers Silverback Films, in conjunction with the World Wildlife Fund, aimed to bridge the gap between mass audience but environmentally neutral natural history documentaries, and limited audience films with explicit and hard-hitting environmental messaging. We collected and analysed more than two million tweets relevant to *Our Planet* to examine viewers' emotional response to this content before, during and after release of the programme.

We made no specific prediction regarding whether tweets associated with *Our Planet* would be overall positive or negative in sentiment. In fact, we found that this differed depending on the type of tweet data that were used (Figure 2). All tweets including retweets were clearly negative. However this was driven by a massively-retweeted negative outlier. Removing retweets and only considering unique tweets, sentiment was marginally positive.

Over time, however, both all tweets and unique tweets saw an increase in negativity during the *Our Planet* release period, compared to pre-release and post-release (Figure 3). This supports our first prediction (H1) that tweets associated with *Our Planet* become more extreme in their sentiment following the release of the series. Furthermore, tweets containing both species featured in *Our Planet* and the #ourplanet hashtag showed clear negative sentiment at the time of release, declining from positive sentiment pre-release (Figures 4 and 5). Control species not featured in *Our Planet* showed no change over time, suggesting that this increase in negativity was not a general change in sentiment during this period, or caused by some other wildlife or conservation related event.

Our third prediction (H3) that these effects are long-lasting was not well supported. The discrete time analyses showed that, by the third 3-week period, sentiment was already returning to its more positive pre-release levels. The continuous time analyses typically showed a u-shaped relationship between sentiment and time, with the minimum sentiment just after release increasing back to positive at the end of the recording period.

Overall, therefore, we conclude that the release of *Our Planet* coincided with more negative sentiment tweets. This is clear when comparing species mentioned in the series with control species. For the overall sentiment of tweets with the hashtag #ourplanet it depends on the analytical choice: all tweets with the single heavily-retweeted negative tweets, which was negative, or only unique tweets, which was slightly positive. A relevant feature of the data here was extremely high skew due to a single massively retweeted tweet (Figure 1). In the dataset containing only the tweets with the #ourplanet hashtag, retweets of this tweet accounted for 68.9% of all tweets. Because this outlier tweet was strongly negative with an emotion score of -0.65, this skewed the results towards negative sentiment. Given that the distribution in Figure 1 is likely to be typical of many social media-generated big datasets like ours, this is a note of caution for analyses of big data. We therefore repeated all analyses with unique tweets excluding retweets. This yielded some differences, for example the unique tweets had slightly positive sentiment following release compared to the full dataset (Figure 2). However, the general trend of becoming more negative at release was found for both the full dataset and unique tweets.

There is no straightforward way to decide which of these datasets is best to use. Conceptually, from a cultural evolution perspective (Acerbi 2019b; Mesoudi 2011), the unique tweets data can perhaps be seen as a measure of cultural innovation, with each unique tweet representing novel, newly-created information. The full dataset incorporating retweets, meanwhile, additionally contains information about cultural transmission, assuming that 'retweeting' can be seen as a form of transmission to others ('choose-to-transmit' in the terminology of cultural evolution: see Eriksson and Coultas (2014)). If 'fitness' is a measure of replication success, then the latter might be seen as a more appropriate measure of 'cultural fitness'. It may not be a coincidence therefore that the massively retweeted tweet was strongly negative in sentiment, if a negativity bias exists in human cultural evolution (see below). However, a tweet that has been retweeted also becomes more available, and so more likely to be observed and retweeted further, in an example of an informational cascade (Bikhchandani, Hirshleifer, and Welch 1992). This effect may also have been enhanced by the Twitter algorithm producing users' timelines. Our retweet analysis showed that when this outlier was removed, on average more positive tweets were retweeted more. Whether excluding this outlier is justified is, however, debatable. It is an 'outlier' in the statistical sense, but it is valid information that so many people chose to retweet this (negative) tweet in particular.

Our study has several limitations, common to analyses of social media big data. First, the Twitter sample is biased in characteristics such as age and socio-economic status, with Twitter users being younger and more educated compared to the general population (Sloan et al. 2015). We also restricted our sample to English-language tweets, so our results are specific to English speakers and English-language countries. Second, outputs of the Twitter API do not represent an unbiased reflection of activity on social media (Correia et al. 2021), and the exact biases are unknown. The timeline algorithm used by Twitter is also unknown and likely to influence the results. Third, sentiment analysis is a crude tool: while on the aggregate sentiment analysis produces reliable results, it is especially challenging for short texts like tweets, where sentiment must be inferred from just a few words, and contextual effects can be more easily lost (Hutto and Gilbert 2014). More importantly, Twitter activity may not accurately represent actual attitudes or predict behaviour change. Similarly, we cannot determine whether negative sentiment such as fear or anger is being potentially used for positive or negative means. Anger at global inaction over climate change would be classed as negative with an automated sentiment analysis, but might be seen by some as an appropriate and positive response to a crisis in need of urgent action.

Overall, our findings fit with a general negativity bias previously demonstrated in human cultural transmission. Experiments have shown that people preferentially acquire and transmit negative information from and to other people (Bebbington et al. 2017), while analyses of real-world datasets have shown trends towards more negative pop music (Brand, Acerbi, and Mesoudi 2019) and literature (Morin and Acerbi 2017). The same effect is present in online communication, with negative information being disproportionally common in “fake news” (Acerbi 2019a) and advantageously spreading on social media (Schöne, Parkinson, and Goldenberg 2021; Bellovary, Young, and Goldenberg 2021). This negativity bias is argued to be due to the asymmetric costs of false positives and false negatives (Fessler, Pisor, and Navarrete 2014): it is more costly to mistakenly ignore a negative stimulus such as a predator than to mistakenly ignore a positive stimulus such as food. The former gets you eaten, the latter just hungry. Human cognition has therefore evolved to pay more attention to negative stimuli than positive stimuli (Baumeister et al. 2001).

Our results suggest that we need to take this general negativity bias into account when planning environmental campaigns. Comparable studies have found that social media interest towards iconic species, such as rhinoceros, while generally slightly positive in sentiment, is triggered by negatively-valenced events (Fink, Hausmann, and Di Minin 2020). Framing messages positively could result in less engagement, or in the target audience preferentially picking up the negative aspects. How should we then frame campaigns when we want to convey a positive message? While generally robust, the effects of negativity bias are context-specific. First, there is individual variability in the extent to which we preferentially attend to negative information, with some individuals more interested or attracted to negative information than others (Bachleda et al. 2020). Second, there is time variability. Even though medium- and long-term trends in sentiment of, for example, news stories tend to show a negative trend, they are interspersed by cycles where positive sentiment prevails (Leetaru 2011; Rozado, Hughes, and Halberstadt 2022). This can be seen even at the level of single transmissions, where short bouts of positive news break up longer negative broadcasts. As a minimum, if negative sentiment is the norm, positive sentiment can represent a potentially attractive change in pace (Soroka and Krupnikov 2021). Finally, the diversification of platforms can facilitate the creation of niches where more positive news stories are disseminated (e.g. Upworthy), and users can actively search for them (Soroka and Krupnikov 2021). In sum, the existence of a negative bias does not imply that spreading positively-valenced information is always more difficult. A better understanding of this psychological and cultural process could help to successfully plan campaigns, and may allow it to be used to conservationists' advantage, rather than working against it.

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Supporting Information

Supporting Information contains Tables S1-S8 which provide the control and Our Planet species used in the analysis, the texts of the five most positive and most negative tweets with the hashtag #OurPlanet, and full regression results.

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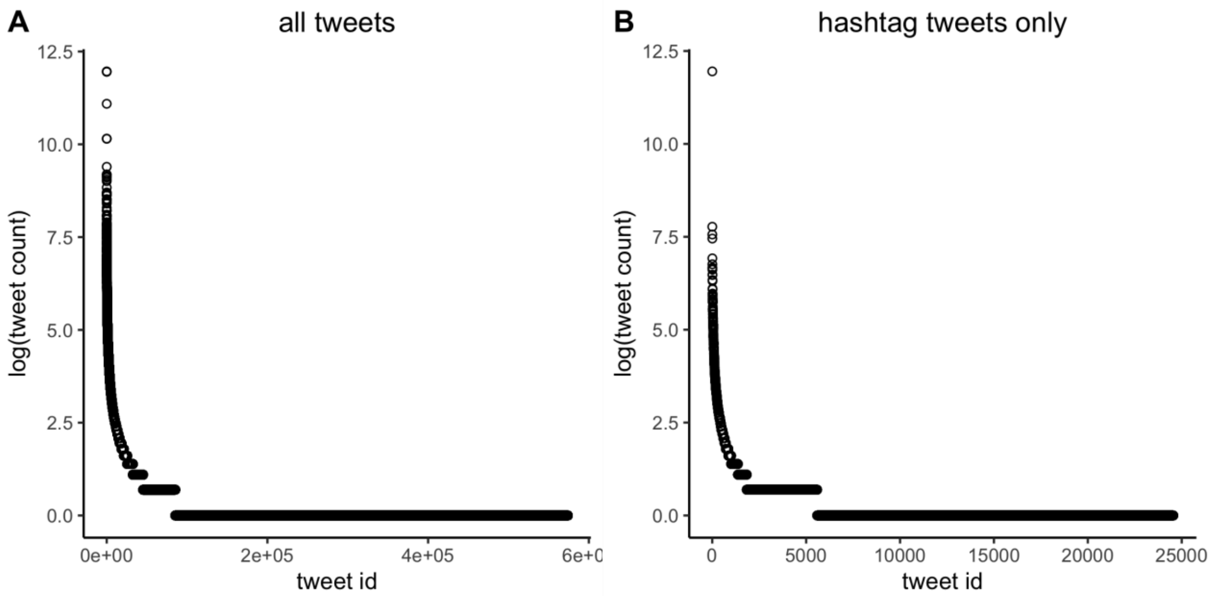

Figure 1. Distribution of tweet counts including retweets, on the log scale, for (A) all tweets in the dataset, and (B) only those tweets including the ourplanet hashtag.

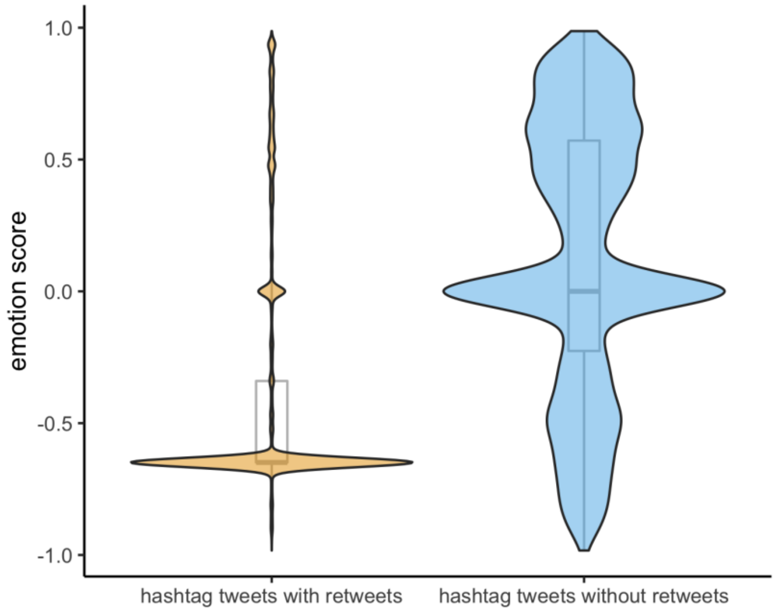

Figure 2. Distribution of emotion score for tweets containing the ourplanet hashtag, separately for all tweets including retweets (left, orange) and unique tweets excluding retweets (right, blue). Boxplots are shown in gray within the violin plots.

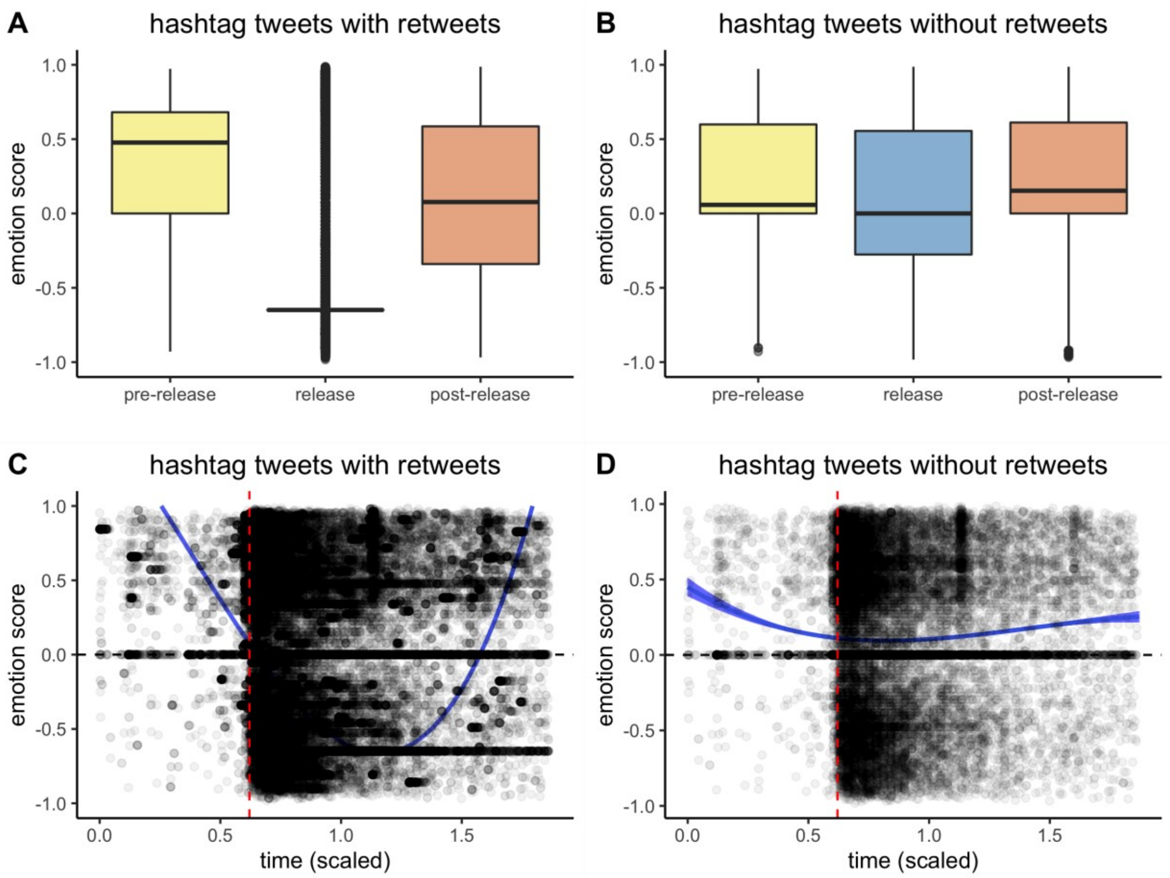

Figure 3. Changes in sentiment over time over the three discrete time periods for (A) all ourplanet-hashtag-containing tweets including retweets and (B) unique ourplanet-hashtag-containing tweets excluding retweets. (C-D) show the same over continuous time. Gregorian time is converted to a numeric value, scaled and set to begin at zero. The vertical red dotted line shows the release date of Our Planet. The blue line shows model prediction for cubic regressions, with shaded blue showing 89 percent percentile intervals using samples from the posterior. Transparent points indicate individual tweets.

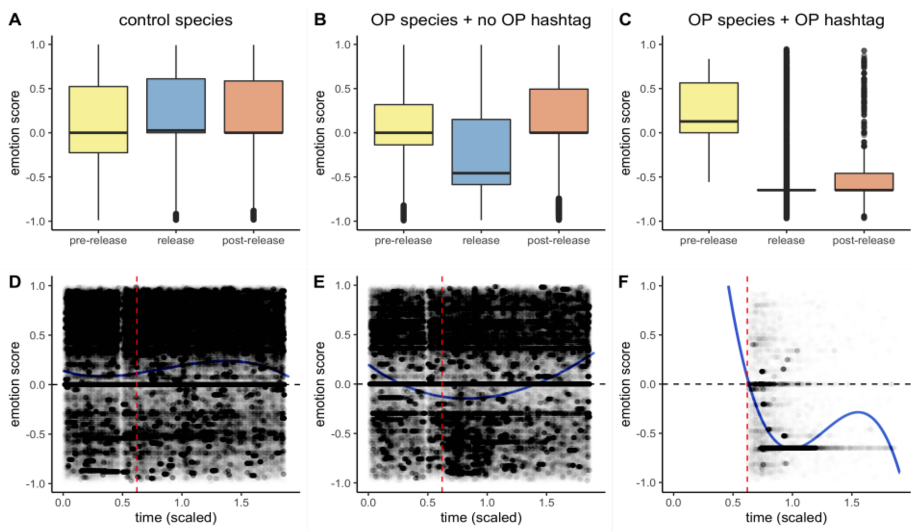

Figure 4. Changes in sentiment over the three time periods for all tweets (including retweets) for (A) control species, (B) Our Planet species with no explicit mention of the documentary, and (C) Our Planet species with Our Planet explicitly mentioned. (D-F) show the same over continuous time (see Figure 3 caption for details).

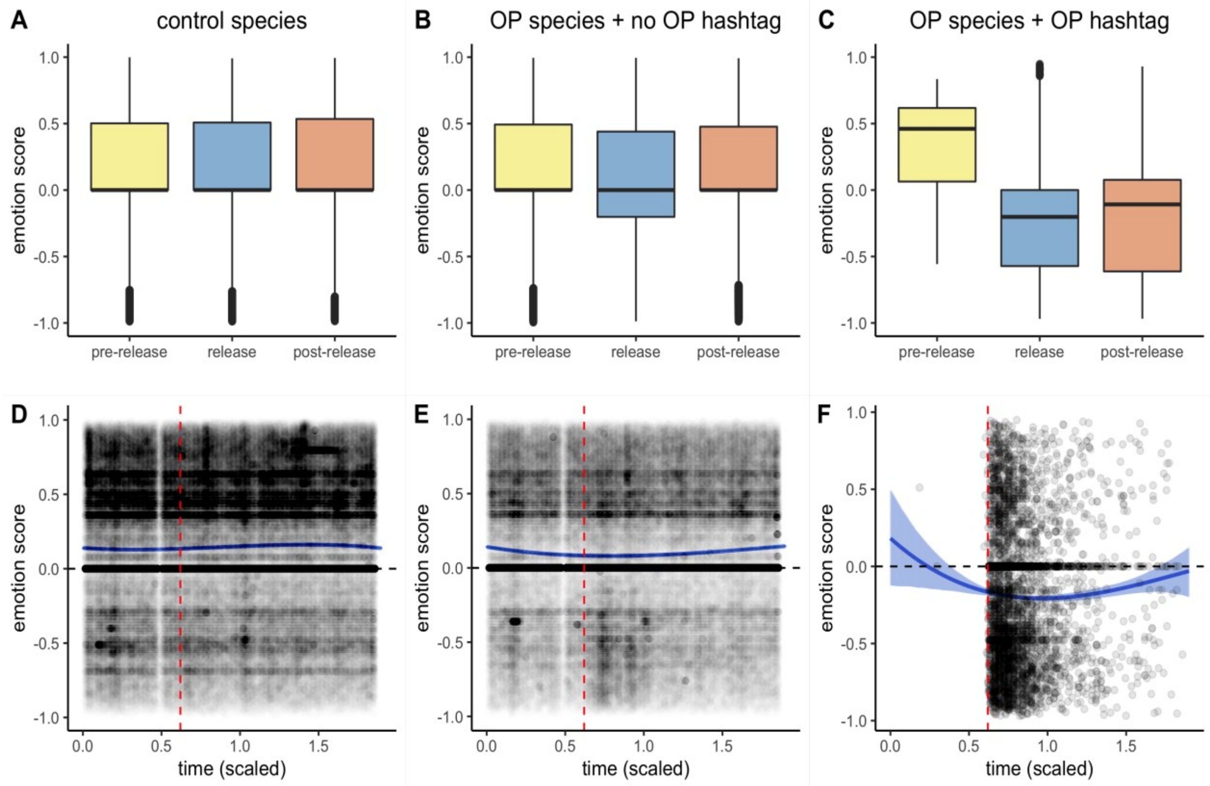

Figure 5. Changes in sentiment over the three time periods for unique tweets (excluding retweets) for (A) control species, (B) Our Planet species with no explicit mention of the documentary, and (C) Our Planet species with Our Planet explicitly mentioned. (D-F) show the same over continuous time (see Figure 3 caption for details).