Conservation Biology

Contributed Paper

Sentiment analysis as a measure of conservation culture in scientific literature

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Abstract: Culturomics is emerging as an important field within science, as 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 a culturomics tool 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; therefore, accurate and effective communication are paramount. We investigated how conservation scientists communicate their findings through scientific journal articles. We analyzed 15,001 abstracts from articles published from 1998 to 2017 in 6 conservation-focused journals selected based on indexing in scientific databases. Articles were categorized by year, focal taxa, and the conservation status of the focal species. We calculated mean sentiment score for each abstract (mean adjusted z score) based on 4 lexicons (Jockers-Rinker, National Research Council, Bing, and AFINN). We found a significant positive annual trend in the sentiment scores of articles. We also observed a significant trend toward increasing negativity along the spectrum of conservation status categories (i.e., from least concern to extinct). There were some clear differences in the sentiments with which research on different taxa was reported, however. For example, abstracts mentioning lobe finned fishes tended to have high sentiment scores, which could be related to the rediscovery of the coelacanth driving a positive narrative. Contrastingly, abstracts mentioning elasmobranchs had low scores, possibly reflecting the negative sentiment score associated with the word *shark*. Sentiment analysis has applications in science, especially as it pertains to conservation psychology, and we suggest a new science-based lexicon be developed specifically for the field of conservation.

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

El Análisis de Opinión como Medida de la Cultura de Conservación en la Literatura Científica Lennox et al.

Resumen: La culturomía está emergiendo como un campo importante dentro de la ciencia pues es una manera de medir las actitudes, creencias y sus dinámicas a través del tiempo y el espacio por medio de un análisis cuantitativo de datos digitalizados a partir de la literatura, las noticias, las películas, las redes sociales y otros medios. El análisis de opinión es una herramienta de la culturomía que, en la última década, ha proporcionado los medios para cuantificar la polaridad de las actitudes expresadas en varios medios. La ciencia de la conservación es una disciplina de crisis;

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

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por lo tanto, la comunicación certera y efectiva es de suma importancia. Investigamos cómo los científicos de la conservación comunican sus hallazgos por medio de los artículos en las revistas científicas. Analizamos 15,001 resúmenes de artículos publicados entre 1998 y 2017 en seis revistas enfocadas en la conservación que fueron seleccionados con base en los índices de las bases de datos científicos. Categorizamos los artículos por año, taxón de enfoque y el estado de conservación de la especie focal. Calculamos la opinión promedio para cada resumen (puntaje z ajustado a la media) con base en cuatro lexicones (Jockers-Rinker, National Research Council, Bing y AFINN). Encontramos una significativa tendencia positiva anual en los puntajes de opinión de los artículos. También observamos una tendencia significativa hacia el incremento en la negatividad a lo largo del espectro de categorías de estado de conservación (es decir, de aquellas de menos preocupación a aquellas en peligro crítico o extintas). Sin embargo, hubo algunas diferencias claras en las opiniones con las cuales se reportaron las investigaciones sobre los diferentes taxones. Por ejemplo, los resúmenes que mencionaron a los peces de aletas lobuladas tendieron hacia los puntajes altos de opinión, lo que podría relacionarse con el redescubrimiento del celacanto como causa de una narrativa positiva. En contraste, los resúmenes que mencionaron a los elasmobranquios tuvieron puntajes bajos, lo que refleja el puntaje de opinión negativa asociado con la palabra *tiburón*. El análisis de opinión tiene aplicaciones en la ciencia, especialmente como parte de la psicología de la conservación, y sugerimos que se desarrolle un nuevo lexicón basado en la ciencia específicamente para el campo de la conservación.

Palabras Clave: biodiversidad, culturomía, especies en riesgo, extracción de datos de sitios web, lenguaje, psicología de la conservación, taxones amenazados

摘要: 文化组学是科学中一个新兴的重要领域, 它可以通过定量分析文学、新闻、电影、社交媒体等来源的数字化数据, 来衡量态度、信仰及其时空变化。情感分析作为文化组学的一种工具, 在过去十年间为量化各类媒体态度倾向的极性表现提供了方法。保护科学作为一门危机分析学科, 其准确有效的沟通至关重要。本研究调查了保护科学家如何通过科学期刊文章来交流他们的发现。我们基于科学数据库索引选择了六个保护学科期刊, 分析了它们 1998 年到 2017 年间发表的 15001 篇文章的摘要。文章按照年份、关注类群及其保护状况进行分类。我们根据四个情感分析的词汇库 (Jockers -Rinker、 国家研究委员会、 Bing 及 AFINN) 计算了每篇摘要的平均情感得分 (均值校正 z 值) 。我们发现文章的情感得分随着年份变化有显著增长的趋势, 且随着保护状态等级变化 (即从无危到极度濒危再到灭绝) 有显著降低的趋势。然而, 对不同类群的研究在情感上存在明显差异。例如, 提到肉鳍鱼的摘要往往情感得分更高, 这可能是因为腔棘鱼的重发现推动了积极正面的叙述。相比之下, 提到板鳃类的摘要得分较低, 反映了与 "鲨鱼" 这个词相关的负面情感得分。情感分析在科学领域有着广泛应用, 特别是在保护心理学领域; 我们建议应为保护领域创建一个基于科学的新词汇库。 **【翻译: 胡怡思; 审校: 聂永刚】**

关键词: 网页抓取, 受胁迫物种, 生物多样性, 濒危类群, 语言, 保护心理学, 文化组学

Introduction

Human thought and behavior are modeled in nonverbal (Roth 2000) and verbal (Michel et al. 2011) communications. Coevolution of society and these verbal and nonverbal languages permitted encephalic growth in hominids and the advent of culture (Aiello & Dunbar 1993). Culture is 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 behavior 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 behavior aggregated in accessible media (Popescu & Strapparava 2014; Ladle et al. 2016). Cultural data (e.g., text, images, and 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 in ~4% of all books 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 with culturomics has been applied to investigate allometric scaling of language (Petersen et al. 2012) and 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 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 websites, 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 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 nonnative 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 to conservation science, a crisis discipline in which science must effectively be communicated to be understood and acted on (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; Buijs & 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). Conservation scientists have been characterized as both optimistic (Papworth et al. 2018) and overly negative (Swaisgood & Sheppard 2010). Using bibliometric tools to identify abstracts in the conservation literature and automated sentiment analysis algorithms, we tested hypotheses on 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 as they relate to conservation status (International Union for Conservation of Nature [IUCN] Red List). We also compared sentiment scores among species groups. We predicted that scientific literature focused on conservation would have increasingly negative sentiments over time as a consequence of an ongoing mass extinction and associated conservation crises (Brooks et al. 2006; Ceballos et al. 2015). We also predicted 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 some of the first to apply sentiment analysis to conservation literature, we considered potential opportunities for applying this tool as well as drawbacks and warnings to conservation scientists planning to apply 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 3 key scientific citation and indexing databases: Thompson–Reuters database Web of Science, Scopus, and Google Scholar. As a result, 6 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 Web of Science Core Collection database for articles published in these journals from 1998 to 2017. Because the search focused on original articles, reviews, and conference proceedings, other article types, such as editorial material, corrections, news items, and letters, were omitted from the data set. Following search and download of the data set, which contained 15,247 articles, all publications lacking abstracts were excluded from the data set, yielding a final data set with 15,001 articles. Abstracts were used because they are a suitable reflection of the paper and likely have the widest impact in science because they are often the only part of the article that is read (King et al. 2006).

All analyses were performed in R (R Core Team 2018). Article metadata were generated in R with the taxize package (Chamberlain & 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 that matched indexed taxonomic names, which were then passed through the classification function to identify the 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 with the packages tidytext (Silge & Robinson 2016), textdata (Hvitfeldt 2019), and sentimentr (Jockers 2017; Rinker 2018*a*). The sentimentr package relies on the Jockers–Rinker sentiment lexicon (Rinker 2018*b*) 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 3 common sentiment lexicons, Bing (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 AFINN (−5 to +5; 1.0 interval) were classified continuously, whereas NRC and Bing 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 with each lexicon was transformed to a standardized abstract sentiment score with the following equation:

$$\text{Standardized abstract sentiment value} = \frac{\text{Sentiment} - \mu(\text{sentiments})}{\sigma(\text{Sentiments})} + \mu(\text{Sentiments}).$$

The standardized abstract sentiment values for the 4 lexicons were summed to calculate a sentiment score. Across the 4 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*, and *parasite* [Supporting Information]). This was conducted to identify words in sentiment lexicons that could confound sentiment analyses based on these lexicons. Supporting Information contains words that researchers may wish to exclude from sentiment analysis should they apply to use of this technique in their research.

Data Analyses

Linear regression was used to identify the correlation among the 4 sentiment lexicons and their standardized scores with the lm function in R (R Core Team 2018). The same function was also used to analyze annual trends in sentiments with linear regression of years and the standardized sentiment score.

Taxonomic information was reported at the class and phylum levels but were 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.

The IUCN Red List categories related to low risk that are no longer in use (i.e., lower risk conservation dependent, lower risk near threatened, and lower risk least concern) were grouped in the category least concern (LC). Categories were given numeric, ordinal equivalents: LC, 1; near threatened (NT), 2; vulnerable (VU), 3; endangered (EN), 4; critically endangered (CR), 5; extinct in the wild (EW), 6; and extinct (EX), 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. 2019) with random intercept for the study title to generalized least squares model (gls function in nlme) with Akaike information criterion (AIC) value.

Assumptions of normality were checked graphically. Plots were drawn with the R library ggplot2 (Wickham 2009).

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 4 sentiment lexicons were significantly correlated such that all $|t| > 40.75$ and all $p < 0.01$. However, R^2 correlation coefficients ranged from 0.10 to 0.40, suggesting relatively weak fit of the correlations. The Bing and Jockers–Rinker libraries had the highest degree of congruence ($R^2 = 0.40$) but were correlated poorly with the NRC lexicon ($R^2 = 0.13$ and 0.12, respectively). The NRC lexicon was notably negative. Average sentiment value across abstracts was −7.30 (SE 0.04), whereas the average value for AFINN, the most positive, was 2.88 (0.07).

Among 12,627 words, we identified 350 (2.8%) as having the potential to be confounded with conservation terms. The Jockers–Rinker library had 299, NRC had 227, Bing 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, and was a positive word in the NRC lexicon, but was not scored by AFINN or the Bing lexicon. Based on sum of standardized sentiment scores for each of the 4 libraries, abstract sentiment scores ranged from −20.50 to 12.21 (mean = −3.03 [SE 0.03]). There was substantial variation within years; mean annual sentiment scores ranged from −3.28 (0.11) (2013) to −2.74 (0.11) (2017). There was evidence supporting a positive shift in the sentiment scores of conservation literature during the 20 years we investigated ($t = 3.59$, $p < 0.01$) (Fig. 2). The AFINN, Bing, and Jockers–Rinker lexicon scores all similarly increased across time, whereas the NRC lexicon decreased significantly (Fig. 2).

Abstracts mentioning sarcopterygii, the lobe-finned fishes including coelacanth and lungfish, had the second highest sentiment scores (Fig. 1). Abstracts mentioning extinct species had the smallest average sentiment scores among the IUCN Red List categories (−5.73 [SE 0.57]), whereas those mentioning least concern species were most positive, on average (−3.62 [0.06]) (Fig. 3). There

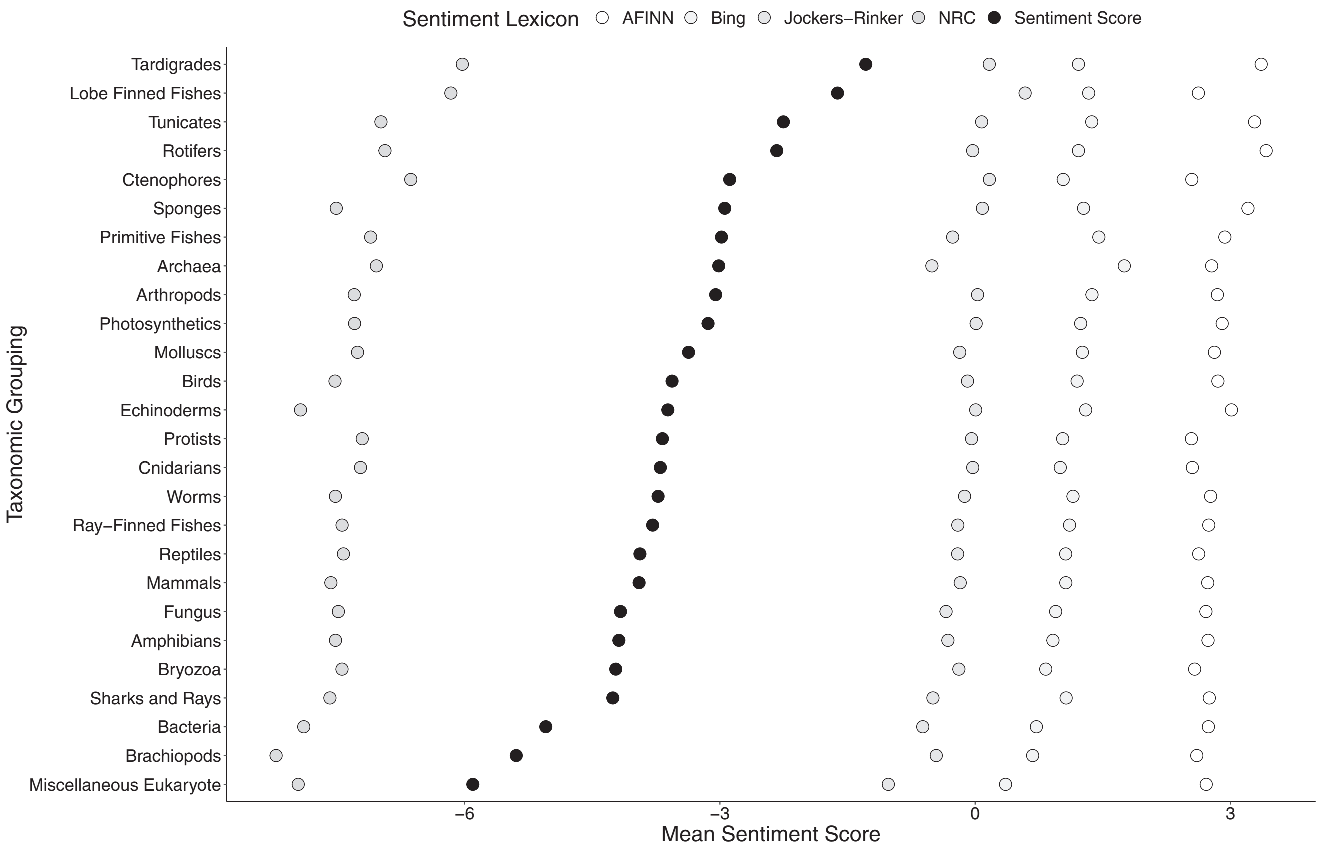

Figure 1. Mean sentiment scores of abstracts referring to species from various taxonomic groupings for 4 sentiment lexicons (light shading, means of each sentiment lexicon; black, aggregated sentiment scores). Note that from left to right in the figure is NRC, Sentiment Score, Jockers-Rinker, Bing, and AFINN.

was a significant effect of IUCN status on the sentiment score based on mixed-effects regression; each paper was considered to have a random intercept ($t = 2.38$, $p = 0.02$) (Fig. 3), 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 revealed a significant positive trend across time and a negative trend for species of greater conservation concern. Our findings emphasize the tendency for conservation- and species-related terminologies to be polarized as negative or positive words in common lexicons. We also found differences among taxonomic groupings with potential implications for the implementation and consideration of conservation literature. Our findings are especially important when considering how conservation research is interpreted and evaluated by readers.

Temporal Trends

We predicted the conservation literature would become increasingly negative over our analysis period 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). The slope of the relationship between sentiment score and time was relatively small, reflecting the high variation among studies that can be expected from articles written on different subjects and species and by authors having various perspectives. However, the change over time was significantly positive for the aggregated sentiment score as well as for 3 of the 4 lexicons individually. Despite the considerable challenges faced by conservation scientists and managers that may inspire negativity, there are also movements toward conservation optimism and positivity to combat upsetting storylines. Conservation optimism focuses on reporting success stories and progress toward the ultimate goals of biodiversity conservation, such as

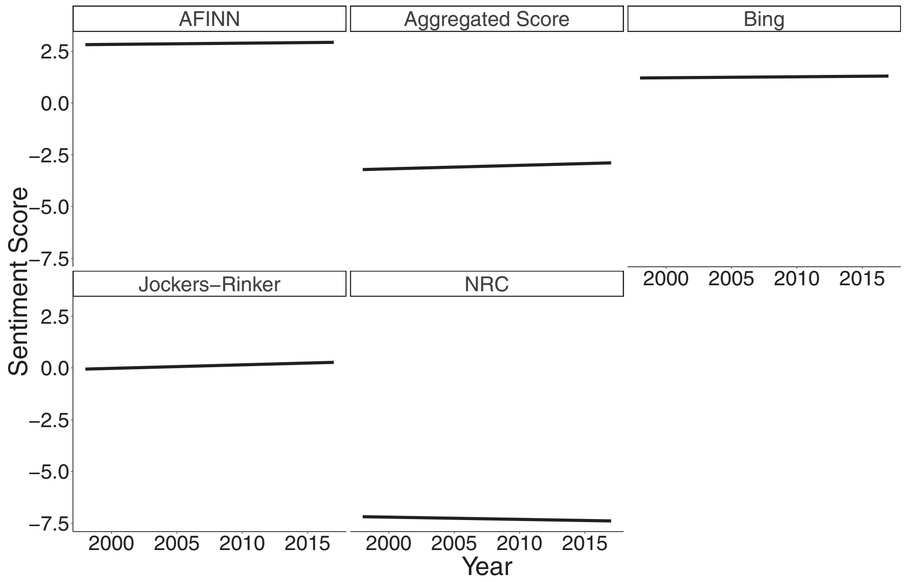

Figure 2. Smoothed trends of sentiment scores across time in 4 lexicons. For reference, the mean-adjusted standardized scores are shown for each lexicon (AFINN, Bing, Jockers-Rinker, and NRC) as well as for the aggregated (summed) score on which regression was performed to show a significant increase across time.

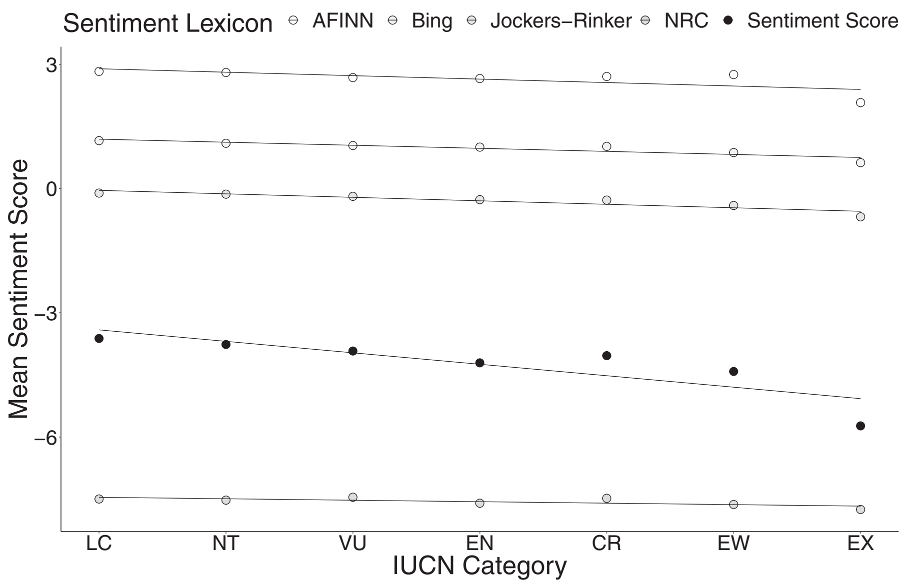

Figure 3. Mean sentiment scores for 4 lexicons calculated from abstracts of articles published in the conservation literature for species in International Union for Conservation of Nature (IUCN) Red List categories (lightly shaded, values for each sentiment lexicon; black, aggregated sentiment score; lines, slope of the relationship between the sentiment score and IUCN category organized from least concern [1] to extinct [7]).

down listing of species at risk, successful enhancement or reintroduction of species, and restoration of habitat (e.g., Swaisgood & Sheppard 2010; Garnett & Lindenmeyer 2011). Whether conservation sentiment continues to become increasingly positive or shifts toward negativity from this point forward will have implications for how it is received by stakeholders and management.

Taxonomy and Language

Across IUCN conservation statuses, we observed a negative relationship for species at 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 additionally observed disparity in the sentiments attributed to papers focused on different taxa. Lobe-finned fishes, comprising coelacanths and lungfishes, had the second 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 among the 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 bites, 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

Table 1. A sample of words that could be confounded (i.e., misinterpreted as positive or negative) in conservation contained in the 4 lexicons we used in an examination of sentiments in conservation literature.*

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			

**The Jockers-Rinker and AFINN lexicons provide continuous quantitative sentiment values, whereas NRC and Bing rate sentiments as positive or negative. The full list of confounding words is in Supporting Information. Blank cells indicate absence from that lexicon.*

relevance of our findings and supports the notion that attitudes toward 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. Words, such as *shark*, *parasite*, and *leech*, used as metonyms for exploitative traits in common English language would have contributed a negative bias in the sentiment scoring of texts that used these words in an academic, not colloquial, context. Alternatively, *conservation*, the eponym of conservation science, has positive polarity, meaning that we would have expected conservation science literature to have a slightly positive bias for this reason. This is a great example of how word choice matters; alternative words with negative connotation could also be used, such as *endangered*, *risk*, or *extinction*. 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 and Mohammad (2018) suggest that sentiment analysis algorithms can return results biased by the author's demographic. 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 warnings to conservation scientists planning to use it.

Reflections on Using Sentiment Analysis for Conservation

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 researchers aspiring to use sentiment analysis should consider them. Honsey et al. (2018) suggested that conference abstracts could be analyzed for sentiment to determine whether it affected attendance at presentations; however, such analyses would need to account for 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. The sentiment scores we calculated performed well and provided a method to consider multiple sources of information for our study, but tools are needed to assist researchers in selecting sentiment analysis lexicons suited to their purposes. However, there were differences among lexicons. The NRC lexicon was much more negative overall and then the others, which lowered the summed sentiment scores used for analysis. This method will benefit from the development of more accurate sentiment analysis tools 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: how does word choice influence interpretations of scientific research? How do different actors respond to statements presenting a *species of conservation priority* compared with an *endangered species*? Does negative language necessarily emphasize the urgency of action, or does positive language provide hopefulness that action could be impactful (example in 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 terms 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 expanding field as it becomes increasingly obvious that human values, emotion, and attitudes contribute substantially to the outcome of conservation research and environmental management (Saunders 2003). One can harness intellect by understanding how actions cause harm and how discourse affects one's 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 play 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).

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 an annual ecology horizon scan, and this present article 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 sentiment in conservation literature is increasingly positive may be suggestive of a shift toward conservation optimism (Papworth et al. 2018). Efforts to mitigate the negative polarization of some conservation-related terms (e.g., parasite and shark) will be an important avenue for generating more interest in conservation and less antagonism about certain species. 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.

Supporting Information

The full list of confounding words and a spreadsheet of words from the 4 lexicons we ascertained to be relevant to conservation (Appendix S1) are available online. A column for each lexicon shows the value (continuous quantitative for Jockers-Rinker and AFINN and categorical for Bing and NRC) and an additional column indicates whether the word was selected for the example in Table 1. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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