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**Article** *in* Conservation Biology · August 2019

DOI: 10.1111/cobi.13404



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# Sentiment analysis as a measure of conservation culture in scientific literature

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Running head: Sentiment analysis

Keywords: web scraping, species at risk, biodiversity, threatened taxa, language, conservation psychology, culturomics

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1111/cobi.13404.

Article impact statement: Scientific literature on biodiversity conservation is increasingly polarized, but shows no trend toward positivity or negativity over time.

## Abstract

Culturomics is emerging as an important field within science, a way to measure attitudes and beliefs and their dynamics across time and space via quantitative analysis of digitized data from literature, news, film, social media, and more. Sentiment analysis is an emerging tool for culturomics that, within the last decade, has provided a means to quantify the polarity of attitudes expressed within various media. Conservation science is a crisis discipline and one in which accurate and effective communication are paramount to success. We investigated how conservation scientists communicate their findings through one of their primary media: scientific journal articles. We analysed 15,001 abstracts from papers published in conservation-focused journals published in the last 20 years, 1998-2017. Papers were categorized by year, focal taxa, and their conservation status; the mean sentiment scores were then extracted from the abstract using four lexicons (Jockers-Rinker, NRC, Bing et al., and AFINN). We found no annual trend in the sentiment scores of papers across conservation literature but analysis of absolute values suggested increasing polarization of language over time (i.e. less neutral). We also observed a trend towards increasing negativity along the spectrum of IUCN Red List categories (i.e. from Least Concern to Critically Endangered to Extinct), though this relationship was not significant. There were some clear differences in the sentiments with which research on different taxa were reported, however. For example, abstracts mentioning lobe finned fishes tended to have high sentiment scores, which we hypothesize may be related to the rediscovery of the coelacanth driving a positive narrative. Contrastingly, abstracts mentioning

elasmobranchs had low scores, reflecting the negative sentiment score associated with the word "sharks". Sentiment analysis is an exciting frontier with applications in science and we suggest a new science-based lexicon be developed for applying this tool to conservation.

## Introduction

Human thought and behaviour are modeled in non-verbal (Roth 2000) and verbal (Michel et al. 2011) communications. Co-evolution of society and these verbal and non-verbal languages permitted encephalic growth in hominids and the advent of culture (Aiello & Dunbar 1993). Culture became codified in written, audio, and video recordings or traditions contributing to a collective memory, allowing culture to be transmitted among generations (Vansina 1985; Clifford & Marcus 1986; Halbwachs 1992; Michel et al. 2011). Across time, the establishment and change of culture can therefore be quantified and tracked with direct analysis of the media that reflect the culture of origin in both geography and era. Interest in the description and analysis of cultural phenomena has yielded the field of culturomics, an analytical field striving to quantify trends in thought, opinion, or behaviour of humans relative to certain topics of interest (Michel et al. 2011; Ladle et al. 2016).

Culturomics focuses on the study of human thought or behaviour aggregated in accessible media (Popescu & Strapparava 2014; Ladle et al. 2016). Cultural data (e.g. text, images, coordinates) gathered from websites, web searches, or published literature are parsed and analyzed to reveal trends and associations. Michel et al. (2011) quantified human culture in a database comprising words published in ~4% of the books ever published to that point. Acerbi et al. (2013) reported an analysis of human emotions in 20th century literature to describe contemporary culture. Testing of hypotheses using culturomics has been applied to investigate allometric scaling of language (Petersen et al. 2012) or evidence for evolution of language (Sindi Dale 2016). The frequency and diversity of words determine the meaning of a given text. Words have connotations and text strings can convey context including state of thought such that the selection of words can convey sentiment to a human or computer consumer of the text (Hirschberg & Manning 2015). An emerging tool for culturomics is therefore sentiment analysis, a utility for text mining that exploits the denotation of words and assigns sentimental value to text strings by an algorithm (Bravo-Marquez et al. 2014). Sentiment analyses have focused in particular on quantifying public attitudes by scraping text posted on web sites, for example providing feedback on the attitudes of Chinese citizens to dam construction (Jiang et al. 2015) and visitors to the Great Barrier Reef (Becken et al. 2017).

Choice of words and effective communication of ideas is indeed of critical importance to convey messages about the importance and relevance of science to stakeholders and society (Vinkers et al. 2015; Doubleday & Connell 2018). In decision-making, choice of language (i.e. native or non-native tongue) has been shown to affect moral decisions, suggesting an importance of language in message conveyance (Costa et al. 2014). This is of particular salience in the field of conservation science, a crisis discipline in which science must effectively be communicated in order to be understood and acted upon (Soulé 1985; Schultz 2011; Cooke et al. 2017). Conservation emerged as a multidisciplinary field of inquiry integrating biological, economic, and social sciences to address the accelerating biodiversity crisis (Soulé 1985). As an inherently emotional science (Saunders 2003; Bujis & Lawrence 2013; Campbell & Veríssimo 2015; Nelson et al. 2016), there are considerable consequences for the interpretation of conservation science and decision-making (Wilson 2008; Garnett & Lindenmayer 2011; Lerner et al. 2015). Language of certainty and foreboding in scientific literature can increase the likelihood of media attention, which may also exaggerate findings (Ladle et al. 2005). Komonen et al. (2019) outline how dramatic adjectives such as “shocking”, “drastic”, and “devastating” catalyzed media frenzy and panic over the results of a literature review.

The role of emotion in conservation science is not well understood but could provide relevant feedback to scientists (Vinkers et al. 2015; Drijfhout et al. 2016). Various literature has characterized conservation scientists as being both optimistic (Papworth et al. 2018) and overly negative (Swaisgood & Sheppard 2010). Using bibliometric tools to fetch abstracts of conservation literature and automated sentiment analysis algorithms, we tested hypotheses about the sentiments conveyed by primary conservation literature with the aim of providing critical feedback to the discipline. Specifically, we aimed to identify temporal trends in conservation literature sentiment and trends by conservation status listed in the IUCN Red List. We also compare sentiment scores among species groups. We predicted that scientific literature focused on conservation biology would have increasingly negative sentiments over time as a consequence of an ongoing mass extinction event and associated conservation crises (Brooks et al. 2006; Ceballos et al. 2015). We also predicted that there would be differences among taxa, and that species with more critical IUCN Red List (IUCN 2019) statuses would be reflected by more negative language. As one of the first papers to apply sentiment analysis to conservation literature, we discuss potential opportunities for applying sentiment analysis as well as drawbacks and cautions to conservation scientists planning to implement it.

## Methods

A text database was established by searching for literature published in journals focused on biodiversity conservation. Journals were selected based on their appearance on lists of biodiversity conservation journals in each of the three key scientific citation and indexing databases: Thompson-Reuters database Web of Science, Scopus, and Google Scholar. As a result, six journals were included in our study: Animal Conservation, Biodiversity and Conservation, Biological Conservation, Conservation Biology, Conservation Letters, and Oryx. A database of abstracts from these journals was obtained by searching within Web of Science Core Collection database for articles published in selected journals during 1998-2017. Because the search was focused on original articles, reviews and conference proceedings, all other article types such as editorial material, corrections, news items, and letters were omitted from the dataset. Following search and download of the dataset, which comprised the total number of 15,247 articles, all publications lacking abstracts were excluded from the dataset, yielding the final dataset with 15,001 articles. Abstracts were used as they are a suitable reflection of the paper and likely have the widest impact in science as they are often read by the reader in lieu of the rest of the paper (King et al. 2006).

All analyses were performed in R (R Core Team 2018). Article metadata were generated within R using the taxize package (Chamberlain and Szöcs 2013; Chamberlain et al. 2018); topics (containing the article title, abstract, and keywords) were first passed through the *scrapenames* function to parse words or word strings within the topic matching with indexed taxonomic names, which were then passed through the *classification* function to identify the taxonomic class and phylum. Taxonomic names were further passed through a custom function applied to detect the IUCN Red List status of any species that was detected in the article topic, based on the *rl_search* function in the rredlist package (Chamberlain 2019).

Sentiment analyses were performed on abstracts using the packages tidytext (Silge Robinson 2016) and sentimentr (Jockers 2017; Rinker 2018a). The sentimentr package relies on the Jockers-Rinker sentiment lexicon (Rinker 2018b) with which it assigns polarity to words in strings with valence shifters (e.g. detects "not happy" as negative instead of just noting the single word "happy"). The tidytext package provides access to three common sentiment lexicons, Bing et al. (Liu 2012), NRC (Mohammad Turney 2013), and AFINN (Nielsen 2011). From the NRC lexicon only "positive" and "negative" sentiments were considered (i.e. excluded other sentiments such as "surprise"). Negative and positive sentiments of words from the

Jockers-Rinker (-1 to +1; 0.1 interval) and Bing (-5 to +5; 1.0 interval) were classified continuously, whereas NRC and AFINN lexicons were quantified binomially as -1 or +1, respectively, and the sum in each abstract was calculated. For comparison among lexicons, which are measured on different scales, the abstract sentiment value calculated for each lexicon was transformed to a standardized abstract sentiment score by the following equation:

$Standardized\ Abstract\ Sentiment\ Value = \frac{sentiment - \mu(sentiments)}{\sigma(sentiments)} + \mu(sentiments)$ . The standardized abstract sentiment values for the four lexicons were summed to calculate a sentiment score. Across the four lexicons, 12,627 words have been scored and we manually searched for words whose colloquial meaning could be confounded by their more neutral implementation in conservation literature (e.g. shark, lion, parasite; Supplementary File 1). This was conducted to identify words in sentiment lexicons that could confound sentiment analyses using these lexicons and the Supplementary File could be consulted by future researchers to identify words that they may wish to exclude from sentiment analysis should they apply this technique for their research.

## Data Analyses

Linear regression was used to identify the correlation among the four sentiment lexicons and their standardized scores using the *lm* function in R (R Core Team 2018). The same function was also used to analyze annual trends in sentiments, using linear regression of years and the standardized sentiment score. In consideration of potential changes in the polarization of sentiments over time (i.e. both increasingly negative and increasingly positive), we also conducted a linear regression on absolute values of sentiment scores. Absolute value transformation resulted in a skewed distribution of sentiment scores, so we square root transformed the absolute values (residuals followed a normal distribution but there was some evidence of non-normality for this test because of the nature of analyzing absolute values).

Taxonomic information was reported at the class and phylum level but are analyzed in consolidated groups, e.g. miscellaneous eukaryotes, bacteria, archaea, fungi, vermiform, and plant taxa. Dominant invertebrate phyla and chordate classes were reported distinctly. Linear regression was implemented with the *lm* function with the standardized sentiment score as the dependent variable and taxon level as the independent variable. Multiple comparisons were performed by the Tukey HSD test *glht* function in the multcomp R package (Hothorn et al. 2008).

IUCN Red List categories related to low risk that are no longer in use (i.e. LR/cd, LR/ct, LR/nt) were grouped within the category Least Concern (LC). Categories were given numeric, ordinal equivalents, with LC classified as one, followed by Near Threatened (NT), Vulnerable (VU), Endangered (EN), Critically Endangered (CR), Extinct in the Wild (EW), and Extinct (EX) along a scale of 1-7. Because sentiment scores could be nested within a publication, and in consideration of publications addressing multiple species, we compared a mixed-effects model implemented with the *lme* function in the R package nlme (Pinheiro et al. 2018) with random intercept for the study title to generalized least squares model (*gls* function in nlme) by AIC value.

Assumptions of normality were checked graphically. Plots were drawn using the R library ggplot2 (Wickham 2009) and the extension ggridges (Wilke 2018). Means are presented ± SE.

## Results

Automated taxonomic classification revealed that chordates and tracheophytes were the most frequently mentioned phyla, followed by arthropods, molluscs, and ascomycetes. At the class level, mammals, magnilopsids, birds, and insects were most frequently mentioned.

Using the sum of standardized scores to generate the overall sentiment score generated more spread in the sentiment scores and emphasized studies that were consistently positive or negative (Fig. 1). All four sentiment lexicons were significantly correlated such that all $|t| > 61.98$ and all $P < 0.01$. However, $R^2$ correlation coefficients ranged from 0.10 to 0.27 suggesting relatively weak fit of the correlations. The Bing and AFINN libraries had the highest degree of congruence ($R^2 = 0.27$) but were correlated poorly with the NRC lexicon ($R^2 = 0.13$, $R^2 = 0.10$, respectively). The Jockers-Rinker lexicon had the highest correlations with all three other libraries used. Among 12,627 words, we flagged 350 (2.8%) as having the potential to be confounded with conservation terms. The Jockers-Rinker library had 299, NRC 227, Bing et al. had 111, and the AFINN lexicon only had 73 (see examples in Table 1). The most common word, "conservation," was used 29,171 times in the 15,001 abstracts, which had a high positive polarity in the Jockers-Rinker lexicon, was a positive word in the NRC lexicon, but was not scored by AFINN or the Bing et al. lexicon. Using the sum of standardized sentiment scores for each of the four libraries, we found abstract sentiment scores ranging from -19.31 to 15.79 (mean = 0.53 ± 0.03 SE). There was substantial variation within years with high variance such that mean annual sentiment scores ranged from 0.84 ± 0.11 SE (2011) to 0.33 ± 0.11 SE (2013). There was no evidence supporting a temporal shift in the sentiment scores of conservation literature during the 20 years we investigated ($t = 1.37$, $P = 0.17$; Fig. 2). Inspection of the spread of scores (Fig. 2), however, suggested increasing polarization, and absolute values of sentiment scores suggested a significant positive change over time ($t = 8.83$, $P < 0.01$).

Abstracts mentioning sarcopterygii, the lobe-finned fishes including coelacanth and lungfish, had the highest sentiment scores (Fig. 3). Abstracts mentioning extinct species had the smallest average sentiment scores among the IUCN Red List categories (-1.77 ± 0.59 SE) whereas those mentioning LC species were most positive, on average (0.04 ± 0.06 SE; Fig. 4). There was no effect of IUCN status on the sentiment score based on mixed effects regression with each paper considered to have a random intercept ($t = 0.01$, $P = 0.99$), although there was evidence of kurtosis on the model residual distribution that may have somewhat affected performance.

## Discussion

Culturomics is emerging as an important scientific subdiscipline and we believe it has the potential to generate an important scientific set of metrics in conservation science (Sutherland et al. 2018). Understanding attitudes is critical to effective conservation (Becken et al. 2017; Davies et al. 2018; Fidino et al. 2018), including those expressed by scientists that are communicating with each other as well as with various stakeholders (Honsey et al. 2018). Our results did not reveal any significant trends across time or for species of different conservation status, but there was evidence of increasing polarization of language over time. What our findings do emphasize, however, is tendencies for conservation- and species-related terminologies to be polarized as negative or positive words in common lexicons. We also revealed differences among taxonomic groupings with potentially different implications for the implementation and consideration of conservation literature. The findings of this review are especially important when considering how conservation research is interpreted and evaluated by readers.

Temporal Trends

We predicted that conservation literature would have become increasingly negative over the timescale that we analyzed due to increasing habitat fragmentation, changes to global climate, augmenting number of extinct and at-risk species, and limited time with which to resolve many global environmental concerns (Ceballos et al. 2015, 2017). However, we found no such temporal trend. Despite the considerable challenges faced by conservation biologists and managers that may inspire negativity, there are also movements towards conservation optimism and positivity to combat upsetting storylines. Conservation optimism focuses on reporting success stories and progress towards the ultimate goals of biodiversity conservation, such as down listing of species at risk, successful enhancement or reintroduction of species, restoration of habitat, etc. (e.g. Swaisgood & Sheppard 2010; Garnnett & Lindenmeyer 2011). Although it did not manifest in this study, time will likely swing conservation literature in one of these directions, and whether conservation sentiment becomes increasingly negative or positive from this point forward will have implications for how it is received by stakeholders and management. Although we did not identify any increase in positivity or negativity alone, there was evidence from absolute values of sentiment scores that conservation sentiments have become increasingly polarized over time. This suggests that both positivity and negativity are increasing relative to more neutral language to describe conservation results. Such a trend could arise for a variety of reasons, including declining conservation statuses and increasing advocacy/optimism by scientists (Lackey 2007; Swaisgood & Sheppard 2010) or pressure to produce papers that are catchy or engaging to gain traction with the audience (Fanelli 2010). However, this can risk exaggerating findings that can have damaging impacts on scientific integrity (Komonen et al. 2019).

Taxonomy and Language

Across IUCN conservation statuses, we observed a negative but non-significant trend towards increasing negativity for species of greater risk. We hypothesize that confounding factors such as negative sentiments attributed to non-native species with low risk categories may have diminished this trend. We did, however, observe disparity in the sentiments attributed to papers focused on different taxa. Lobe-finned fishes, comprising coelacanths and lungfishes, had the most positive sentiment scores, which perhaps could be related to the rediscovery of coelacanth that was thought to have gone extinct 66 million years ago (Zablocki et al. 2016). The positive sentiments related to lobe-finned fishes contrasted with another group of fishes, the elasmobranch sharks and rays, which were the second most negative. The reason for this became clear after investigating the words included in the sentiment lexicons, which included “shark” as a negative term. Nolan et al. (2006) described how perceptions of animals prime human attitudes, a factor that can yield a mismatch between perception and reality as it pertains to wildlife. For sharks, fear associated with attacks, amplified by negative portrayals of sharks, may be resulting in the negative sentiments related to this word (Philpott 2002; Neff 2015). Ethnobiological studies have investigated the consequences of human attitudes as a driver of species conservation, which supports the relevance of our findings and supports the notion that attitudes towards wildlife can influence their conservation (Ceríaco 2012).

Biological terms are frequently adapted in common vernacular, which can complicate automated analyses of language (also discussed in Correia et al. 2017). Some species engender positive or negative responses from people based on various factors. This is a cultural phenomenon that manifests in sentiment dictionaries as we found that words such as “shark,” "parasite," or "leech", used as metonyms for exploitative traits in common language, would have contributed a negative bias in the sentiment scoring of texts that use these words in an academic, not colloquial, context. Alternatively, "conservation", the namesake of conservation biology, has positive polarity, meaning that we would have expected conservation biology literature to have a slightly positive bias for this reason. This is a great example of how word choice matters, though, because negative alternatives such as "endangered", "risk", and "extinction" exist. The observation that sentiment scores can be confounded by incorrectly coded words is not unique to conservation science, and there are reasons to be concerned about the potential biases associated with sentiment. For example, results from Kiritchenko & Mohammad (2018) suggest that sentiment analysis algorithms can return results biased by the writer's gender or race. Sentiment analysis is a developing method with exciting potential but some issues are yet to be rectified (Hussein 2018). Revealing these issues will allow refinement of the methods to develop sentiment libraries that will perform better in the many applications for which they could be suitable. Two important aims of our study were to reveal both potential opportunities for applying sentiment analysis as well as drawbacks and cautions to conservation scientists planning to implement it.

<u>Reflections on using sentiment analysis for conservation</u>

We used novel tools available through open source software packages in the R library to complete our analysis. Manual identification of taxa in each of the 15,001 abstracts would have been resource intensive but the taxize package in R provided a simple and reproducible platform with which to make rapid classifications. Donaldson et al. (2016) manually identified taxa for their study on taxonomic bias in conservation research, a process that was greatly simplified here by using the taxize package. The rredlist package provided similar functionality to automatically gather details on the conservation statuses of species mentioned by their binomial names. However, the method is less accurate than manual classification because it misses species names or synonyms that do not include taxonomic information (Correia et al. 2018).

Sentiment lexicons available in the R environment provided access to data necessary for investigating our research question without manually scoring each word. Sentiment lexicons are developed through manual scoring (e.g. Mohammad & Turney 2013) or scraping polarized microblogs or reviews to identify positive or negative words (e.g. Nielsen 2011). Problems with applying these lexicons developed using colloquial language to scientific writing are clear and provide some caution to other researchers aspiring to implement sentiment analysis for their research. Honsey et al. (2018) suggested that conference abstracts could be analyzed for sentiment to determine whether it affected attendance at presentations; however, any such analysis would need to be aware of biases, for example, that talks mentioning sharks would be down-weighted by the analysis. It is likely that novel sentiment lexicons will need to be created for science that are distinct from those implemented for colloquial language analyses. We used the z-score method to aggregate sentiment scores in an effort to consider multiple lexicons rather than arbitrarily select one to use. Although the sentiment scores that we calculated performed well and provided a method to consider multiple sources of information for our study, tools are needed to assist researchers in selecting sentiment analysis lexicons suited to their purposes. Going forward, this method will benefit from the development of more accurate sentiment analysis methods that can better handle word connotation biases, valence shifting, scientific jargon, and scientific writing styles. With the increasing accessibility for scientists to use machine learning in data analysis, we expect that neural network word vectorization techniques (word2vec: https://patents.google.com/patent/US9037464B1/en) could reduce bias and help deal with the novelty of language used in scientific publications by implementing out-of-vocabulary techniques for unknown words. Organizing the data to train such algorithms remains the largest barrier to wider implementation of sentiment analysis in science, including conservation, in the future.

Implications for Science Communication

Although we focused on the presentation of primary conservation literature, there are also implications for how that literature is understood and interpreted. A critical example of this is reported by Lineman et al. (2015), who identified more negative expressions on Twitter.com associated with “global warming” than with “climate change”. Key terms related to conservation emerged as emotionally polarized in our study. This has been discussed qualitatively for invasion biology, in which antagonistic language may be used in contrasting native and non-native species, language that has been pointed out as counterproductive (Larson 2005). This inspires the question of how word choice may influence interpretations of the research? How do different actors respond to statements presenting a “species of conservation priority” compared to an “endangered species”? Does negative language necessarily emphasize the urgency of action, or does positive language provide hopefulness that action could be impactful (see again the example of Lineman et al. 2015)? Such questions are beyond the scope of this study, but our implementation of sentiment analysis provides an important catalyst for investigating how culture affects conservation. Therefore, our study not only reveals important details about sentiment trends in conservation but also has relevant ethnobiological implications, specifically, that negative connotations of some biological words may yield undesirable consequences for conservation.

Translating science into action is one of the largest challenges that applied scientists confront in their research (Cook et al. 2013). Conservation psychology is an emergent discipline as it becomes increasingly obvious that human values, emotion, and attitudes contribute substantially to the outcome of conservation research and environmental management (Saunders 2003). We can harness intellect that gives us the capacity to alter the environment with a better understanding of how our actions have the potential to cause harm and how our discourse affects our ability to do anything about it. Goldman et al. (2018) identified language (specifically the implementation of the terms "vulnerability", "resilience", and "adaptation) as the first focal area for advancing climate change considerations in policy. Articulated in different ways in disciplines ranging from conservation directly to psychology, marketing, and beyond, human culture and language plays a critical role in decision-making and must be integrated as a consideration in building bridges along the science-action interface (Cook et al. 2013).

## Conclusions

Sentiment analysis is an exciting tool with broad applications for culturomics. Sutherland et al. (2018) identified culturomics as one of the emergent tools in conservation science in their annual horizon scan and this paper is among the first to provide sentiment analysis data for conservation scientists. Our findings are intended to inspire other researchers to integrate sentiment analysis within their research questions including those relevant to stakeholder engagement and science communication (Cooke et al. 2017). We observed that the language used in scientific literature can differ greatly from the language of modern social media, news, and other accessible data sources that are often used to train lexicons and neural networks. However, evidence that words in the literature are increasingly polarized suggests a decrease in neutral language and potentially more strong stances from scientists producing literature (Lackey 2007). Strategies to mitigate the negative polarization of some conservation-related terms was revealed as an important avenue for generating more interest in conservation and less antagonism about certain animals. We submit that sentiment analyses of scientific literature is a tool with the potential to provide better data for addressing the human side of conservation by developing fields such as conservation psychology that will allow scientists to better develop and communicate messages about conservation both within and beyond the scientific community.

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## Tables

Table 1. We searched 12,672 terms from the four sentiment lexicons for words that could be confounded in conservation and revealed 350 that could be misinterpreted as positive or negative by the sentiment lexicons. The full list of 350 is found in the Supplemental Material and here we present salient examples. Blank cells indicate absence from that lexicon.

| Word | Jockers-Rinker | NRC | Bing | AFINN |
|---|---|---|---|---|
| alive | 0.5 | positive | | 1 |
| altruistic | 1 | | positive | |
| analyze | 0.25 | | | |
| aphid | | negative | | |
| badger | -0.5 | negative | | |
| calf | | positive | | |
| carnivorous | | negative | | |
| competition | -0.25 | negative | | |

| | | | | |
|---|---|---|---|---|
| conservation | 0.8 | positive | | |
| cuckoo | -0.25 | negative | | |
| desert | -0.5 | negative | negative | |
| dolphin | | positive | | |
| dove | 0.25 | positive | | |
| elder | 0.4 | positive | | |
| glacial | -0.4 | negative | | |
| grizzly | -0.8 | negative | | |
| iron | | positive | | |
| leech | -0.5 | negative | negative | |
| lion | 0.1 | positive | | |
| lure | -0.5 | negative | negative | |
| oak | | positive | | |
| organic | 0.4 | positive | | |

| | | | | |
|---|---|---|---|---|
| pacific | | positive | | |
| pine | | negative | | |
| porcupine | | negative | | |
| quail | | negative | | |
| raptors | | negative | | |
| recreational | 0.8 | positive | | |
| scientific | 0.4 | positive | | |
| sea | | positive | | |
| seal | | positive | | |
| sex | 0.1 | positive | | |
| shark | | negative | negative | |
| snake | -0.25 | negative | | |
| spruce | | positive | | |
| stress | -0.75 | negative | negative | |

| | | | | |
|---|---|---|---|---|
| sucker | -0.5 | negative | negative | |
| swim | | positive | | |
| termite | -0.25 | negative | | |
| viper | -0.25 | negative | negative | |
| virus | -0.5 | negative | negative | |
| wild | -0.25 | negative | negative | |
| wolf | -0.25 | | | |

## Figures

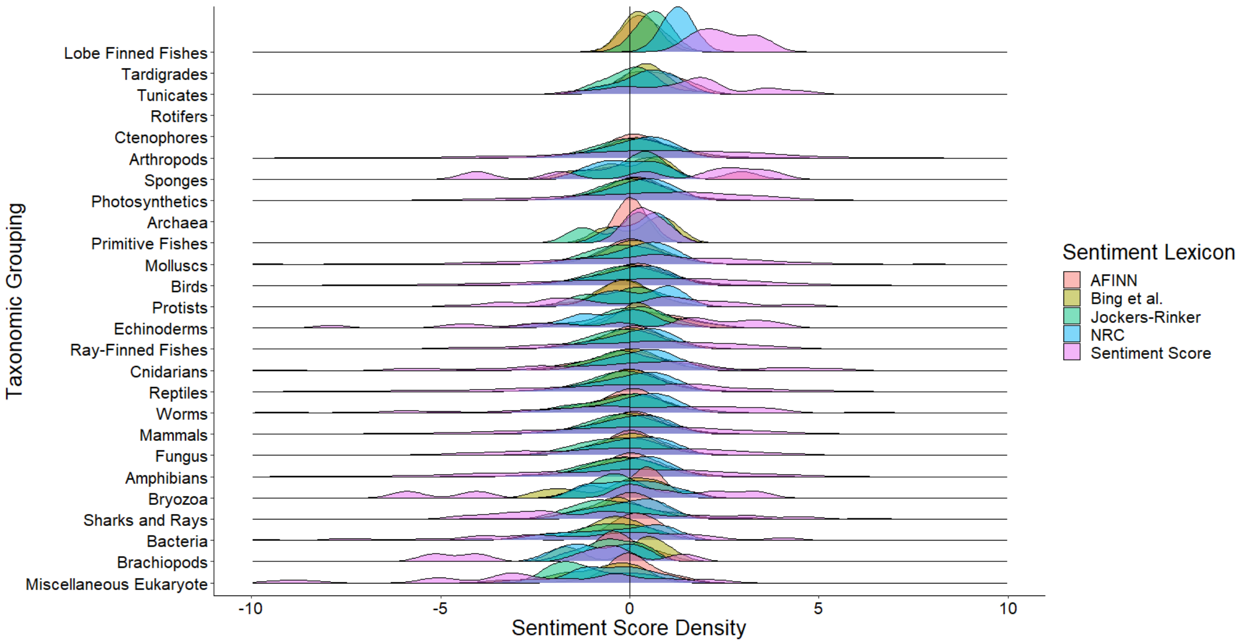


Fig. 1. Sentiment distributions (standardized) for each of the four sentiment lexicons and the aggregated value, sentiment score, which was used for analyses. The vertical line is at x=0. Colour available online only. Note the x-axis is truncated between -10 and 10 for legibility.

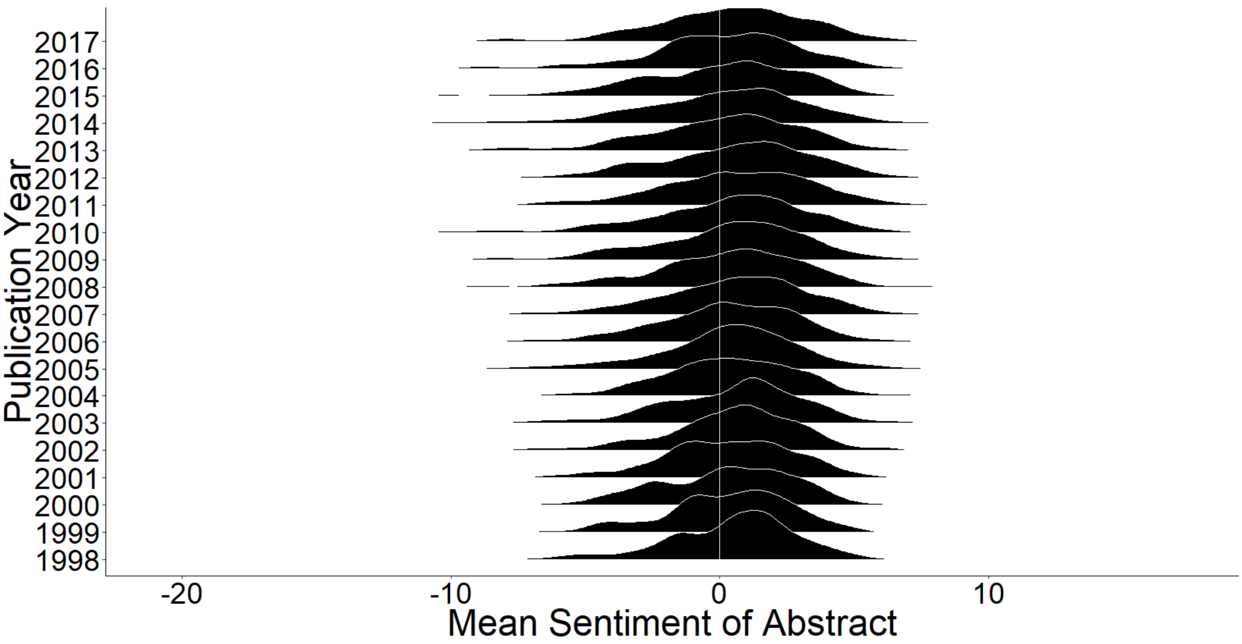


Fig. 2. Ridge plot of the distributions of sentiment scores in conservation literature abstracts from 1998-2017. Sentiment scores were calculated as the sum of standardized sentiments from four lexicons (Jockers-Rinker, Bing et al., AFINN, NRC). Article publication years are presented as factors for the purposes of this figure and the vertical white line is at zero to provide a point of contrast.

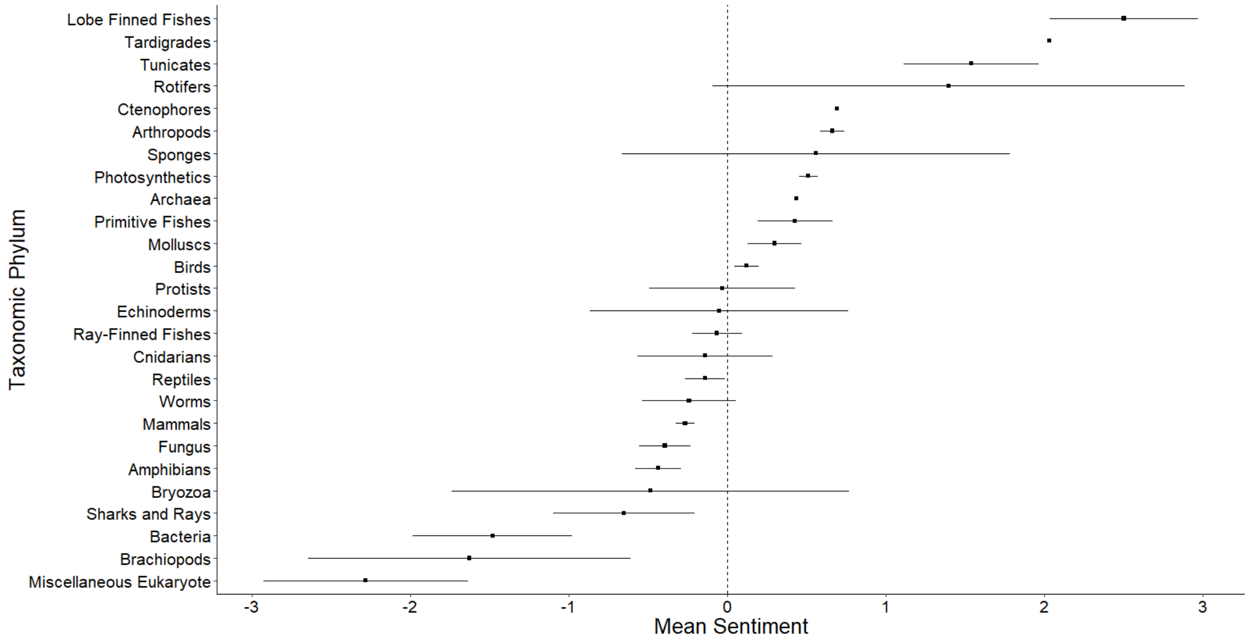


Fig. 3. Sentiment scores by taxonomic groups. Key chordate classes and invertebrate phyla are presented distinctly. Mean ± SE values for each group; both are sorted from smallest value to largest. The vertical dashed line at x=0 indicates the neutral point for the sentiment score.

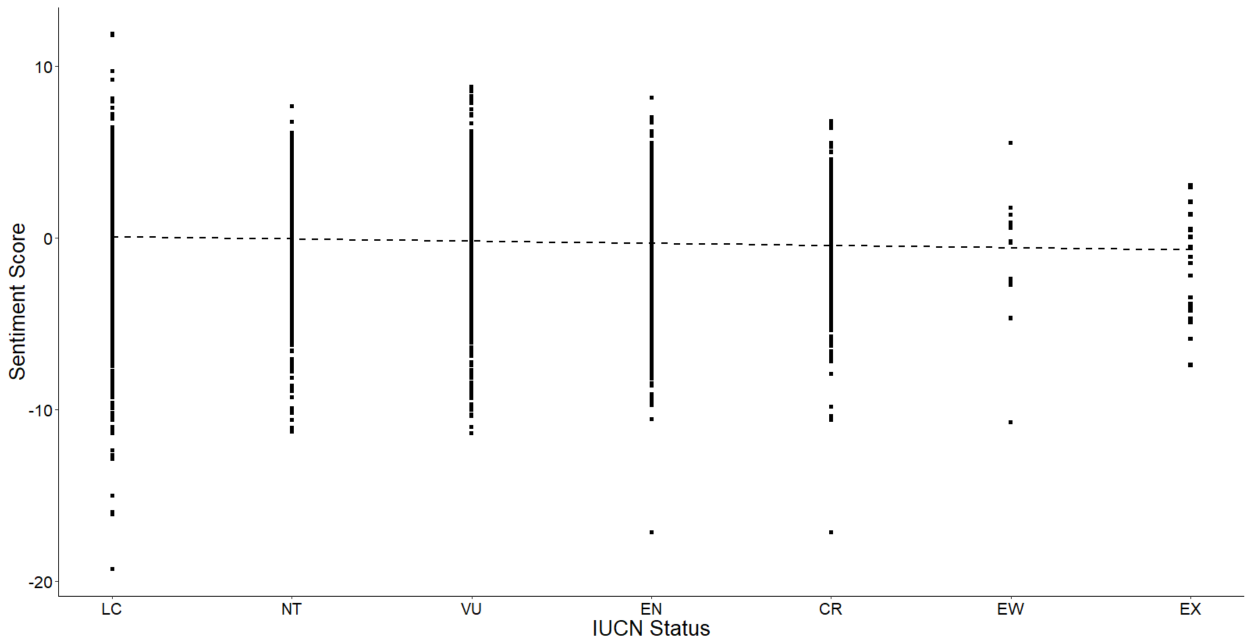


Fig. 4. Sentiment scores associated with species in eight IUCN Red List categories. Species names revealed in the topic of 15,001 conservation-related studies were scraped and the IUCN category was ascertained. Categories were converted to 1-7 numeric scores from Least Concern to Extinct. The dashed line indicates the linear regression line, having a slope of approximately zero based on mixed effects regression (see Results).