



33 **ABSTRACT**

34 Conservation conflicts involve an important emotional component that has been little  
35 investigated so far. In particular, the study of emotions involved in conservation conflicts  
36 have been limited in their scope (e.g. negative vs. positive sentiments) by the language  
37 studied (mostly English). Natural Language Processing (NLP) approaches combined with  
38 informed expert knowledge constitute a promising tool to analyze the occurrence of  
39 discrete emotions in textual contents. We applied NLP on the textual content of German  
40 print and online news publications featuring the return of wolves (*Canis lupus*) in the Saxony  
41 region of Germany (n=3,096), to investigate the occurrence of 7 basic emotions and their  
42 associations with 9 stakeholder groups. All emotions could be detected with different  
43 accuracy levels, and except for *interest* that was detected in all articles, negative emotions  
44 tended to dominate the articles' emotional content (*anger* in 74% and *fear* in 36% of the  
45 articles). *Anger* was most frequently detected in articles featuring *farmers* (20%) and  
46 *hunters* (15%), as was *fear* (17% with *farmers*, 14% with *hunters*). Our study of a diverse set  
47 of emotions, in local language, demonstrates the usefulness of NLP approaches to broaden  
48 the understanding of local conservation conflicts, in which the news organizations have a  
49 pivotal, yet often neglected role.

50

51 **KEYWORDS**

52 Artificial Intelligence, Conservation conflicts, Emotion Detection, Framing effects, Human-  
53 carnivore coexistence, Media Content Analysis, Sentiment analysis

54

55 **HIGHLIGHTS**

56

57 We used Natural Language Processing (NLP) to detect emotions in wolf press articles

58

59 Negative emotions (fear and anger) dominated press articles content in Germany

60

61 Anger and fear were mostly detected in articles featuring farmers and hunters

62

63 NLP applied to languages other than English is a promising tool for local conflicts

64

## 65 INTRODUCTION

66 Conservation conflicts and the underlying tensions between stakeholders over wildlife  
67 management can generate heated debates (Chapron and López-Bao, 2020; Nyhus, 2016),  
68 involving strong emotions. The role of emotions in conservation conflicts has been  
69 recognized in recent years (Chapron et al., 2014; Jacobs and Vaske, 2019; Jacobs, 2012;  
70 Nelson et al., 2016), as they influence our dispositions towards wildlife (Jacobs & Vaske  
71 2019) and seem tied to attitudes (Landon et al., 2019; Sponarski et al., 2015; Straka et al.,  
72 2020). However, they remain seldom studied. To date, studies on emotions towards wildlife  
73 have mostly focused on fear (Flykt et al., 2013; Johansson et al., 2012). The current lack of  
74 knowledge on emotions in the context of conservation probably owes to the lack of  
75 consensus around the definition of emotions (Izard, 2007; Jacobs, 2012), their diversity  
76 (Jackson et al., 2019) and their cultural and language specificities (Aman and Szpakowicz,  
77 2007). The study of emotions in the context of conservation conflicts thus requires strong  
78 interdisciplinary integrations and appropriate tools to address these challenges.

79 In recent years, Natural Language Processing (NLP) approaches, i.e. Artificial  
80 Intelligence techniques that allow computers to read and interpret information from natural  
81 language texts (Thessen et al., 2012), have been broadly used in multidisciplinary  
82 biodiversity projects (Thessen et al., 2012). Recent studies have highlighted the usefulness  
83 of Artificial Intelligence methods in conservation, as they can be used to identify  
84 conservation icons (Ladle et al., 2016), track illegal wildlife trade on social media (Di Minin et  
85 al., 2018; Xu et al., 2019), investigate human-nature interactions (Toivonen et al., 2019) or  
86 sentiments towards iconic species like white rhinoceros (Fink et al., 2020). We argue that  
87 NLP approaches, , combined with informed expert knowledge (Dadvar et al., 2014;  
88 Hirschberg and Manning, 2015; Hovy, 2015; Mohammad, 2016) constitute a promising  
89 avenue to investigate emotions in conservation conflicts, as they can be applied to a broad  
90 set of textual resources, to a wide range of contexts, and most importantly, to datasets  
91 containing an amount of data that cannot be processed manually. However, to date,  
92 automatic detection of emotions in textual content (i.e. sentiment analysis) applied in  
93 conservation have been limited by (i) the dichotomy between positive and negative  
94 emotions, although emotions are more diverse than simple polarizations (see Hausmann et

95 al. 2020 for a recent illustration in South African National Parks), and (ii) the focus on English  
96 language resources, which is, in many cases, of limited local conservation relevance.

97 In this study, we applied NLP in automatic analysis of emotions on the textual  
98 content of print and online news publications featuring the return of wolves (*Canis lupus*) in  
99 the Saxony region of Germany, where they have been present since their recolonization of  
100 Germany in 2000 (Reinhardt et al., 2019). Wolf conservation is one of the most contentious  
101 conservation topics in human-dominated landscapes (Darimont et al., 2018), and its return  
102 to Germany has sparked important media coverage. Stories involving returning carnivores  
103 are good candidates for being selected by news organizations, as they are perceived to be  
104 relevant to a broad readership (although few people interact with carnivores), involve a  
105 charismatic animal and often feature negative news (e.g. depredation events, concerns for  
106 human health) (Harcup and O’Neill, 2001). Hence, human-carnivore coexistence is  
107 frequently featured in the press (Bombieri et al., 2018; Fernández-Gil et al., 2016; Killion et  
108 al., 2018) and contains an important emotional component that play an important role in  
109 the mechanisms behind the effect of news frames on opinions, or framing effects (Lecheler  
110 et al., 2015). Here, we investigated a set of seven basic emotions, namely *interest*, *surprise*,  
111 *joy*, *sadness*, *fear*, *anger* and *disgust* (Jacobs et al., 2014). In addition, we investigated the  
112 co-occurrence of the seven emotions and nine specific wolf conservation stakeholders,  
113 namely *politics*, *research*, *Non-Governmental Organizations*, farmers, hunters, military,  
114 news agencies, media, Saxony’s Wolf Information Office.

115

## 116 **MATERIALS and METHODS**

### 117 *Corpus of news*

118 Since wolf return to Saxony in 2000, the Wolf Information Office “Kontaktbüro Wölfe in  
119 Sachsen” has been continuously compiling press clippings featuring wolves, in print and  
120 digitized formats. The sampling protocol has evolved through time: at first, articles were  
121 collected manually by surveying local (i.e., from the region of Saxony) and national press,  
122 and opportunistically collecting news on wolves from other federal states; then, the advent  
123 of online newspapers allowed automatized data collection based on keyword entries. It is  
124 therefore possible that some articles were missed, but we assume that this would have

125 mostly affected articles from sources outside Saxony, and we do not anticipate specific  
126 biases in terms of topics or emotional content. We obtained 4,000 newspaper articles, all in  
127 German, that covered the entire period from 2000 to 2018, to investigate their content. As  
128 most articles were indeed published in Saxony (n=2,556) or were from national sources  
129 (n=764), we excluded articles from German federal States other than Saxony and focused on  
130 a set of 3,320 newspaper articles. Each article was scanned and processed with an Optical  
131 Character Recognition program. We only extracted the textual information and excluded  
132 articles containing unrecognized text (n=224), resulting in a total of 3,096 articles for our  
133 analysis.

#### 134 *Natural Language Processing*

135 We pre-processed the texts using the Natural Language Toolkit in Python: we removed stop  
136 words and non-informative symbols and punctuations, and used stemming to reduce them  
137 to their word stem. The identification of emotions followed several steps (see Supporting  
138 Information Fig. S1). First, we developed our own lexicons to identify the seven emotions in  
139 the articles' texts, by compiling words referring to each of the seven emotions. We used the  
140 SentimentWortschatz (V1.8) dictionary (Remus et al., 2010) to further enhance our list and  
141 find synonyms to the words associated with each of the seven emotions (see Supporting  
142 Information Table S1). Second, we used the Term Frequency-Inverse Document Frequency  
143 (TF-IDF) numerical approach (Aizawa, 2003) to identify the most informative and distinct  
144 words in each text and to investigate whether they included the words related to the  
145 emotions. Third, we identified the presence of emotions in each text based on the  
146 frequency of occurrence of words related to a specific emotion (Whitelaw et al., 2005).  
147 Fourth, we used a word-level n-gram model (here bigram, n=2) that takes into account the  
148 co-occurring words within a given window around the words associated with the specific  
149 emotions. This provided the possibility to further look into the context that a word has been  
150 used for, rather than only the frequency of its occurrences.

151

#### 152 *Stakeholder categorization and extraction*

153 We created a lexicon for each of the stakeholder groups by populating a list of the keywords  
154 based on our own expertise. We further improved the lexicon using an inductive approach  
155 and adding terms that we found in the newspapers during the labelling process (see

156 Evaluation). We included *politics, research, Non-Governmental Organizations, farmers,*  
157 *hunters* as these groups are most active in wolf conservation debates. We further included  
158 *military* (military training areas have been critical for wolf recolonization in Germany)  
159 (Reinhardt et al., 2019), *news agencies, media* (i.e. people involved in cultural and artistic  
160 activities associated with wolves e.g. books, films, exhibits, etc.) and the *Wolf Information*  
161 *Office* as these were frequently mentioned in the articles. We then used the lexicons as a  
162 proxy to detect the occurrence of the stakeholders in each article (see Supporting  
163 Information Table S2, Fig. S1).

#### 164 *Evaluation*

165 The evaluation dataset consisted of 498 articles manually and independently labelled for  
166 presence/absence of the seven emotions by two annotators with a social-ecological  
167 background. The inter-annotator agreement was 0.80 (average agreement over the 7  
168 emotions) meaning that in 80% of the labelled cases, the reviewers labelled the newspaper  
169 articles to the same emotion categories (see Table 1).

170 We used the manually labeled dataset, where both annotators were in agreement,  
171 to evaluate the accuracy of the NLP approach and to report the precision and the recall of  
172 the identified emotions. For a specific emotion, precision is the fraction of accurately  
173 detected instances (true positives) among the detected instances by the NLP (true positives  
174 + false positives), whereas recall is the fraction of accurately detected instances (true  
175 positives) among the total amount of relevant instances, i.e. texts that genuinely contained  
176 that specific emotion (true positives + false negatives). Accuracy also reported the F1-Score  
177 which is the number of correctly identified emotions divided by the number of all correctly  
178 identified emotions returned. Finally, to investigate the co-occurrence of emotions and  
179 stakeholder groups in the newspaper articles, we used pairwise Pearson correlation tests  
180 between the seven emotions and the nine stakeholder groups, and implemented a  
181 bonferroni correction on p-values to account for multiple tests.

182

## 183 **RESULTS**

184 The classification accuracy was different among emotions (Table 1). *Disgust* (1.00) and  
185 *interest* (0.84) had the highest precision whereas *joy* (0.43) and *surprise* (0.62) had the

186 lowest. *Interest* (1.00) and *anger* (0.61) had the highest rates of recall whereas *disgust* (0.08)  
187 and *joy* (0.09) had the lowest rates. Hence, *interest* (0.91) and *anger* (0.63) had the highest  
188 F1-scores, whereas *disgust* (0.14) and *joy* (0.15) had the lowest (Table 1). Across 3,096  
189 newspaper articles on wolves, *interest* (1.00), *anger* (0.74) and *fear* (0.36) were the most  
190 frequently detected emotions (Fig. 1).

191 We identified *politics* (0.56) and *farmers* (0.54) as the most frequently found  
192 stakeholders in the articles (Fig. 1). Comparatively, the *Wolf Information Office* (0.04) and  
193 the *military* (0.04) were the least featured stakeholders in the articles (Fig. 1). The most  
194 frequently detected co-occurrences between emotions and stakeholders in the newspaper  
195 articles were between *farmers* and *anger* (0.20,  $t=11.33$ ,  $p < 0.001$ ), *farmers* and *fear* (0.17,  
196  $t=9.68$ ,  $p < 0.001$ ), *hunters* and *anger* (0.15,  $t=9.68$ ,  $p < 0.001$ ) and *hunters* and *fear* (0.14,  
197  $t=7.82$ ,  $p < 0.001$ ) (Fig. 2). The highest correlation between two emotions was found  
198 between *anger* and *fear* (0.36,  $t=21.57$ ,  $p < 0.001$ ).

199

## 200 **DISCUSSION**

### 201 *Main findings*

202 Overall, our approach using NLP to detect emotions in German articles featuring wolves  
203 demonstrated that all emotions could be detected in the corpus of 3,096 articles, and that  
204 the approach could be applied to another language than English, increasing its local  
205 relevance for conservation. Although emotion detection accuracy was sometimes low, we  
206 detected a domination of negative emotions like *anger* and *fear*. The detection of *fear* and  
207 *anger* in news articles featuring *farmers* and *hunters*, although reflecting the challenges of  
208 human-carnivore coexistence, may hint at an unbalanced representation of wolf  
209 conservation in the news.

210

### 211 *Natural Language Processing' relative efficiency to detect emotions*

212 Emotion detection is a challenging task because it is language- and topic-specific (Aman and  
213 Szpakowicz, 2007). The inter-annotator agreement of ca. 80% illustrated the challenge of  
214 labelling texts containing specific emotions. However, this value was in the range of  
215 previous sentiment analysis in German (Momtazi, 2012) and other languages (Mozetič et al.,  
216 2016). Furthermore, the F1-scores, reflecting quantity and quality of detected emotions,

217 were also in line with previous findings (Balahur et al., 2012; Kušen et al., 2017), reporting  
218 higher precision for negative emotions and lower recall values for positive emotions (Table  
219 1), meaning that negative emotions are more accurately detected, and positive emotions  
220 occur less frequently in the news. Such pattern probably echoes the news tendencies to  
221 select and frame negative news more frequently (Harcup and O'Neill, 2001). *Interest* may  
222 not be a relevant emotion as it was detected in all newspaper articles, which publication  
223 probably already reflects an expression of interest, thereby artificially inflating recall values  
224 (1.00).

225         Except for *interest*, the prevalence of negative emotions like *anger*, *fear* and *sadness*  
226 reflected the overall negative framing of human-carnivore coexistence in the news  
227 (Bombieri et al., 2018; Nanni et al., 2020). The domination of *anger* and *fear* is problematic  
228 for carnivore conservation, as emotions play an important role in mediating news framing  
229 effects on people's attitudes (Lecheler et al., 2015). In fact, it is widely accepted that  
230 negative information has a stronger impact on people's attitudes than positive information  
231 (Soroka, 2006). As only few people directly interact with wolves (Arbieu et al., 2020) or  
232 other conflict-prone wildlife, human-wildlife relations are mainly shaped by information and  
233 not personal experience. Therefore, at a time where human activities increasingly encroach  
234 on wildlife habitats and potentially generate more conservation conflicts, the conservation  
235 community should embrace the complexity of emotions in conservation conflicts, for long-  
236 term human-wildlife coexistence. We demonstrated that NLP approaches are promising  
237 tools in this regard.

238

### 239 *Emotions and stakeholders' representation*

240 News organizations play an important role in giving a voice to conservation actors, and  
241 stakeholder recognition is a critical aspect of conservation conflict management (Redpath et  
242 al., 2017). We are aware of only few studies investigating stakeholder occurrence in the  
243 media (see e.g. Rust, 2015; Webb and Raffaelli, 2008). Our approach using NLP to  
244 investigate the co-occurrence between stakeholder and emotions revealed that the highest  
245 associations between *hunters*, *farmers*, and *anger* and *fear* depicted a bleak image of  
246 human-wolf coexistence in Saxony. This finding is at odds with a previous study that found  
247 rather neutral attitudes expressed by the broad public towards wolves in this region (Arbieu  
248 et al., 2019), reflecting an attenuation of the conflict over time. This discrepancy between



249 the negative and emotional content found in the newspapers that focus on the short-term,  
250 often negative news and people's rather neutral attitudes that reflect longer timeframes of  
251 learning to coexist with carnivores, illustrates the news agencies' narrow focus and  
252 perception of human-carnivore coexistence. Understanding stakeholder's as well as news  
253 agencies' perceptions (Bennett et al. 2016) may be critical to restore a more balanced and  
254 fair representation of human-carnivore coexistence in the media. In addition, the  
255 prevalence of *politics* and the under-representation of *research* demonstrates that the  
256 information conveyed by news organizations may not always be evidence-based, and calls  
257 for improved communication from the scientific community. Therefore, NLP approaches can  
258 be a useful tool to investigate local conservation conflicts and potential polarizations (Webb  
259 and Raffaelli, 2008). Besides, they are useful to analyse big textual datasets and resources,  
260 such as online social media platform contents and news archives. However, most existing  
261 tools and technical resources, such as training datasets and gold standards for automatic  
262 detections have mainly been developed for the English language. Therefore, having these  
263 tools and classification models developed for other languages, such as our study in German,  
264 could be beneficial to local conservation contexts. In particular, this will help identifying  
265 imbalances in stakeholder representation, investigating emotional contents, and developing  
266 strategies to produce evidence-based information that do not mainly focus on short-term  
267 negative news.

268

### 269 *Outlook*

270 This work calls for further investigations of the role of emotions in news featuring  
271 conservation topics. First, to improve the accuracy of emotion detection, we would  
272 recommend manually labeling an evaluation dataset that covers sufficient numbers of each  
273 emotion to train a machine learning model, prepared by at least 3 annotators. Second,  
274 further investigations could go beyond emotion occurrence and address emotional  
275 intensity, and investigate changes at different spatial and temporal scales. Such  
276 investigations would be very important in contexts of rapid social-ecological changes. Third,  
277 comparisons across charismatic species could inform on discrepancies in species framings  
278 (Bombieri et al., 2018). Most importantly, we encourage conservation scientists to embrace  
279 interdisciplinarity and develop collaborations with scholars across journalism studies,  
280 natural and computer sciences.

281 **Acknowledgements**

282 The authors thank the members of the Kontaktbüro “Wölfe in Sachsen” for the collection of  
283 newspaper articles and S. Liehn for coordinating the data handover; we thank the members  
284 of the Lupus Institute for Wolf Monitoring and Research including I. Reinhardt and G. Kluth  
285 for their support; we thank A. Renthrop, E. Bauer and A. Höfer for their help in designing the  
286 emotion lexicons and annotating the articles to create the evaluation dataset. This study  
287 was supported by the Robert Bosch Foundation

288

289 **AUTHOR CONTRIBUTION**

290

291 UA, AN and TM conceptualized the manuscript. UA, AN and MD developed the  
292 methodology. MD developed the Natural Language Processing approach. KH collected the  
293 data from the press articles. UA, AN and KH performed the analyses. UA prepared the  
294 results visualization. UA prepared the initial draft of the manuscript and all authors  
295 contributed substantially to the redaction of the final version.

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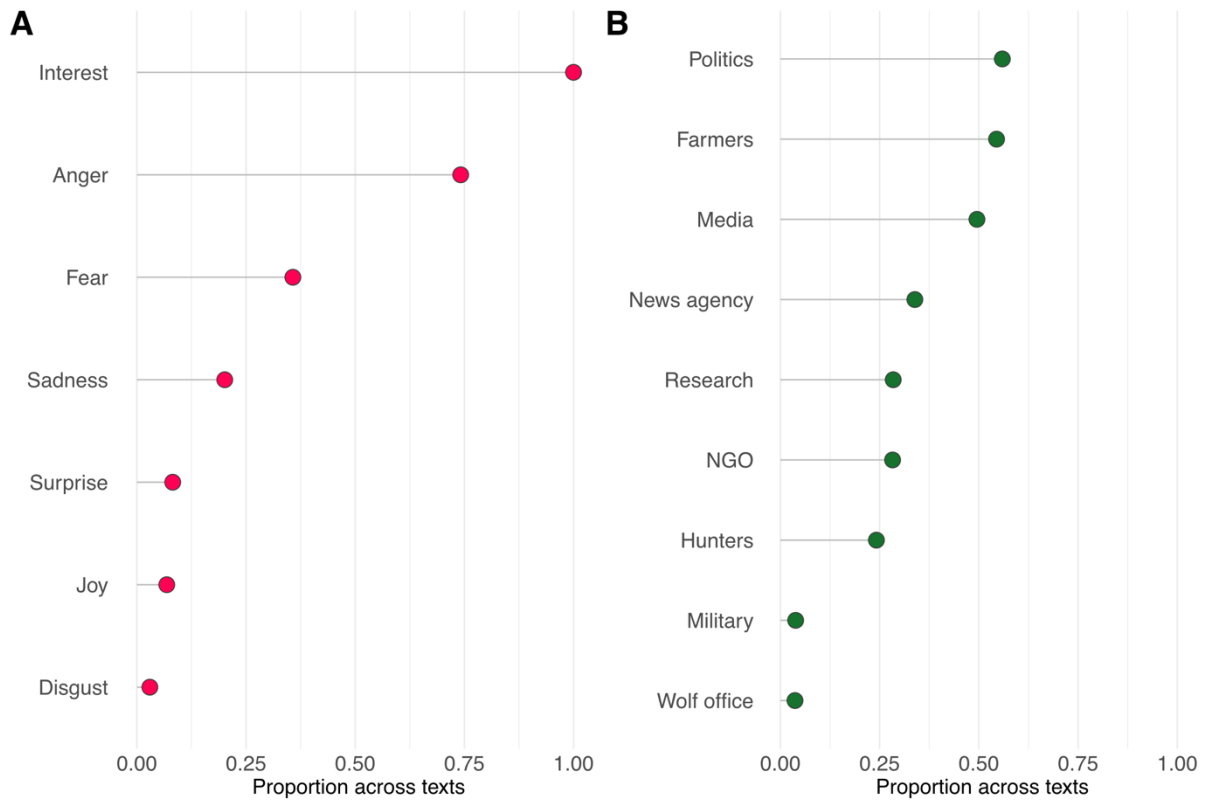
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421 **Table 1.** Annotators' categorization (among  $N_{\text{total}} = 498$ ), inter-annotator agreement and  
 422 classification accuracy (precision, recall and F1-scores) of the automatically identified  
 423 emotions across 498 newspaper articles from Saxony, Germany  
 424

	<b>Annotator 1 categorization (N articles)</b>	<b>Annotator 2 categorization (N articles)</b>	<b>Inter-annotator agreement</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-score</b>
Interest	402	269	0.72	0.84	1.00	0.91
Anger	275	235	0.86	0.65	0.61	0.63
Fear	220	162	0.83	0.76	0.41	0.53
Sadness	189	143	0.80	0.68	0.34	0.46
Surprise	209	100	0.72	0.62	0.13	0.21
Joy	185	150	0.85	0.43	0.09	0.15
Disgust	147	67	0.81	1.00	0.08	0.14

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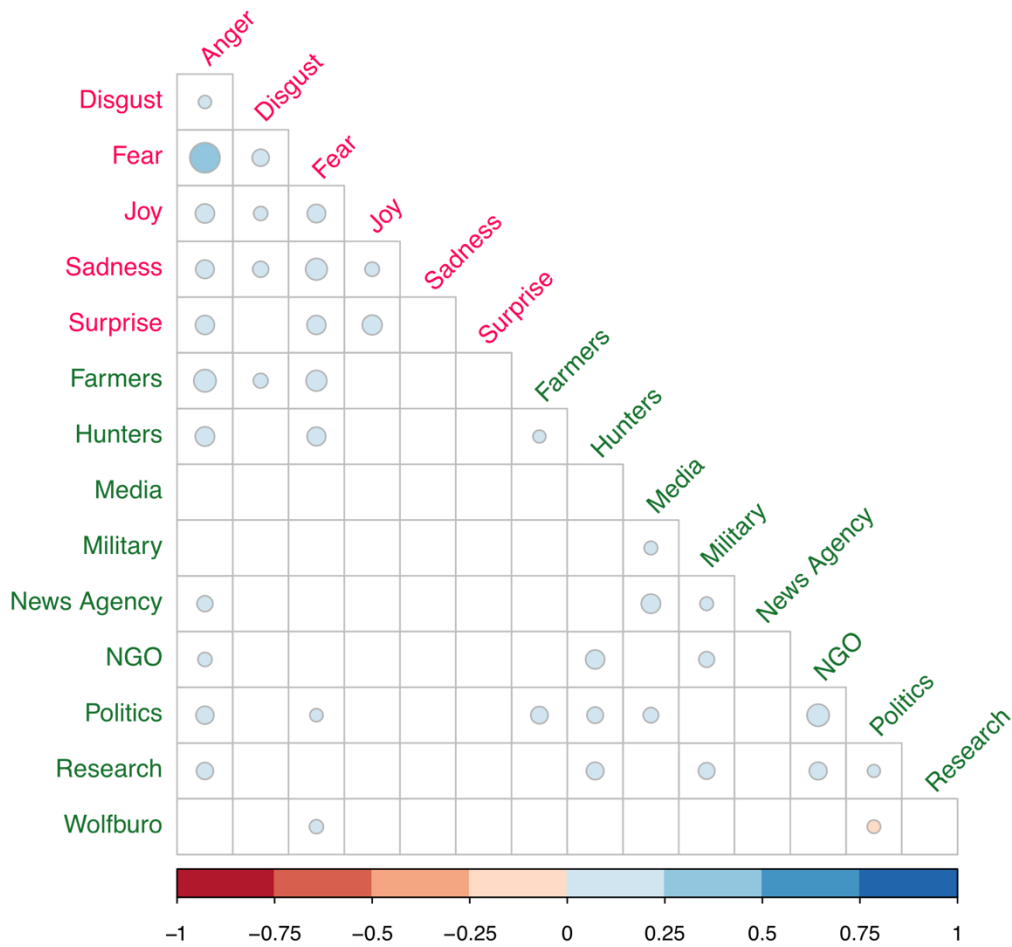
426 **Figure 1.** Distribution of emotions (A) and stakeholders (B) across 3,096 press articles  
427 reporting on the wolf topic in Saxony, Germany.



428



429 **Figure 2.** Correlations between emotions (pink) and stakeholders (green) across 3,096 press  
 430 articles reporting on the wolf topic in Saxony, Germany. Non-significant correlations (5%  
 431 threshold, p-values adjusted with bonferroni correction) are blanked. We excluded *interest*  
 432 from the plot, as it was detected in all newspaper articles (recall = 1.00, see Fig. 1). The size  
 433 of the circles represents the correlation strength.



435

## Supporting Information

436

437 **Natural Language Processing as a tool to evaluate emotions in conservation conflicts**

438

439

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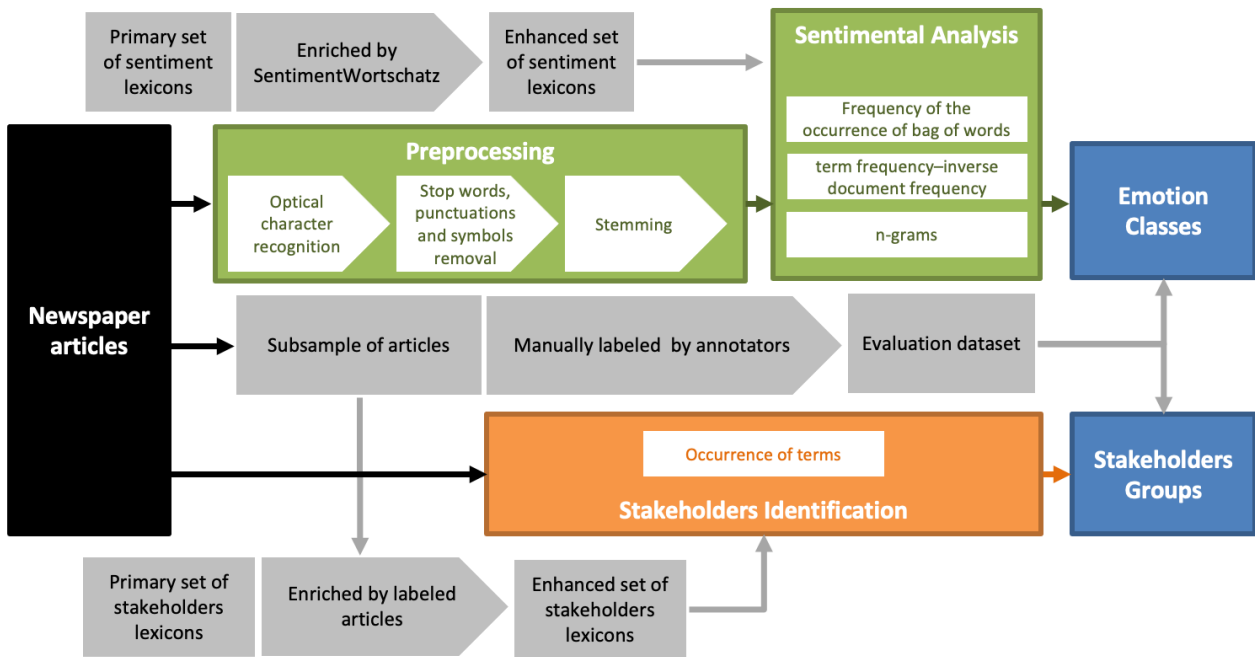
449 **Table S1.** Lexicons used for the detection of seven emotions (Fear, Anger, Interest, Joy,  
450 Sadness, Disgust, Surprise) in German language, in 3,098 newspaper articles from Saxony,  
451 Germany.

Fear	Anger	Interest	Joy	Sadness	Disgust	Surprise
Angst	Ärger	Interesse	Freude	Traurigkeit	Ekel	Bescherung
Verschüchterung	Unmut	Engagement	Jubel	Trübsinn	Schauer	Überraschung
Panik	Unwille	Eifer	Triumph	Pein	Grauen	Fassungslosigkeit
Beklommenheit	Anfall	Nachfrage	Verzückung	Weltschmerz	Abseheu	Aufregung
Bedenken	Gereiztheit	Schwäche	Begeisterung	Gram	Antipathie	Verwunderung
Kümmernis	Schlamassel	Neugier	Hochgefühl	Last	Schurke	Verblüffung
Schüchternheit	Verdrießlichkeit	Belange	Seligkeit	Schwermut	Übersättigung	Überfall
Erschrecken	Unwilligkeit	Zug	Frohmut	Hypochondrie	heimtückisch	Überrumpelung
Lampenfieber	Gekränktheit	Geschmack	Vergnügtheit	Kümmernis	Scheusal	Happening
Beunruhigung	Aufgebrachtheit	Kauffreude	Lustigkeit	Einformigkeit	Abneigung	Befremden
Horror	Laune	Angelegenheiten	Wollust	Misere	Ressentiment	Erstaunen
Hemmungen	Unannehmlichkeit	Wert	Zufriedenheit	Trübsal	Widerwille	unglaublich
Mutlosigkeit	Mißmut	Beteiligung	Freudenruf	Sorge	ungeahnt	befangt
Kleinmut	Ungemach	Lerneifer	Frohsinn	Jammer	Widerling	außergewöhnlich
Bangigkeit	Verdruß	Kaufinteresse	Frohsein	Schmerz	Lump	beachtlich
Beengung	Raserei	Anteilnahme	Glück	Marter	Biest	verdutzt
Phobie	Unzufriedenheit	Konzentration	Befriedigung	Verzweiflung	Ungeheuer	verwirrt
Sorge	Verärgerung	Sympathie	Munterkeit	Not	Greuel	verwundert
Ängstlichkeit	Tobsucht	Tendenz	Heiterkeit	Kreuz	Degout	perplex
Heidenangst	Empörung	Neigung	Vergnüglichkeit	Unglück	Barbar	erstaunt
Schreck	Rage	Bedürfnis	Humor	Martyrium	Ekelgefühl	baff
Furchtsamkeit	Mißgunst	Rang	Lachen	Qual	Überdruß	ratlos
Befangenheit	Belästigung	Forschergeist	Daseinsfreude	Wehmut	Schauer	verblüfft
Feigheit	Anufwallung	Bedarf	Gaudium	Trostlosigkeit	Scheu	bewegungslos
Höllnangst	Ingrimm	Wichtigkeit	Erheiterung	Seelenschmerz	Opfer	konsterniert
Erstarrung	Stinkwut	Belang	Lebensmut	Trauer	Blutig	befangt
Bammel	Wutanfall	Beachtung	Lebensfreude	Leid	Massaker	sprachlos
Scheu	Verstimmung	Kaufneigung	Kurzweil	Kummer	unschuldig	geplättet
Hasenherzigkeit	Erregtheit	Augenmerk	Spaß	überfahren	arm	wider erwarten
Verlegenheit	Streit	Hang	Jauchzen	tot	wiederlich	jäh
Furcht	Frustration	Aufmerksamkeit	Rausch	getötet	schrecklich	überraschenderweise
Zaghaftigkeit	Verletzttheit	Vorteil	Belustigung	krank	grausig	plötzlich
Zähneklappern	Erhitzung	Achtsamkeit	Frohlocken	ungerecht	schlimm	ungewöhnlich
Grauen	Wut	Bedeutung	Gaudi	schlimm	erschreckend	unerwartet
Beklemmung	Jähzorn	Kauflust	Entzücken	zerrüttet	Schuld	unvorbereitet
Unentschlossenheit	Furor	Wissbegier	Vergnügen	melancholisch	verlassen	unvermittelt
Kleinmütigkeit	Übellaunigkeit	Tatendrank	Wonne	resigniert	zugerichtet	schlagartig
Unsicherheit	Trübsal	Faible	Behagen	niedergeschlagen	übergriff	aus heiterem Himmel
Schiff	Bitterkeit	Anteil	Lebenslust	kraftlos	hinterhältig	unvermutet
Todesangst	Erregung	Gefallen	Lust	schwermütig	tückisch	unversehens
Schwüle	Erbostheit	Gewicht	Glücksgefühl	niedergeschmettert	arglistig	unabsehbar
Platzangst	Zorn	Nutzen	Unterhaltung	Schicksal	niederträchtig	unvorhersehbar
Verfolgungswahn	Enttäuschung	Bedacht	Pläsier	betrübt	Teufel	erstaunlich
eingeschränkt	Grimm	Wissensdurst	Genuß	entmutigt	teuflisch	überraschend
bange	Zores	Gespanntheit	Wohlgefallen	bang	räudig	verblüfft
Risiko	Scheiß	Zuneigung	Ergötzen	miserabel	kalt	namenlos
Besorgnis	not	notwendig	Glückseligkeit	bedauern	rücksichtslos	entgegen
Unbehagen	Auseinandersetzung	Wichtig	Hochgenuß	depressiv	Blutrausch	zufällig
Furcht	Konflikt	relevant	Schwärmerei	trübsinnig	Monster	Ausnahme
Argwohn	Feind	information	Fröhlichkeit	tieftraurig	erbarmungslos	aus der Reihe
Unruhe	Gegner	informativ	Beglückung	tiefbetrübt	unmenschlich	außerordentlich
Respekt	Zwietracht	wissen	Wunderbar	katastrophal	hemmungslos	auffällig
Schauer	Stunk	reizvoll	Spektakulär	verheerend	brutal	sprunghaft
Ungewiss	Gefecht	aufschlussreich	Cool	verhängnisvoll	rabiati	Zufall
Zweifel	Reiberei	aufklären	Beeindruckend	qualvoll	bitter	besonders
zittern	Entrüstung	Sinn	jung	fürchterlich	mörderisch	anders
Gänsehaut	Aggression	Hintergrund	Fest	tragisch	grausam	<b>E7.Surprise</b>
Herzrasen	Aggressivität	Gewinn	Feier	jämmerlich	hartherzig	Bescherung
Grusel	Rage	Wirkung	Gesellig	wehmütig	schonungslos	Überraschung
Befürchtung	Feind	Teilnahme	Erfolg	getrübt	gefühlskalt	Fassungslosigkeit
Skrupel	Missklang	Einsatz	zufrieden	bitter	gnadenlos	Aufregung
entsetzen	Zerwürfnis	Hingabe	freude	demütigend	horrend	Verwunderung
fassungslos	Anacke	Präferenz	Eifer	bekümmert	gewissenlos	Verblüffung
erschrocken	Verdruss	Konzept	Glück	todunglücklich	Räuber	Überfall
Herzensangst	Aufgebracht	Anliegen	Begeistert	mitgenommen	Mörder	Überrumpelung

Schreckgespenst Albtraum Furcht	Dilemma Notlage Unstimmig Unwille Erbittert Fanatismus Unsinn Unzufrieden	wissen lernen Aspekt Bericht Aufruf Ermittlung Daten forschen Einblick Reportage Report faszinierend inspirierend	Beifall erholsam froh lustig heidenspaß Eintracht ideal spitze ausgezeichnet überragend exzellent beispielhaft außerordentlich optimal Sensation begeistert beeindruckt großartig fantastisch herausragend unvergleich unübertroffen wunder angenehm gut niedlich süß zauberhaft genial attraktiv ansprechend klasse	elend mitleiderregend bemitleidenswert geknickt untröstlich kreuzunglücklich trübsinnig mutlos aufgeschmissen trostlos	meucheln ekel grauen Knochen gestohlen eingefallen gewaltsam kaltblütig unbarmherzig greulich drakonisch skrupellos furchtbar unappetitlich Gedärme abgebrüht umtriebzig	Happening Befremden Erstaunen unglaublich ungeahnt außergewöhnlich beachtlich verdutzt verwirrt verwundert perplex erstaunt baff ratlos verblüfft bewegungslos konsterniert befangen sprachlos geplättet wider erwarten jäh überraschenderweise plötzlich ungewöhnlich unerwartet unvorbereitet unvermittelt schlagartig aus heiterem Himmel unvermutet unversehens
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453 **Table S2.** Lexicons used to evaluate the occurrence of nine stakeholders of wolf conservation  
 454 in Germany (Hunters, Farmers, Politics, Non-Governmental Organizations, News Agencies,  
 455 Media, Research, Wolf Information Office “Wolfbüro”, Military), in 3,098 newspaper  
 456 articles from Saxony, Germany.

Hunters	Farmers	Politics	NGO	News Agency	Media	Research	Wolfbüro	Military
Jäger Wildhüter Waidmann Grünrock Treiber Jagdverband	Schäfer Hirt Hüte Tierhalter Viehzüchter Landwirt	Politik Linke Grüne SPD CDU Union	Tierschützer Naturschutzbund NaBu PETA IFAW Vier Pfoten	Presse Fernseh LR Journalisten BILD Sprecher	Fernseh Buch Film Theater Ausstellung Kunst	Wissenschaftler Experte Lupus Leibnitz-Institut Senckenberg Gellnhausen	Kontaktbüro Sophia Liehn Ehrlichthof Wolfsscheune Jana Endel Vanessa Ludwig	Militär Soldat Bundeswehr Truppe Panzer Übungsplatz Munster Nord Sperrgebiet Lieberoser Heide
Wildschütz Jagd	Bauer Schaffhirte	Freie Demokraten Christdemokraten	WWF Naturschützer	Journalist Schreiberling	Fotograf Bilder	Gesa Kluth Ilka Reinhard	Rissgutachter	Nord Sperrgebiet Lieberoser Heide
Jägerei Hubertus- jünger Jagdwesen Jagdhund	Hüter Farmer Weide Zucht	CSU AFD FDP Die PARTEI	Freiwilliger Helfer Organisation Naturschutz Freundeskreis freilebender Wölfe	Redakteur Berichterstatter Reporter SZ	Werke Moderator Autor Blogger	Monitoring Forscher Fachfrau		Brück Lehnhin Jüterbog
Hochsitz	Wirt	Minister Landwirtschafts- minister Beauftragter Landesumweltamt Umweltamt Amt		Boulevardjournalist	Talkshow	Fachmann		Altengrabow
Weidmann Treibjagd Grauhund Ansitz Pirsch	Halter Besitzer Koppel Flatterband Stromzaun Viehhalter Viehhalter Viehwirt Vieh Schafsriss Bauernverband Landmann Ökonom Agrar Agrarverband Nutztierhalter Milchproduzent Traktor Zuchtverband	Landwirtschafts- minister Beauftragter Landesumweltamt Umweltamt Amt Bundesamt Wolfsberater Landeskabinett Landtagsabgeordneter Umweltministerium Umweltminister Politiker Bürgermeister Bundes Landes Kommunal Parlament Staat Staatsführung Fraktion Bündnis		Sensationsreporter Publizist Zeitung Sächsische Zeitung DDP	Medien Kolumnist Sendung Beitrag Band Roman Geschichte Reportage Dokumentation	Spezialist Biologe Experte		Grafenwöhr Sperrzone



458

459 **Figure S1.** Flowchart describing the different steps involved to detect emotions and

460 stakeholders in 3,096 press articles reporting on the wolf topic in Saxony, Germany.