

1 Many IUCN Red List Species have Names that Evoke Negative Emotions

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32 (v0.2.0) (Rinker, 2017; Silge & Robinson, 2016). Raw data files and R program scripts used in
33 data processing and analysis can be obtained from the corresponding author.

Abstract

1
2 Species common names underpin communication between researchers, stakeholders and the
3 public. Changing unappealing (e.g., Rough-skinned Horned Toad), misleading (e.g., Lesser Bird
4 of Paradise) or even immemorable (e.g., Little Grassbird) species names could be an effective,
5 and inexpensive, way to improve engagement with and support for threatened species. We use
6 two sentiment lexicons to analyze the common names of 26,794 IUCN Red List animal species
7 to understand which words drive sentiment in species names. Words driving common name
8 sentiment varied across taxonomic class and threat status; highly-frequent words associated with
9 human emotions included anger, fear, disgust and joy. We identified key words for future
10 targeted research on strategic name changes (e.g., greater, golden, least, lesser, false). This article
11 provides essential grounding for future species common name research and improving public
12 engagement with threatened species.

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14 **Keywords:** interdisciplinary conservation science, public engagement, strategic
15 communications, message framing, threatened species

16

Introduction

The words we use make a difference. Because of this, message design and framing theory are increasingly used to achieve public engagement objectives for threatened species conservation (Echeverri, Chan, & Zhao, 2017; Kusmanoff, 2017; Weinstein, Rogerson, Moreton, Balmford, & Bradbury, 2015). Fostering a public or stakeholder connection with individual species can be crucial for their conservation; for example, by using charismatic species as campaign flagships, or targeting species in particular need of local community support and protection (Novacek, 2008; Veríssimo et al., 2017; Woinarski, Garnett, Legge, & Lindenmayer, 2017). While previous research has identified traits of typical charismatic or flagship species (Smith, Veríssimo, Isaac, & Jones, 2012), few studies have investigated how common names may influence public enthusiasm for a species (Braithwaite, Morton, Burbidge, & Calaby, 1995; Ehmke, Fitzsimons, & Garnett, 2017; Karaffa, Draheim, & Parsons, 2012; Scott, 2015). None have specifically investigated the sentiment of a large database of species common names, such as the International Union for the Conservation of Nature (IUCN) Red List of Threatened Species (<https://www.iucnredlist.org/>), the most comprehensive global list of animal and plant species and their conservation status (i.e. risk of extinction).

Sentiment analysis is the analysis of text with the intention of measuring some aspect of opinion or feeling (i.e., sentiment), including polarity (i.e., positive, negative or neutral), intensity (e.g., continuous measure of positivity or negativity), or specific emotions (e.g., anger, sadness, joy) expressed in the text (Liu, 2012). Sentiment analyses have become increasingly popular as data becomes more available and accessible. In particular, social media data can be analysed to establish current attitudes towards particular products, corporations or social issues (Mäntylä, Graziotin, & Kuutila, 2018). Conservation science stands to benefit from the use of sentiment analyses, particularly for exploring the level of public engagement and public attitudes towards particular conservation issues or threatened species (Drijfhout, Kendal, Vohl, & Green,

1 2016; Toivonen et al., 2019). Freely-available lexicons are constantly improving in terms of size
2 and sentiment scoring accuracy, and they can be rich datasets for analyzing the sentiment or
3 emotional association of specific words, providing insight into the perceptions and emotions
4 evoked by them.

5 We performed a sentiment analysis on the English common names of 26,794 animal
6 species on the IUCN Red List of Threatened Species – a key resource for conservation scientists
7 and decision-makers – to explore how species names might be connected to sentiment polarity
8 (i.e., positive vs negative) and human emotions such as joy, fear, disgust and sadness.

9 **Methods**

10 We used data exported from the IUCN Red List (IUCN, 2017), incorporating all listed
11 species within the kingdom Animalia, alongside sentiment data from two sentiment lexicons: the
12 labMT 1.0 dataset ('dodds_sentiment') in the R package 'lexicon' version 0.7.4, and the NRC
13 dataset ('nrc') from the R package 'tidytext' version 0.2.0 (Rinker, 2017; Silge & Robinson,
14 2016). The labMT sentiment scores are an average obtained from a U.S. survey in which
15 participants scored (from 1–9) how a given word made them feel ($n = 50$ per word), with higher
16 scores indicating greater positive feelings (e.g., $\text{labMT}_{\text{avg}}(\text{laughter}) = 8.50$, $\text{labMT}_{\text{avg}}(\text{hate}) =$
17 2.34) (Dodds, Harris, Kloumann, Bliss, & Danforth, 2011). The NRC sentiment lexicon
18 associates words with one or more of 10 categories, including sentiment polarity ('positive',
19 'negative') and emotions ('anger', 'anticipation', 'disgust', 'fear', 'joy', 'sadness', 'surprise',
20 'trust') (Mohammad & Turney, 2010, 2013). These lexicons were chosen from five freely
21 available datasets (Table 1) because they provided scores for the most words in the common
22 names ($n_{\text{NRC}} = 545$, $n_{\text{labMT}} = 1,595$, covered 1,855 unique words together). Using both lexicons
23 allowed for a more holistic sentiment analysis of common names. The labMT dataset's
24 continuous measure of sentiment polarity (score of 1–9) allowed us to identify the 10 highest-
25 and 10 lowest- scoring highly-frequent words (i.e., words driving sentiment), while the NRC

1 lexicon’s categorical attribution of human emotions allowed us to explore how words in common
2 names might be associated with specific human emotions. By considering the sentiment polarity
3 or emotion of each word individually we avoided common pitfalls of sentiment analyses (e.g.,
4 homonyms, sarcasm) that aim to establish overall sentiment of a text by adding or averaging
5 multiple sentiment scores across the desired level of analysis (i.e., a sentence, paragraph or entire
6 text) (Liu, 2012).

7 [Table 1. placed around here]

8 To determine which words were driving sentiment of common names, we used the
9 labMT lexicon (‘happiness_average’ variable, 1–9) to identify the 10 highest- and 10 lowest-
10 scoring words that are frequently-used; prioritizing sentiment score (i.e., values close to the polar
11 extremes of 1 and 9) and frequency of occurrence. To identify high- and low-scoring words we
12 first filtered out neutral scoring words (defined as words with sentiment scores between 4.5 and
13 5.5; 5 is true neutral in the labMT dataset), and then ranked the remaining words by sentiment
14 score, with low- (< 4.5) and high- (> 5.5) scoring words ranked separately. We then prioritized
15 high frequency words within these subsets by setting a required frequency ($n = 160$) and then
16 decreasing frequency thresholds (by $n = 5$ each iteration) until 10 high- and 10 low- sentiment
17 scoring words were identified. This method resulted in effective prioritization of frequently-used
18 words with the highest (or lowest) sentiment scores preventing a bias towards very highly
19 frequent words with only mildly positive (or negative) sentiment (e.g., color and morphology
20 words, such as ‘white’, ‘blue’, ‘headed’). We targeted these words because of their capacity to
21 have the strongest overall influence on common name sentiment, due to their affect (i.e., high or
22 low sentiment scores eliciting a strong emotional effect) and ubiquity (i.e., being highly frequent
23 in common names). To determine whether the words driving sentiment varied across taxonomic
24 class and IUCN threat status, we carried out this same process across five taxonomic classes
25 (each had more than 10,000 words within the list of common names: *Actinoterygii* (ray-finned

1 fishes), *Amphibia* (amphibians), *Aves* (birds), *Mammalia* (mammals) and *Reptilia* (reptiles)), and
2 across the eight IUCN Red List threat statuses (i.e., *Extinct*, *Extinct in the Wild*, etc.). In the case
3 of the *Extinct in the Wild* threat category, no words had a sentiment score below 4.5 (Figure.
4 2cii), however only 21 species fell into this category.

5 To identify frequently-occurring words in common names that are associated with
6 specific human emotions, we used the NRC lexicon to identify words across all common names
7 that are associated with emotions - anger, fear, disgust, sadness, anticipation, joy, trust, and
8 surprise - but are not captured by the labMT lexicon (i.e. we excluded the NRC lexicon
9 sentiment categories, 'positive' and 'negative'). We then identified the 10 most frequently
10 occurring words in each of the eight emotion categories. We carried out all data processing and
11 analysis in R v3.5.1 (R Core Team, 2018).

12 Results

13 Together, the labMT and NRC lexicons analysed sentiment for 1,855 unique words
14 within the IUCN Red List English common names (11% of unique words); 26,794 listed species
15 were at least partially analyzed (69% of listed species with English common names). The
16 number of words and species analysed varied across individual lexicons (Table 1). The words
17 analyzed were distributed as expected by chance across IUCN Red List threat status and animal
18 class (Table 1) and covered 56 of the 100 most frequent words in the IUCN Red List English
19 common names. Of the 44 unanalyzed but frequently occurring words, most were related to taxa
20 (59%, e.g., 'gecko') or morphology (39%, e.g., 'crested').

21 [Figure 1. placed around here]

22 Frequently-occurring words driving positive sentiment in species common names
23 included 'golden' (labMT = 7.30, $n = 478$), and 'great' (labMT = 7.88, $n = 171$). Frequently-
24 occurring words driving negative sentiment included 'rat' (labMT = 3.04, $n = 924$), 'lesser'
25 (labMT = 4.10, $n = 343$), 'false', (labMT = 3.18, $n = 189$), and 'blind' (labMT = 2.58, $n = 166$)

1 (Figure. 1a). Words driving sentiment varied across taxonomic class and included taxon-specific
2 words like ‘snake’ (*Reptilia, Actinopterygii*), ‘rat’ (*Mammalia*) and ‘dove’ (*Aves*) and non-
3 taxonomic words such as ‘sucker’ (*Actinopterygii*), ‘poison’ (*Amphibian*) and ‘lesser’
4 (*Mammalia* and *Aves*) (Figure. 1b). No words drove sentiment across all taxonomic classes
5 (though some drove across all but one e.g., ‘golden’, ‘dark’, ‘false’, ‘tree’). Words driving
6 sentiment also differed slightly across IUCN threat categories but with less clear differences
7 (Figure. 1c). Commonly-occurring words included ‘golden’ (across all 8 IUCN threat
8 categories), ‘tree’, ‘snake’ and ‘rat’ (7 of 8 threat categories), and ‘great’ and ‘false’ (6 of 8
9 threat categories). At least one of ‘least’ and ‘lesser’ drove sentiment in all but *Extinct in the*
10 *Wild* and *Critically Endangered*.

11 [Figure 2. placed around here]

12 The NRC lexicon identified high-frequency common name words that are associated with
13 key human emotions (Figure 2): anger (e.g., ‘tyrant’), disgust, (e.g., ‘rat’), joy (e.g., ‘dove’),
14 surprise (e.g., ‘worm’), anticipation (e.g., ‘long’), fear (e.g., ‘snake’), sadness (e.g., ‘blue’), and
15 trust (e.g., ‘ground’). The emotions anger and surprise were least-commonly represented in
16 species common names (Figure 2).

17 Discussion

18 We explored broad sentiment associated with species common names by drawing on the
19 large IUCN Red List dataset, and focussing explicitly on the sentiment of individual words and
20 associations with eight human emotions. This is, to our knowledge, the first sentiment analysis of
21 species common names across such a comprehensive species list. The sentiment associated with
22 common names may influence conservation outcomes in multiple ways, including by affecting
23 the perception of and conservation support for species by the general public (Karaffa et al., 2012;
24 Wright et al., 2015), as well as influencing decisions about which species to research or classify
25 under particular threat listings (Clark & May, 2002; Clucas, McHugh, & Caro, 2008; Metrick &

1 Weitzman, 1996; Possingham et al., 2002). If common names have any influence at all on a
2 species' likelihood of extinction, revising them may be a simple and cost-effective way to
3 improve conservation outcomes. We discuss implications of our findings for perceptions of
4 threatened species and future research below.

5 **Using Sentiment Analysis to Target Strategic Name Changes**

6 Commonly-occurring words driving sentiment in species common names included
7 positive words (e.g., 'golden', 'great'), and negative words (e.g., 'rat', 'lesser', 'false', and
8 'blind'). Further investigation revealed that some positive scoring sentiment words were
9 associated with particular human emotions, including 'dove' (joy, anticipation and trust), 'green'
10 (trust and joy), and 'tree' (anger, disgust, joy, anticipation, trust, surprise). The same is true for
11 negative scoring sentiment words such as 'snake' and 'rat' (disgust and fear), 'lesser' (disgust),
12 'worm' (anticipation and surprise), and 'dark' (sadness). These words, which are associated with
13 emotions that may be off-putting in a public engagement or decision-making context, could be
14 targeted for strategic name changes.

15 Our results also highlighted that the words driving sentiment across different taxonomic
16 classes are different. This may be due to differences in the way taxonomic classes are named
17 (Ehmke et al., 2017), or differences in typical morphology that tend to be named in similar ways.
18 Regardless of cause, these differences mean that appropriate targets for strategic name changes
19 in these groups may not always be the same.

20 Taxa-specific words dominate animal common name semantics, accounting for 40 of the
21 100 most frequent words. Some taxa-specific words are negatively loaded because of cultural
22 associations that go beyond common taxonomic biases. The word 'rat', for example, is
23 associated with the human emotions of fear and disgust (Figure 2) because of associations with
24 disease, uncleanliness, and deceitfulness (Smith-Marder, 2008). Therefore, species with common
25 names that include such words may be disadvantaged not only by broader taxonomic biases, but

1 also by other associations the word invokes. While not always possible or desirable, alternatives
2 to negatively-associated taxa-specific words could be considered. Take the *Data Deficient*
3 Persian rat snake (*Zamenis persicus*), disadvantaged not only by the bias against its taxa (and the
4 associated word, ‘snake’), but also by negative emotions evoked by the word ‘rat’. In this case,
5 the presence of ‘rat’ in its name may not be entirely necessary. Examples of the adoption of non-
6 taxa-specific common names can be found in Australia, where names from Indigenous languages
7 have been adopted for some mammal species (e.g., the ‘water rat’ was renamed ‘Rakali’)
8 (Braithwaite et al., 1995) (although we note that these names have not always been chosen with
9 proper attribution to language source or the wishes of language communities). While the impact
10 of such name changes on public perceptions is unknown, our findings suggest that there may be
11 merit in avoiding culturally-loaded words such as ‘rat’, particularly if it is not the only, or most
12 accurate, option.

13 Our findings did not present clear justification for targeting different words based on
14 threat status. It is possible that names may influence conservation support and threat status of a
15 species by influencing its perception and charisma amongst human populations. Disentangling
16 the circular relationships between naming, naming practice, taxonomy and morphology,
17 charisma and true conservation status was beyond the scope of our study. Future research that
18 explores relationships between threat status, conservation support and common names would be
19 valuable for understanding the power of common names for influencing conservation outcomes.

20 Considering how words with a particular taxonomic or historic background may be
21 (mis)interpreted by a public audience or decision-makers may also be useful when naming
22 species. For example, ‘lesser’, ‘least’, ‘greater’ and ‘great’ are typically used to differentiate
23 similar species by size, while ‘false’ is used to describe species that are morphologically similar
24 to another, taxonomically-different, species. These words may be misleading to a non-expert
25 audience, giving the impression that these species are less important than others. By excluding

1 sentimentally neutral words, our sentiment analysis may have missed highly-frequent words of
2 this nature. One such example is ‘common’ (labMT = 4.92, $n = 518$). While the vast majority of
3 species with ‘common’ in their name are of *Least Concern*, there are 5 *Critically Endangered*, 7
4 *Endangered*, and 18 *Vulnerable* species that have this sentimentally neutral but potentially
5 greatly misleading word in their common name. Such words may also be important targets for
6 future research regarding the strategic use of species common names to improve engagement
7 with threatened species conservation.

8 **Establishing an Empirical Evidence Base for Strategic Species Naming**

9 Our findings showed that there are frequently-occurring sentimentally-positive and
10 negative words in English species common names, as well as highly-frequent words associated
11 with human emotions. Further research that focuses on empirically testing the effect of common
12 names on perceptions, attitudes, and willingness to engage with and support threatened species
13 conservation is needed to understand the nuanced effects of common names on human
14 interpretation and engagement. For example, some negative words may be perceived as
15 interesting or exciting in the context of wildlife conservation (e.g., ‘devil’ in Tasmanian Devil),
16 and effects may differ across different audience demographics. In addition, our study focused on
17 individual words, while the interaction between words within species common names also needs
18 to be considered. For example, switching between ‘golden rat snake’ and ‘brown rat snake’ may
19 not have a meaningful effect on perceptions if the taxonomic effect of ‘rat snake’ overpowers
20 this change. While sentiment analyses can provide indications of overall sentiment by averaging
21 scores across words, experimental approaches are needed to provide greater insight into these
22 interactions and masking effects. Furthermore, experimental approaches in common name
23 research may provide an opportunity to test psychological mechanisms behind the effect of
24 different word types. It is possible that, by providing a more concrete construal of a species,
25 descriptive morphological words (e.g., size, color) act to reduce the psychological distance

1 between humans and non-humans, which is known to be linked to concern and action on issues
2 like climate change (Spence, Poortinga, & Pidgeon, 2012). Such research would better inform
3 strategic revision of common names to improve conservation outcomes for individual species.

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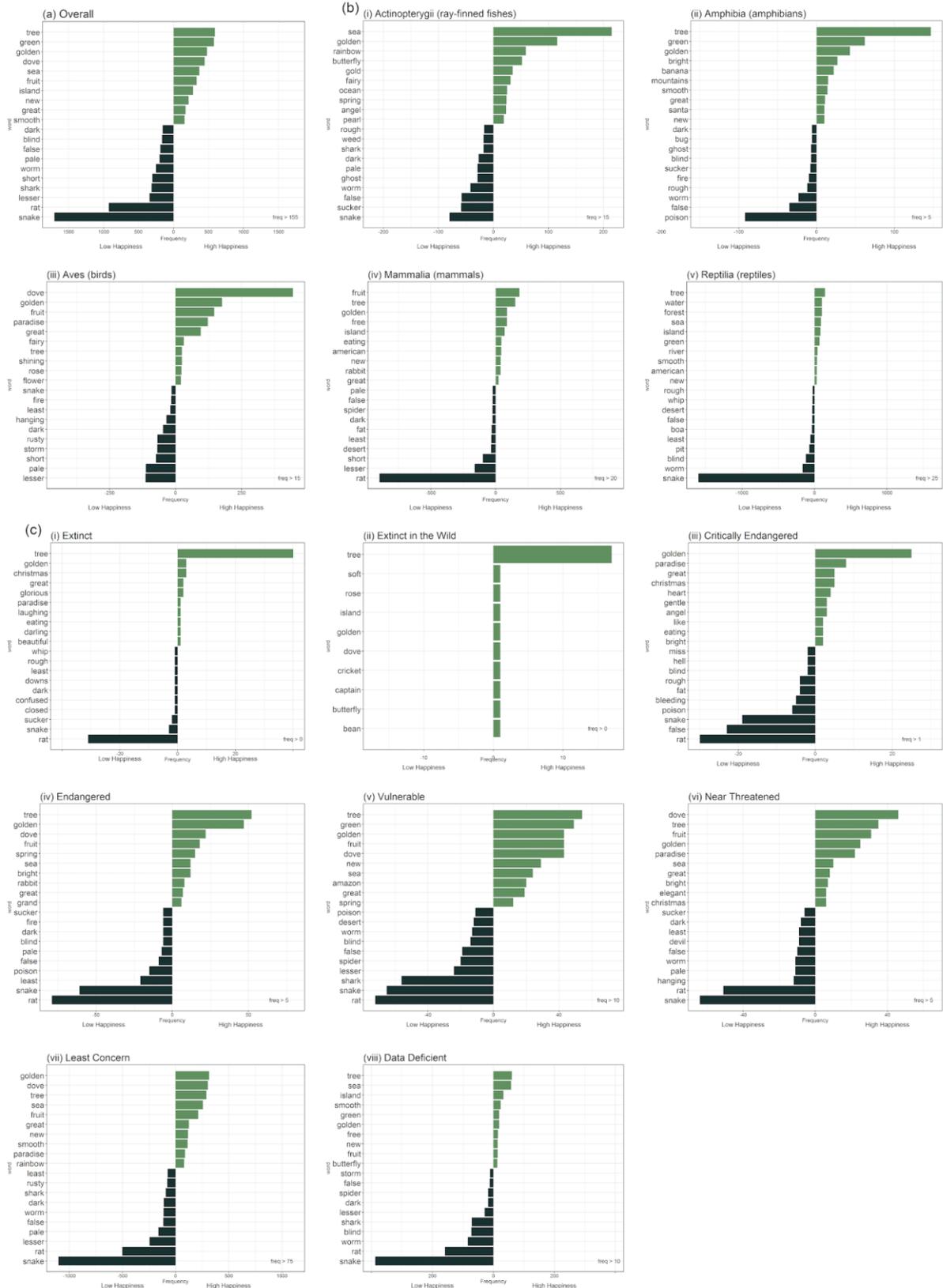
Table 1*Examples of Sentiment Lexicons*

Lexicon	Sentiment variable	Original source	Number of words in lexicon	Number of unique words analysed	Number of species analysed	Notes
NRC	Categorical (multiple categories allowed): <i>positive, negative, anger, anticipation, disgust, fear, joy, sadness, surprise, trust</i>	Mohammad and Turney (2010)	14,000	545 (3.1%) ^a (excluding 'positive' and 'negative' categories for analysis)	12,745 (32.9%)	Used in analysis
labMT 1.0	Continuous score: 1–9	Dodds et al. (2011)	10,222	1,595 (9.5%) ^b	25,681 (66.4%)	Used in analysis
Bing	Binary score: <i>positive, negative</i>	Hu and Liu (2004)	6,782	435	-	Binary polarity score not very informative compared to continuous score (e.g., in labMT and AFINN)
AFINN	Continuous score: -5–5	Nielsen (2011)	2,400	210	-	Intended for customer feedback analysis
Loughran	Categorical: <i>positive, negative, uncertainty, litigious, constraining, superfluous</i>	Loughran and McDonald (2011)	3,916	82	-	Intended for use in financial texts (e.g., 'share' is not necessarily positive)

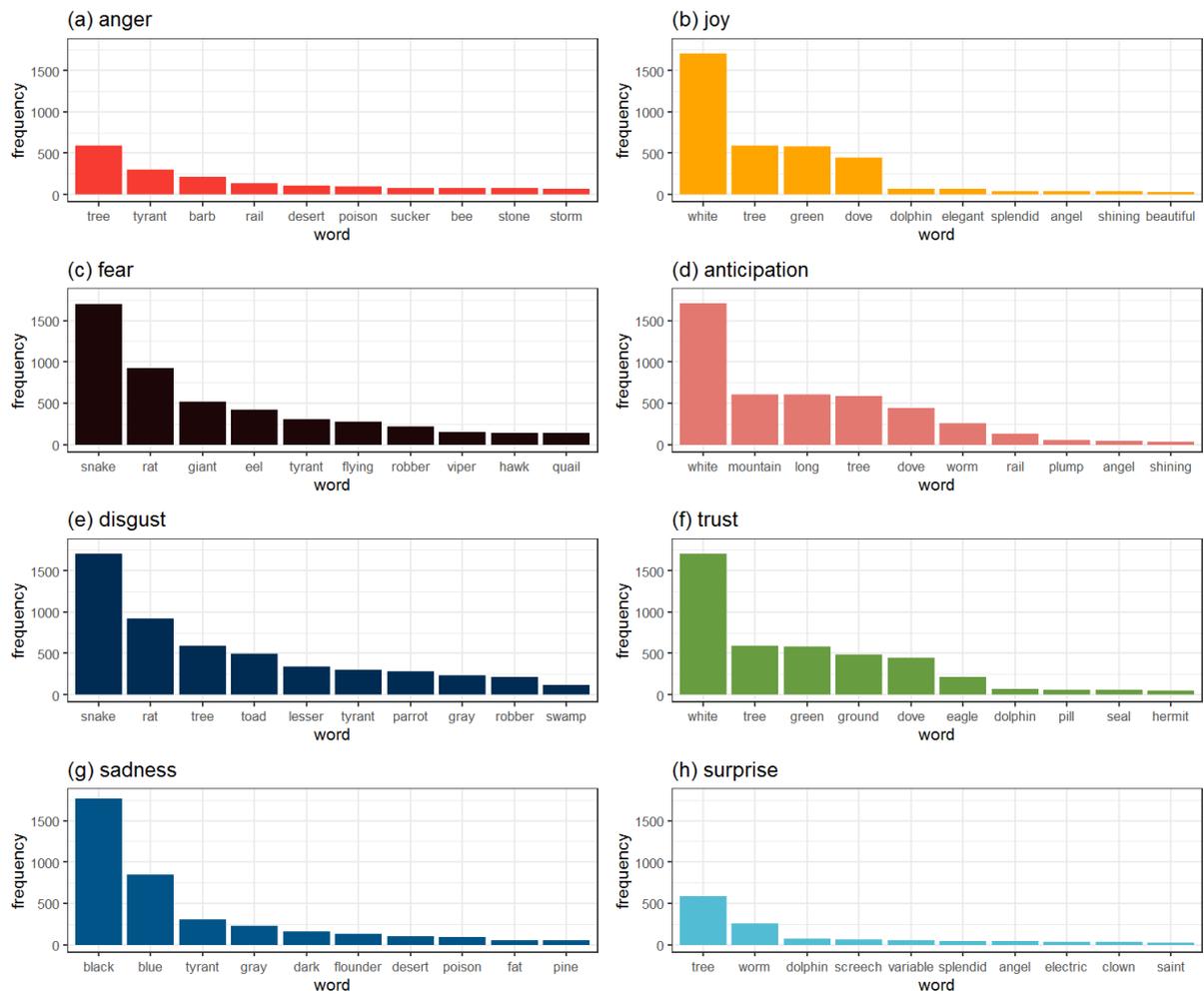
Note. All lexicons were accessed through the 'tidytext' R package (v0.2.0), except for labMT 1.0 which was accessed through the 'lexicon' R package (v0.7.4).

^a Distributed as expected by chance across threat status ($\chi^2 = 56$, $df = 49$, $p = 0.23$) and animal class ($\chi^2 = 620.6$, $df = 594$, $p = 0.23$).

^b Distributed as expected by chance across threat status ($\chi^2 = 56, df = 49, p = 0.23$) and animal class ($\chi^2 = 696, df = 648, p = 0.09$).



1
 2 **Figure 1** Words driving positive and negative sentiment in IUCN Red List threatened species English
 3 common names (i.e. 10 highest scoring and 10 lowest scoring labMT lexicon sentiment scores with high
 4 frequency), (a) overall, (b) across 5 taxonomic classes, and (c) across IUCN Red List threat statuses.



1
 2 **Figure 2** Top 10 most frequent words in IUCN Red List species English common names associated with
 3 different emotions, analysed using the NRC lexicon: **(a)** anger, **(b)** joy, **(c)** fear, **(d)** anticipation, **(e)**
 4 disgust, **(f)** trust, **(g)** sadness, and **(h)** surprise.