

1 **Title:** Individual identity information persists in learned parrot calls after invasion

2

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25 **Abstract**

26 Animals can actively encode different types of identity information in communication signals,

27 such as group membership, individual identity, or social status. The social environments in

28 which animals interact may favor different types of information, but whether identity

29 information conveyed in learned signals is resilient or responsive to short-term changes in the

30 social environment is not well understood. We inferred the type of identity information that

31 was most salient in vocal signals by combining computational tools, including supervised

32 machine learning, with a conceptual framework of “hierarchical mapping”, or patterns of

33 relative acoustic convergence across social scales. We used populations of an invasive vocal

34 learning species as a natural experiment to test whether social environments altered over

35 ecological timescales changed the type of identity information that different populations  
36 emphasized in learned vocalizations. We compared the social scales with the most salient  
37 identity information among native and invasive range monk parakeet (*Myiopsitta monachus*)  
38 calls recorded in Uruguay and the United States, respectively. We also evaluated whether the  
39 identity information emphasized in invasive range calls changed over time. To place our  
40 findings in an evolutionary context, we benchmarked our results with another parrot species  
41 that exhibits well-established and distinctive regional vocal dialects that are consistent with  
42 signaling group identity. We found that native and invasive range monk parakeet calls both  
43 displayed the strongest convergence at the individual scale and minimal convergence within  
44 sites. We did not identify changes in the strength of acoustic convergence within sites over  
45 time in the invasive range calls. These results indicate that the individual identity information  
46 in learned vocalizations was resilient to social environments perturbed over ecological  
47 timescales. Our findings point to exciting directions for further research on the responsiveness  
48 of communication systems to changes in the social environment over different evolutionary  
49 timescales.

50

## 51 **1. Introduction**

52 Animals can use communication signals to transmit identity information, including group  
53 membership, individual identity, social status, sex, or other social characteristics (Bradbury &  
54 Vehrencamp, 1998; Seyfarth, Cheney, Bergman, Fischer, Zuberbühler, et al., 2010). The  
55 types of identity information that animals encode in signals may be an outcome of differences  
56 in the social environment within or among species. Different types of information may be more  
57 or less important for animals to communicate in social environments that can change over  
58 ecological or evolutionary timescales (Bergman, 2010; Hobson, 2020; Hobson, Mønster, &  
59 DeDeo, 2021; Ramos-Fernandez, King, Beehner, Bergman, Crofoot, et al., 2018).

60           Vocalizations are well-studied communication signals that can contain identity  
61 information. For example, voice cues arising from vocal tract filtering can provide receivers  
62 with information about individual identity (Furuyama, Kobayasi, & Riquimaroux, 2016; Prior,  
63 Smith, Lawson, Ball, & Dooling, 2018; Rendall, Owren, & Rodman, 1998). However,  
64 individuals can also use social learning to modify identity information, such as vocal learning  
65 species that can encode both group-level and individual identity information in learned  
66 vocalizations. When individuals imitate vocalizations of their social companions, the resulting  
67 group-level acoustic convergence can be used to recognize group members (Aplin, 2019;  
68 Boughman & Wilkinson, 1998; Nowicki & Searcy, 2014; Sewall, Young, & Wright, 2016).  
69 Learned vocalizations with group identity information, such as vocal dialects, have been  
70 reported in several vocal learning taxa, including cetaceans (Janik & Slater, 1998; Jones,  
71 Daniels, Tufano, & Ridgway, 2020; Nousek, Slater, Wang, & Miller, 2006; Rendell &  
72 Whitehead, 2003; Watwood, Tyack, & Wells, 2004), bats (Boughman, 1998), songbirds  
73 (Mammen & Nowicki, 1981; Sewall, 2009;2011), and parrots (Martinez & Logue, 2020; Wright,  
74 1996). Individuals can also communicate individual identity information by developing  
75 distinctive vocalizations that differentiate them from other individuals. For instance, bottlenose  
76 dolphins (*Tursiops truncatus*) and green-rumped parrotlets (*Forpus passerinus*) can use vocal  
77 learning to produce distinctive individual signatures used for individual vocal recognition  
78 (Berg, Delgado, Okawa, Beissinger, & Bradbury, 2011; Berg, Delgado, Cortopassi, Beissinger,  
79 & Bradbury, 2012; Janik, Sayigh, & Wells, 2006; Kershenbaum, Sayigh, & Janik, 2013).

80           These findings from closely related taxa suggest that changes in the social  
81 environment can influence the identity information that animals encode in learned  
82 vocalizations. For instance, living in large social groups or interacting repeatedly with many  
83 different individuals may favor signaling individual identity information (Pollard & Blumstein,  
84 2011; Seyfarth et al., 2010; Tibbetts & Dale, 2007). However, the degree to which identity

85 information encoded in learned communication signals dynamically responds to changes in  
86 the social environment is not well understood. To test whether identity information in  
87 vocalizations is resilient or responsive to short-term changes in the social environment, we  
88 need two analytical approaches: a way to quantify the relative salience of different types of  
89 identity information in learned signals, and comparisons of identity information across groups  
90 with different social characteristics.

91         First, new tools are needed to better quantify the salient types of information in  
92 vocalizations. Computational approaches like machine learning can be applied within a  
93 conceptual framework that links patterns of vocal convergence to identity signaling.  
94 Individuals should use vocal learning to converge on vocalizations across different scales of  
95 social organization (Smith-Vidaurre, Araya-Salas, & Wright, 2020), and such vocal  
96 convergence should yield “hierarchical mapping” patterns, which are patterns of relative  
97 acoustic convergence that vary across social scales (Bradbury et al., 1998). To evaluate  
98 hierarchical mapping patterns, we can use machine learning tools to quantify relative acoustic  
99 convergence over different social scales, for example, from individuals to flocks or regional  
100 populations. From hierarchical mapping patterns, we can use the social scale with the  
101 strongest relative acoustic convergence to infer the most salient type of identity information  
102 encoded in vocalizations.

103         Second, we need to compare hierarchical mapping patterns among groups with distinct  
104 social environments to test whether identity information in learned vocalizations is resilient or  
105 responsive to changes in the social environment. We can leverage different types of natural  
106 experiments for this comparison, including species invasions, which can cause founder  
107 effects that influence traits transmitted by genetic inheritance and by social learning in  
108 invasive populations (Aplin, 2019; Dlugosch & Parker, 2008). Biological invasions should also  
109 perturb the social environment, particularly at early stages, due to changes in population size

110 and the disruption of population contiguity with respect to original native range populations.  
111 Social perturbation could be reduced by the gradual re-establishment of social environments  
112 similar to those in undisturbed populations, or could persist after the early stages of  
113 population establishment. For example, invasive range populations should be small when  
114 newly founded and then can either remain small, grow to sizes comparable to source  
115 populations in the native range, or outstrip source populations (Blackburn, Pysek, Bacher,  
116 Carlton, Duncan, et al., 2011). Reduced population sizes may change the social environment,  
117 such as limiting the overall number of individuals available for social interactions, which could  
118 alter the cognitive costs of social recognition for receivers (Sewall et al., 2016; Tibbetts et al.,  
119 2007), and in turn, alter the type of identity information that signalers convey in learned  
120 vocalizations compared to the native range.

121 In this study, we focused on native and invasive range populations of monk parakeets  
122 (*Myiopsitta monachus*) to test how changes in the social environment due to invasion could  
123 cause changes in the type of identity information encoded in contact calls. Parrots are  
124 suitable for this research because they can use social learning to both acquire and modify  
125 contact calls (Bradbury & Balsby, 2016). Monk parakeets in particular are also suitable  
126 because they have established new populations worldwide through the pet trade since the  
127 late 1960s, enabling comparisons between native and invasive range populations. The  
128 independently established invasive range populations share a common origin, with the  
129 majority of these populations stemming from native range populations in Uruguay and the  
130 surrounding region of northern Argentina (Edelaar, Roques, Hobson, Goncalves Da Silva,  
131 Avery, et al., 2015; Hobson, Smith-Vidaurre, & Salinas-Melgoza, 2017; Russello, Avery, &  
132 Wright, 2008; Smith-Vidaurre, 2020). We used invasive range populations in the United  
133 States (U.S.) as independent experimental replicates of social environments perturbed over  
134 ecological timescales compared to native range populations in Uruguay.

135 We used call recordings to infer which type of identity information was most salient in  
136 learned monk parakeet vocal signals. We used this approach on both native and invasive  
137 range calls to test whether the type of identity information was the same or differed between  
138 the native and invasive ranges. We expected that if populations had recovered from the  
139 invasion process, then the type of identity information in invasive range calls would not  
140 change. However, if the invasion process was sufficiently disruptive, then we expected that  
141 invasive range parakeets would diverge from the type of identity information used in the  
142 native range. We placed our results in context by benchmarking against another parrot  
143 species with strong call convergence at higher social scales and distinctive vocal dialects. Our  
144 integration of quantitative approaches with a conceptual framework of identity information  
145 encoding can be used to evaluate learned identity signaling more broadly across taxa.  
146 Together, our rigorous computational approach and comparisons provide new insight into how  
147 identity information in learned vocal signals is resilient or responsive to the social environment  
148 over ecological and evolutionary timescales.

149

## 150 **2. Methods**

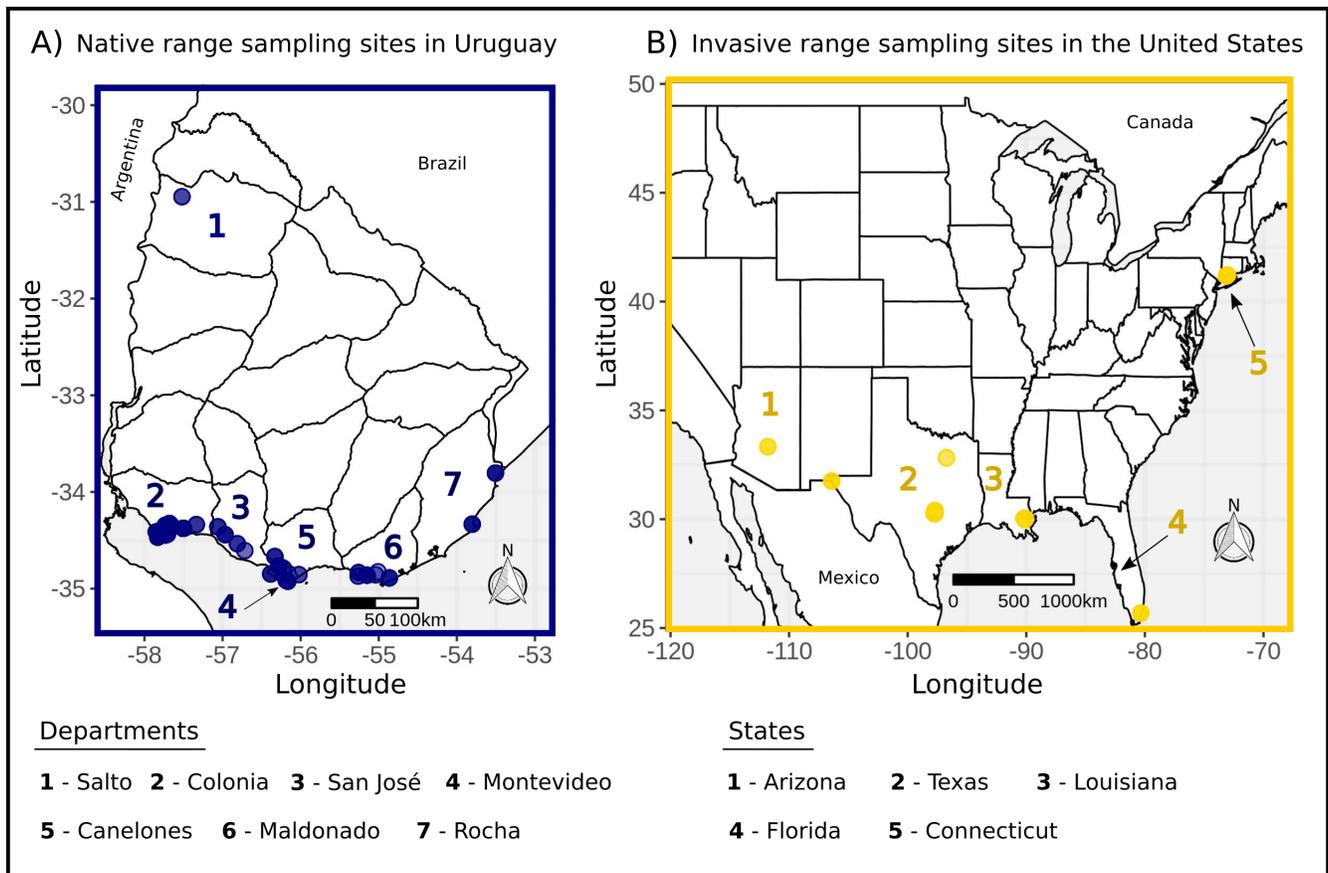
### 151 *2.1 Recording contact calls*

152 We recorded contact calls from native range monk parakeets in 2017 at 37 sites across 7  
153 departments in Uruguay in our previous work (Smith-Vidaurre et al., 2020). Our invasive  
154 range dataset included contact calls recorded at 26 sites across 5 states in the U.S. in 4  
155 different sampling years: 2004, 2011, 2018, and 2019. In 2004, invasive range contact calls  
156 were recorded in Connecticut, Florida, Louisiana, and Texas (calls were provided by  
157 Buhrman-Deever, Rappaport, & Bradbury, 2007). We recorded parakeets in Texas and  
158 Louisiana in 2011, Arizona in 2018, and Texas again in 2019. For our temporal analyses  
159 below, we relied on calls that we recorded in Texas in 2004, 2011, and 2019 (3 sampling

160 years), and calls recorded in Louisiana in 2004 and 2011 (2 sampling years, see  
161 supplementary section 1).

162           Recording sessions in 2004 used Marantz PMD670 or PMD690 recorders with  
163 Sennheiser ME67K6 shotgun microphones, and these recordings were digitized at 48000 Hz  
164 and 16 bit depth (Buhrman-Deever et al., 2007). In all other recording sessions we used  
165 Marantz PMD661 MKII and PMD660 solid state recorders, Sennheiser ME67 long shotgun  
166 microphones and foam windscreens, and we digitized our recordings at 44100 Hz sampling  
167 rate and 16 bit depth (Smith-Vidaurre et al., 2020; Smith-Vidaurre, Perez-Marrufo, & Wright,  
168 2021). All recorded individuals were unmarked, with the exception of a few marked individuals  
169 in the native range (Smith-Vidaurre et al., 2020).

170



172 **Figure 1:** Map of call recording sites for (a) native range populations in Uruguay and (b)  
 173 invasive range populations in the United States (U.S.). We recorded parakeets across 7  
 174 departments in Uruguay and 5 states in the U.S. Our geographic sampling was more  
 175 contiguous in the native range, which reflected the natural contiguity of populations across the  
 176 southeastern coast of Uruguay, compared to the more geographically isolated populations in  
 177 the U.S. invasive range.  
 178

## 179 *2.2 Pre-processing contact calls*

180 We manually selected contact calls from our field recordings. For our invasive range  
181 recording sessions in later years, we selected contact calls using Raven version 1.4 (The  
182 Cornell Lab of Ornithology Bioacoustics Research Program, 2014), consistent with native  
183 range call selection in Smith-Vidaurre et al. (2020). The previously published invasive range  
184 calls from 2004 were provided as clips of original recordings (Buhrman-Deever et al., 2007).  
185 We performed pre-processing for all invasive range calls, including the 2004 clips, with the  
186 warbleR package in R (Araya-Salas & Smith-Vidaurre, 2017) to implement the same quality  
187 control pipeline we had previously used for native range calls (supplementary section 1,  
188 Smith-Vidaurre et al., 2020;2021). Our quality control criteria included calls with signal to  
189 noise ratios of 7 or higher (e.g. calls that were at least 7 times louder than background noise)  
190 that also did not display loud signals or other background noise that overlapped with call  
191 structure.

192

## 193 *2.3 Social scales represented in our contact call datasets*

194 We obtained calls at two different social scales for the purposes of this study: the individual  
195 scale, and a group scale that represented a higher level of social organization. To determine  
196 call convergence at the individual scale, we repeatedly sampled known individuals to obtain  
197 multiple exemplar calls produced by the same individual. This individual-level dataset  
198 included 229 total calls from 8 native range birds (3 marked, 5 unmarked) recorded at 3  
199 different sites in 2017, and 9 invasive range birds (all unmarked) recorded at 7 different sites  
200 in either 2004, 2011, or 2019 (see Table A5 in Smith-Vidaurre et al. (2021)). Each individual  
201 was recorded at one site only, and because the birds we recorded were generally unmarked,  
202 we recorded repeat calls from particular individuals while the calling bird was producing  
203 multiple calls within a short period of time (e.g. a few minutes (Smith-Vidaurre et al., 2020)).

204 After pre-processing calls, our individual scale dataset included a median of 10 (range: 4 - 25)  
205 calls for the native range individuals and a median of 12 (range: 5 - 28) calls for the invasive  
206 range individuals. Our individual scale dataset provided us with sufficient sampling depth per  
207 individual to assess acoustic convergence at the individual scale, or individual vocal  
208 signatures.

209 To address call convergence at a group scale, we recorded and compared calls across  
210 nesting sites. We used sites as groups because parakeets likely interact frequently with other  
211 individuals at the same site. Monk parakeet nesting sites include clusters of single or multi-  
212 chambered stick nests that are often built in close proximity (Eberhard, 1998), and parakeets  
213 from nearby clusters of nests engage in social interactions (Hobson, Avery, & Wright, 2014),  
214 making it difficult to determine the boundaries of a nesting colony. In this study, we  
215 characterized recording sites as groups of nests that were geographically separate (the  
216 shortest distance among sites was 0.15 km). For our site scale dataset, we obtained a single  
217 contact call per bird at each site. Because the parakeets usually produced a single contact  
218 call when leaving or returning to their nests, we sampled a single call per unmarked individual  
219 at this higher social scale.

220 After pre-processing, our site scale dataset included 1353 total calls recorded at 63  
221 sites across 37 native and 26 invasive range sites (some invasive range sites were repeatedly  
222 sampled in different sampling years, see Tables A3 and A4 in Smith-Vidaurre et al. (2021)).  
223 This dataset contained a median of 15 (range: 5 - 53) and 15.5 (range: 5 - 91) calls across the  
224 native and invasive range sites, respectively. Since we recorded a single call per unique  
225 individual at each site, our site scale dataset did not provide sufficient resolution of individual  
226 vocal signatures. However, this dataset allowed us to compare patterns of acoustic variation  
227 at a higher scale of social organization over broader geographic areas in each range (Figure  
228 1).

229 To compare hierarchical mapping patterns between the native and invasive ranges, we  
230 used 37 native range sites separated by 0.15 – 513.59 km across 7 departments in Uruguay,  
231 and 18 invasive range sites across 5 U.S. states that were separated by 0.74 – 3502.98 km  
232 (Smith-Vidaurre et al., 2020;2021). To compare hierarchical mapping patterns over time in the  
233 invasive range, we used a subsample of sites in Texas and Louisiana that were recorded in  
234 more than one sampling year (see the respective number of sites and geographic distances in  
235 supplementary section 1). For our analyses at the site scale, we also generated 3 versions of  
236 the site scale dataset to account for the possibility that some calls could represent repeated  
237 sampling of the same unmarked individual(s) (supplementary section 2). These 3 datasets  
238 included the full dataset of calls, as well as the full dataset filtered by either clustering or  
239 visual classification methods to remove calls were likely to represent such repeated individual  
240 sampling (supplementary sections 3 - 7). Following call similarity measurements, we  
241 performed all subsequent analyses with these 3 site scale datasets to compare the degree of  
242 repeated individual sampling in each of the native and invasive ranges, as well as to assess  
243 the robustness of our results at this higher social scale.

244

#### 245 *2.4 Measuring contact call similarity with spectrographic cross-correlation*

246 We used contact call similarity measurements to quantify hierarchical mapping patterns. Call  
247 similarity measurements formed the basis for our comparisons of calls within and among  
248 social groups to assess hierarchical mapping patterns, or the relative strength of acoustic  
249 convergence across different social scales. For instance, if individuals were converging on  
250 shared calls within sites, then we expected that contact calls compared within the same site  
251 would exhibit high similarity measurements, and lower similarity measurements when  
252 compared to calls from different sites. We measured call similarity with spectrographic cross-  
253 correlation (SPCC) (Clark, Marler, & Beeman, 1987), which has traditionally been used in

254 studies reporting patterns of acoustic variation consistent with social learning of vocalizations  
255 in parrots (Balsby & Bradbury, 2009; Berg et al., 2011; Bradbury, Cortopassi, & Clemmons,  
256 2001; Buhrman-Deever et al., 2007; Eberhard, Zager, Ferrer-Paris, & Rodríguez-Clark, 2022;  
257 Guerra, Cruz-Nieto, Ortiz-Maciel, & Wright, 2008; Salinas-Melgoza & Wright, 2012; Salinas-  
258 Melgoza & Renton, 2021; Scarl & Bradbury, 2009; Smith-Vidaurre et al., 2020; Wright, 1996;  
259 Wright, Dahlin, & Salinas-Melgoza, 2008). We performed SPCC with a Hanning window, a  
260 window length of 378 samples, and a window overlap of 90 samples for Fourier  
261 transformations, as well as Pearson's correlation method and a bandpass filter of 0.5 to 9kHz  
262 (Araya-Salas et al., 2017). Unless otherwise specified, we used these same parameters for  
263 subsequent spectrum-based analyses. We conducted SPCC with all calls across the native  
264 and invasive ranges, which allowed us to use this similarity measurement in subsequent  
265 quantitative assessments of hierarchical mapping patterns.

266

### 267 *2.5 Measuring contact call similarity with supervised machine learning*

268 We also measured similarity among monk parakeet contact calls using a supervised machine  
269 learning approach that identifies biologically relevant patterns of variation in avian acoustic  
270 signals (Humphries, Buxton, & Jones, 2018; Keen, Ross, Griffiths, Lanzone, & Farnsworth,  
271 2014; Smith-Vidaurre et al., 2020). As in our previous work (Smith-Vidaurre et al., 2020),  
272 measuring similarity with a traditional method (SPCC) and a newer method (supervised  
273 random forests), allowed us to verify that the hierarchical mapping patterns we identified were  
274 not an artifact of using a single similarity method. We built supervised random forests models  
275 with 1844 acoustic and image features, including features derived from spectrographic cross-  
276 correlation (SPCC) and dynamic time warping similarity measurements, standard spectral  
277 acoustic measurements, descriptive statistics of Mel-frequency cepstral coefficients, and  
278 spectrogram image measurements (see supplementary sections 8 - 9). We trained random

279 forests models to classify calls back to 4 repeatedly sampled individuals in each of the native  
280 and invasive ranges (156 calls and 8 individuals total, see supplementary section 10)  
281 (Breiman, 2001).

282         We built our first model with the full set of 1844 acoustic and image features. We built a  
283 second model by performing automated feature selection and using the most important  
284 features (114 total) from that analysis (supplementary section 11). We used our second model  
285 with 114 features for final analyses, as this model outperformed the first. To predict the  
286 similarity of the individual scale calls that we used for validation, as well as the site scale calls,  
287 we ran the remaining individual scale calls (73 total calls, 4 and 5 repeatedly sampled native  
288 and invasive range individuals, respectively) and the 1353 site scale calls down the final  
289 model. We extracted the resulting proximity matrix as the random forests similarity  
290 measurements (Humphries et al., 2018; Keen et al., 2014; Keen, Odom, Webster, Kohn,  
291 Wright, et al., 2021; Odom, Araya-Salas, Morano, Ligon, Leighton, et al., 2021; Smith-  
292 Vidaurre et al., 2020). To validate model performance, we used these similarity  
293 measurements to cluster the validation calls with Gaussian mixture modeling, which allowed  
294 us to determine whether the random forests model identified biologically relevant patterns of  
295 acoustic variation within and among calls of new individuals (e.g. individuals that were not  
296 present in the training dataset).

297         After confirming that the final model captured relevant patterns of variation among the  
298 individuals we used to validate model performance, we used random forests similarity  
299 measurements to generate low-dimensional acoustic space for the individual scale validation  
300 calls and the site scale calls. Since we had used the individual scale calls to train and validate  
301 the random forests model that we used to predict call similarity, we did not use random forests  
302 similarity measurements to perform quantitative analyses of acoustic convergence at the  
303 individual scale. Instead, we used the training classification performance of our final random

304 forests model, and the clustering performance during validation with random forests similarity,  
305 to support our individual scale analyses with SPCC similarity.

306

### 307 *2.6 Comparing native and invasive range hierarchical mapping patterns in acoustic space*

308 To assess hierarchical mapping patterns in each of the native and invasive ranges, we  
309 compared patterns of acoustic convergence in low-dimensional acoustic space at the  
310 individual and site social scales. To generate acoustic space we optimized non-metric  
311 multidimensional scaling (MDS) to reduce the dimensionality of the SPCC and random forests  
312 similarity matrices, respectively (supplementary section 12). For acoustic space at the  
313 individual scale, we used 4 native range parakeets recorded at 3 sites in the department of  
314 Colonia, Uruguay in 2017, and 4 invasive range birds recorded at 3 sites in Austin, United  
315 States in 2019. We used random forests similarity obtained during model validation. For the  
316 site scale, we used 5 native range sites in the department of Colonia, Uruguay in 2017, and 5  
317 invasive range sites in Austin, United States in 2019. We also filtered MDS coordinates by  
318 calls in each of the 3 site scale datasets that we used to address repeated sampling of  
319 individuals (see section 2.3). Acoustic space can be interpreted on the same axes for each  
320 similarity method. We interpreted calls that grouped together in acoustic space by individual  
321 or site as structurally similar calls (e.g. high convergence), while calls dispersed in acoustic  
322 space were structurally different (e.g. low convergence). We compared hierarchical mapping  
323 patterns between the native and invasive ranges by comparing the relative patterns of overlap  
324 in acoustic space among individuals or sites.

325

### 326 *2.7 Using Mantel tests to compare hierarchical mapping patterns between the native and*

327 *invasive ranges*

328 After assessing hierarchical mapping patterns in acoustic space, we used Mantel tests to  
329 quantify the strength and statistical significance of acoustic convergence at each social scale  
330 for both the invasive and native ranges. We performed Mantel tests with matrices of call  
331 similarity (SPCC for the individual scale; random forests and SPCC for the site scale) and  
332 matrices of binary social identity per social scale over 9999 permutations. These tests allowed  
333 us to ask whether calls were more similar within an individual or site compared to among  
334 individuals or sites for both the native and invasive ranges. We used the magnitude and sign  
335 of Mantel test statistics as indicators of the strength and directionality of the correlation  
336 between matrices of call similarity and binary identity. For example, positive test statistics of  
337 greater relative magnitude pointed to stronger convergence for a given social scale or range.

338 Matrix values were converted to distances by subtracting each matrix value from 1. We  
339 used a partial Mantel test to control for site identity in the individual scale test for the invasive  
340 range, as we had recorded these calls from 3 different sites. For the site scale, we used calls  
341 from the most recent sampling year per site when sites were sampled over time. For this  
342 higher social scale, we also ran Mantel tests for each of the native and invasive ranges with  
343 each of the 3 datasets that we used to address the effect of inadvertent repeated sampling of  
344 individuals. We performed a total of 2 Mantel tests for the individual scale and 12 Mantel tests  
345 for the site scale in this comparison of hierarchical mapping patterns between ranges. We  
346 adjusted alpha of 0.05 to 0.0036 by a Bonferroni correction to account for 14 tests total  
347 (supplementary sections 13 - 14). We compared hierarchical mapping patterns by comparing  
348 Mantel test statistics at each social scale between the native and invasive ranges.

349  
350 *2.8 Evaluating hierarchical mapping patterns over time in the invasive range*

351 We also used Mantel tests to determine whether the degree of acoustic convergence at the  
352 site scale changed over time in the invasive range. For these analyses, we used invasive

353 range populations that we had repeatedly recorded in Austin, Texas and New Orleans,  
354 Louisiana. For each year that we had sampled calls in each city, we performed a Mantel test  
355 to correlate matrices of call similarity against matrices of binary site identity. We performed  
356 Mantel tests per city because we did not always sample the same sites in each year. For  
357 Austin, we performed Mantel tests using different sites recorded in each of 3 sampling years:  
358 3 sites in 2004, 5 sites in 2011, and 6 sites in 2019. For New Orleans, we conducted Mantel  
359 tests using different sites sampled in 2 years: 3 sites in 2004 and 2 sites in 2011. We  
360 conducted Mantel tests with SPCC and random forests similarity measurements, as well as  
361 each of the 3 site scale datasets, and adjusted alpha of 0.05 to 0.0017 account for 30 tests  
362 total (supplementary sections 13 - 14). We assessed whether the strength of site scale  
363 convergence had changed over time in each city by comparing the relative magnitudes of  
364 Mantel test statistics. We also addressed the possibility of population recovery since invasion  
365 by evaluating population trends from eBird checklists in each city over our sampling years  
366 (supplementary section 15).

367

### 368 *2.9 Benchmarking hierarchical mapping patterns with another parrot species*

369 We placed our results in context by quantifying and directly comparing hierarchical mapping  
370 patterns among populations of monk parakeets with a species well-known for having regional  
371 information in their calls, the yellow-naped amazon. These amazon parrots imitate the contact  
372 calls of conspecifics and exhibit distinctive regional vocal dialects that are audibly perceptible  
373 to humans (Wright, 1996). Such vocal sharing may facilitate recognizing familiar group  
374 members (Sewall et al., 2016; Wright, 1996). Regional dialects in yellow-naped amazon calls  
375 have provided a baseline for identifying strong acoustic convergence within social groups for  
376 other vocal learning taxa (Bradbury et al., 2001; Buhrman-Deever et al., 2007; Guerra et al.,  
377 2008), including monk parakeets (Smith-Vidaurre et al., 2020). Here we used yellow-naped

378 amazon calls as a point of reference for strong site-scale acoustic convergence which could  
379 occur in invasive range monk parakeet calls if group membership information became more  
380 important to signal after invasion than individual identity.

381         For our benchmarking analyses, we quantified hierarchical mapping patterns over the  
382 individual and site social scales for native and invasive range monk parakeets (separately),  
383 and over the individual, site, and regional dialect social scales for yellow-naped amazons. We  
384 performed SPCC for each species after matching sampling rates of audio files per species  
385 (supplementary section 17). For yellow-naped amazons, we used previously published  
386 contact calls recorded in Costa Rica in 1994 (Wright, 1996). We selected SPCC values for a  
387 subsample of individuals or groups at each social scale that represented similar sampling  
388 depth and geographic breadth for each range and species (supplementary section 18).

389         We compared hierarchical mapping patterns among native range monk parakeets,  
390 invasive range monk parakeets, and yellow-naped amazons by assessing patterns of relative  
391 overlap among distributions of the subsampled SPCC similarity values within and among  
392 categories (e.g. individuals or social groups). We also used the selected SPCC values in a  
393 bootstrapping analysis in which we randomly selected 5 similarity values within the given  
394 category and 5 similarity values among the given category in each bootstrapping iteration  
395 (supplementary section 19). This random sampling was performed with replacement, such  
396 that SPCC values within or among categories could be randomly selected more than once in  
397 the same iteration. We calculated bootstrapped similarity ratios by dividing similarity values  
398 within the given category by similarity values among the given category. We performed  
399 bootstrapping over 200 iterations and calculated 1000 similarity ratios for exemplars of each  
400 category (individual or group) at each social scale for native range parakeets, invasive range  
401 parakeets, and yellow-naped amazons. Similarity ratios close to 1 pointed to weaker

402 convergence, while we used similarity ratios increasingly greater than 1 as evidence of  
403 stronger convergence (e.g. calls were more similar within categories than among categories).

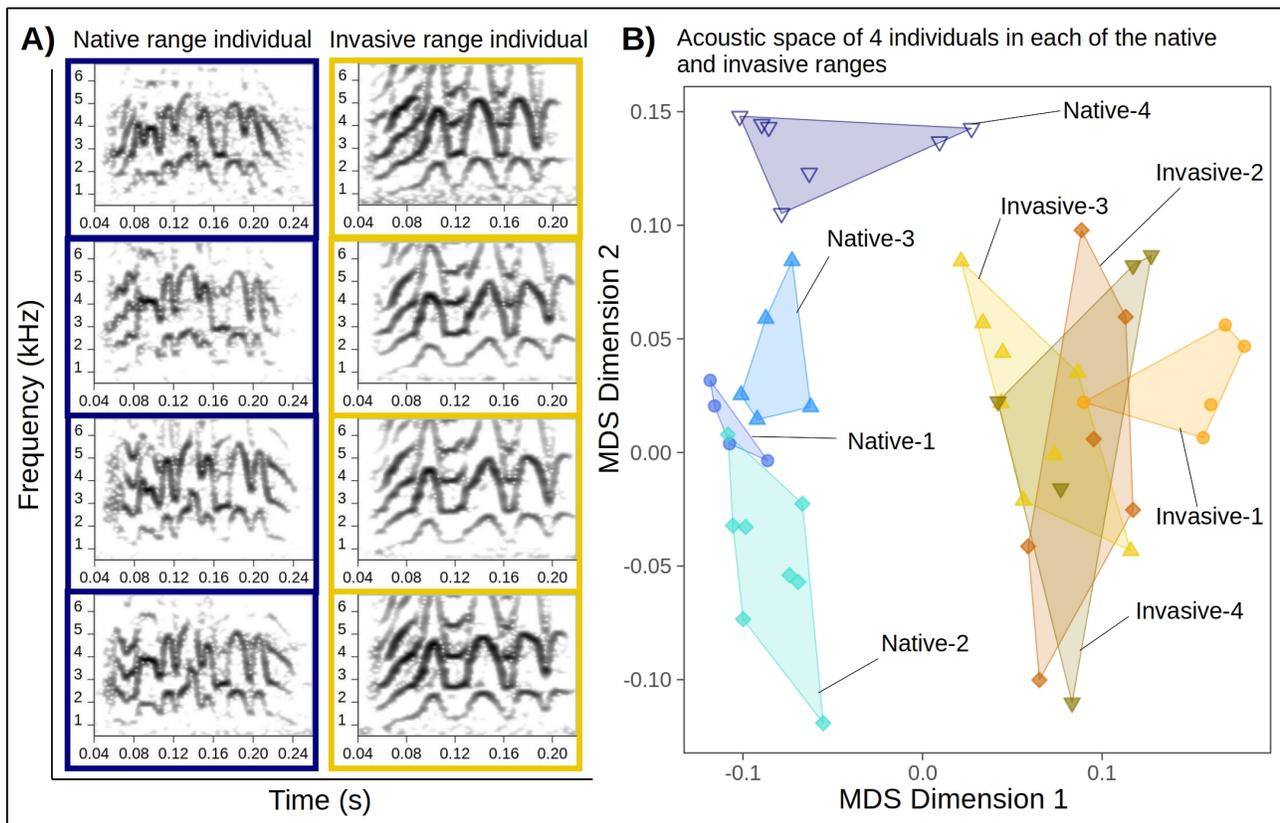
404

### 405 **3. Results**

#### 406 *3.1 Strong individual signatures in native and invasive range contact calls*

407 We identified strong acoustic convergence at the individual scale in contact calls recorded in  
408 both ranges. Call lexicons (or collections of spectrograms) for known repeatedly sampled  
409 individuals indicated that parakeets in each of the native and invasive ranges consistently  
410 produced calls that were distinctive from those of other birds (Figure 2A). This result was  
411 further supported by the general patterns of low overlap among individuals that we identified  
412 in random forests and SPCC acoustic space, although there was higher overlap among  
413 invasive range individuals (Figure 2B, Figure S1).

414 Our predictive modeling results also pointed to strong acoustic convergence at the  
415 individual scale. The final random forests model that we used to predict similarity of the site  
416 scale calls displayed high classification accuracy during training. The model classified calls  
417 back to the individuals that we used for training with 97.44% accuracy (95% CI: 93.57 -  
418 99.30). The mean  $\pm$  SE balanced accuracy of our model's classification performance per  
419 individual (representing the averaged sensitivity and specificity) was similarly high for the 4  
420 native range (99.00%  $\pm$  0.010) and 4 invasive range training individuals (98.75%  $\pm$  0.008).  
421 Finally, Mantel tests also supported strong individual signatures in native and invasive range  
422 contact calls. The Mantel correlation statistics that we identified at the individual scale in each  
423 of the native and invasive ranges were of similar magnitude (Native range:  $r = 0.48$ ; Invasive  
424 range:  $r = 0.50$ , Table 1) and were statistically significant under the Bonferroni-corrected alpha  
425 (Table 1).



428 **Figure 2 Legend:** Native and invasive range monk parakeets displayed strong individual vocal  
 429 signatures. Panel A shows a lexicon with 4 calls for one repeatedly sampled bird in each of  
 430 the native and invasive ranges. In panel B, random forests acoustic space is shown for 4  
 431 native range and 4 invasive range individuals. Each point represents a different call per  
 432 individual, and individual identities are encoded by shapes and hues. The convex hull  
 433 polygons demonstrate the area per individual in acoustic space. The blue palette corresponds  
 434 to the native range and gold-brown to the invasive range. See Table S1 for decoded individual  
 435 identities. Individuals generally produced visibly consistent calls (Panel A) that were also  
 436 distinctive from other individuals (Panel B).  
 437

438 **Table 1.** Assessing the strength and significance of acoustic convergence over two social  
 439 scales with Mantel tests  
 440

Social scale	Similarity method	Range	Site scale dataset	Number of calls	Number of sites	Mantel $r^a$	Permuted p-values
Individual	SPCC	Native	-	78	1	<b>0.48</b>	0.0001
		Invasive	-	52	3	<b>0.50</b>	0.0001
Site	SPCC		Full	598	37	0.06	0.0001
		Native	Clustering	410	37	0.04	0.0001
		Visual classification	336	37	0.04	0.0001	
		Full	579	18	<b>0.20</b>	0.0001	
	Invasive	Clustering	208	18	<b>0.11</b>	0.0001	
		Visual classification	179	18	<b>0.11</b>	0.0001	
		Full	598	37	<b>0.13</b>	0.0001	
	Native	Clustering	410	37	<b>0.10</b>	0.0001	
		Visual classification	336	37	<b>0.10</b>	0.0001	
		Full	579	18	<b>0.29</b>	0.0001	
	Invasive	Clustering	208	18	<b>0.24</b>	0.0001	
		Visual classification	179	18	<b>0.24</b>	0.0001	

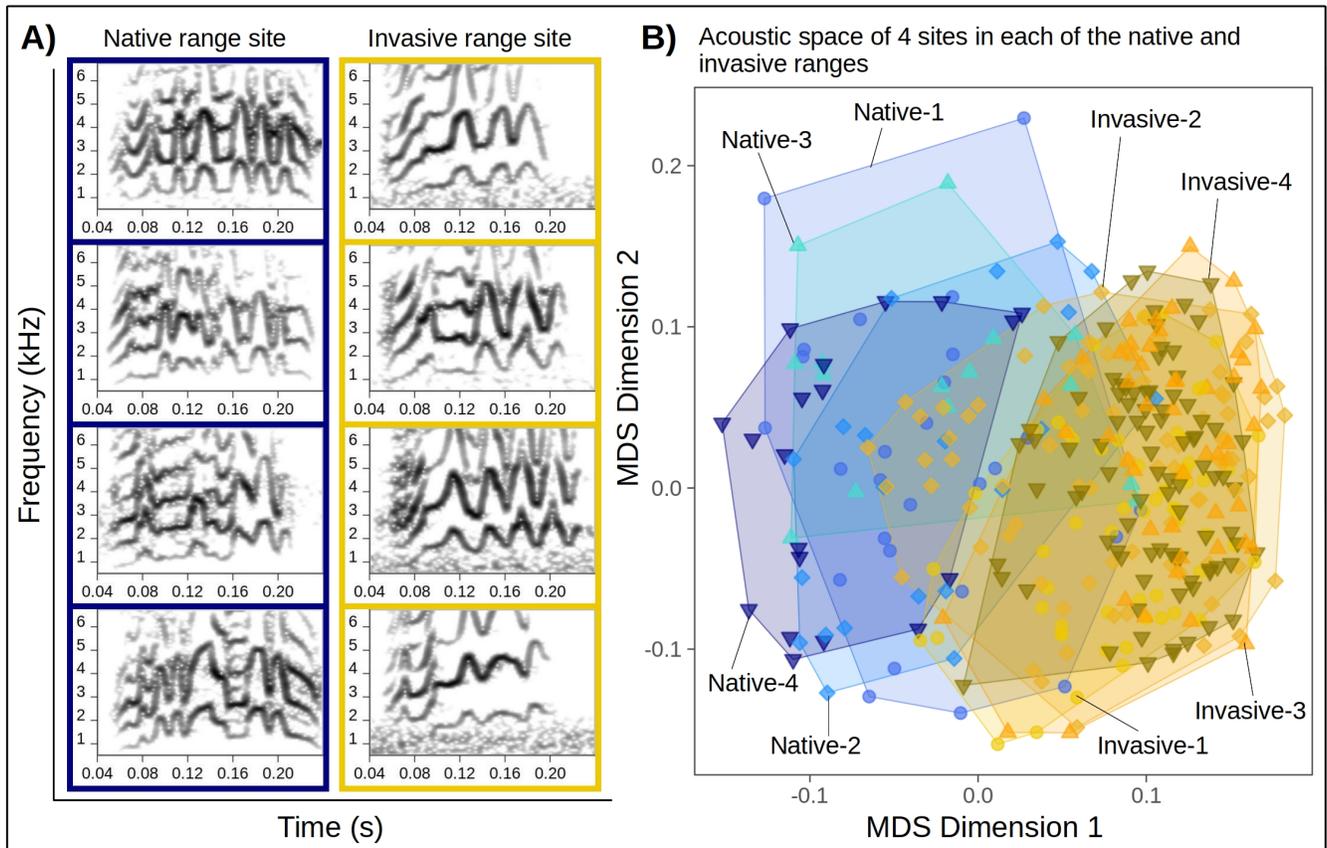
441  
 442 <sup>a</sup>Mantel  $r$  values an order of magnitude greater than the lowest values are shown in bold.  
 443

444 *3.2 Call convergence within sites was low*

445 We found that individuals at the same site did not produce similar calls (Figure 3A). When we  
446 assessed hierarchical mapping patterns in acoustic space, we found that contact calls did not  
447 group by site identity. Instead, calls from the same site were overdispersed, resulting in  
448 substantial overlap among different sites in acoustic space generated using random forests  
449 similarity (Figure 3B), as well as SPCC similarity (Figure S2). The low degree of acoustic  
450 convergence that we identified at the site scale was supported by Mantel test statistics that  
451 were of lower relative magnitude for the site scale compared to the individual scale (Table 1).  
452 This result held across the complementary SPCC and random forests similarity methods that  
453 we used for the site scale Mantel tests.

454 We also compared our Mantel test results across the 3 site scale datasets to determine  
455 how keeping or filtering out calls of potentially repeatedly sampled individuals affected our  
456 results at this social scale. While the Mantel test statistics for the 3 native range site scale  
457 datasets were consistently low, the test statistics for the invasive range varied across the site  
458 scale datasets. The invasive range test statistics for each dataset were uniformly greater than  
459 those we obtained for the native range datasets by each similarity method (Table 1). The  
460 highest Mantel test statistics that we observed at the site scale for the native and invasive  
461 ranges occurred with the full dataset of calls, in which we did not filter out calls attributed to  
462 repeatedly sampled unmarked individuals at this social scale.

463 Figure 3:  
464



466 **Figure 3 Legend:** We identified minimal acoustic convergence at the site scale in the native  
467 and invasive ranges. Panel A shows a lexicon of 4 calls each for one native range site and  
468 one invasive range site, in which each call represents a unique individual. Panel B shows  
469 random forests acoustic space for 5 native range and 5 invasive range sites. The full dataset  
470 of calls was used per site (see Figure S2 for the other site scale datasets). Across panels, the  
471 color palettes, aesthetics, and polygons used are similar to Figure 3, but here encode site  
472 identities. See Table S1 for decoded site identities. Calls within sites were visibly different  
473 (Panel A), and there was low differentiation among sites in acoustic space (Panel B)  
474 compared to the individual scale (Figure 2B).  
475

476 *3.3 Patterns of site scale convergence in the invasive range were consistent over time*

477 We did not identify clear evidence of temporal change in the strength of site scale acoustic  
478 convergence in the invasive range (Table 2). After adjusting alpha for multiple comparisons,  
479 we identified statistically significant acoustic convergence at the site scale in 2011 in the city  
480 of Austin using the full dataset of calls by both similarity methods, and the datasets filtered  
481 after clustering and visual classification, but only by random forests similarity (Table 2). We  
482 also found statistically significant convergence within sites in Austin in 2019 and New Orleans  
483 in 2004 using the full dataset of calls and both similarity methods (Table 2). Although these  
484 Mantel test statistics were statistically significant, the statistics were of lower magnitude  
485 relative to the Mantel test statistics that we identified at the individual scale for each range  
486 (Table 1). We used eBird checklists from these cities in a complementary analysis of  
487 population trends over time, to address the possibility that population size could have  
488 rebounded since establishment. However, we found that the mean annual frequency of monk  
489 parakeets reported in complete checklists in Austin and New Orleans remained low (less than  
490 5% of all species sightings) and was also generally stable from 2004 to 2020 (supplementary  
491 section 15, Figure S3).

492 **Table 2.** Evaluating temporal change in site scale acoustic convergence in the invasive range

Similarity method	City	Year	Dataset	Number of calls	Number of sites	Mantel $r^a$	Permuted p-values
SPCC	Austin	2004	Full	93	3	0.10	0.0796
			Clustering	37	3	0.09	0.1359
			Visual inspection	20	3	-0.03	0.5950
		2011	Full	65	5	<b>0.23</b>	0.0001
			Clustering	43	5	0.08	0.0067
			Visual inspection	54	5	0.07	0.0055
		2019	Full	295	6	<b>0.13</b>	0.0001
			Clustering	83	6	0.01	0.2513
			Visual inspection	56	6	-0.03	0.8498
	New Orleans	2004	Full	49	3	<b>0.18</b>	0.0005
			Clustering	18	3	0.03	0.3272
			Visual inspection	25	3	-0.02	0.6186
		2011	Full	29	2	0.27	0.0045
			Clustering	17	2	0.22	0.0196
			Visual inspection	17	2	0.21	0.0229
Random forests	Austin	2004	Full	93	3	0.03	0.2680
			Clustering	37	3	0.03	0.2912
			Visual inspection	20	3	0.04	0.3015
		2011	Full	65	5	<b>0.37</b>	0.0001
			Clustering	43	5	<b>0.13</b>	0.0004
			Visual inspection	54	5	<b>0.09</b>	0.0015
		2019	Full	295	6	<b>0.17</b>	0.0001
			Clustering	83	6	0.05	0.0099
			Visual inspection	56	6	0.01	0.4115
	New Orleans	2004	Full	49	3	<b>0.19</b>	0.0002
			Clustering	18	3	0.10	0.1161
			Visual inspection	25	3	-0.02	0.6051
		2011	Full	29	2	0.09	0.0826
			Clustering	17	2	0.08	0.1827
			Visual inspection	17	2	0.07	0.1963

493 <sup>a</sup>Mantel  $r$  values that were statistically significant under the corrected alpha are shown in bold.

494

#### 495 *3.4 More repeated sampling of individuals in our invasive range site scale dataset*

496 We attributed more calls in our invasive range site scale datasets to the inadvertent repeated  
497 sampling of unmarked individuals compared to our native range site scale datasets. The  
498 mean numbers of repeated individuals that we identified by our clustering and visual  
499 classification filtering approaches were only slightly higher for the invasive range than the  
500 native range (Table 3). However, we found that the mean number of calls attributed to  
501 repeated individuals was about twofold greater for invasive range sites by each of the  
502 clustering and visual classification approaches that we had used to identify repeated sampling  
503 of individuals in our site scale datasets (Table 3).

504

505 Table 3. Assessing the degree of repeated sampling of individuals for both the invasive and  
506 native ranges.  
507

Filtering approach	Range	Repeated individuals (mean $\pm$ SE)	Calls per repeated individual (mean $\pm$ SE)
Clustering	Native	3.24 $\pm$ 0.38	10.4 $\pm$ 1.61
	Invasive	3.40 $\pm$ 0.47	23.6 $\pm$ 5.53
Visual classification	Native	3.48 $\pm$ 0.39	2.83 $\pm$ 0.15
	Invasive	3.57 $\pm$ 0.54	5.31 $\pm$ 0.64

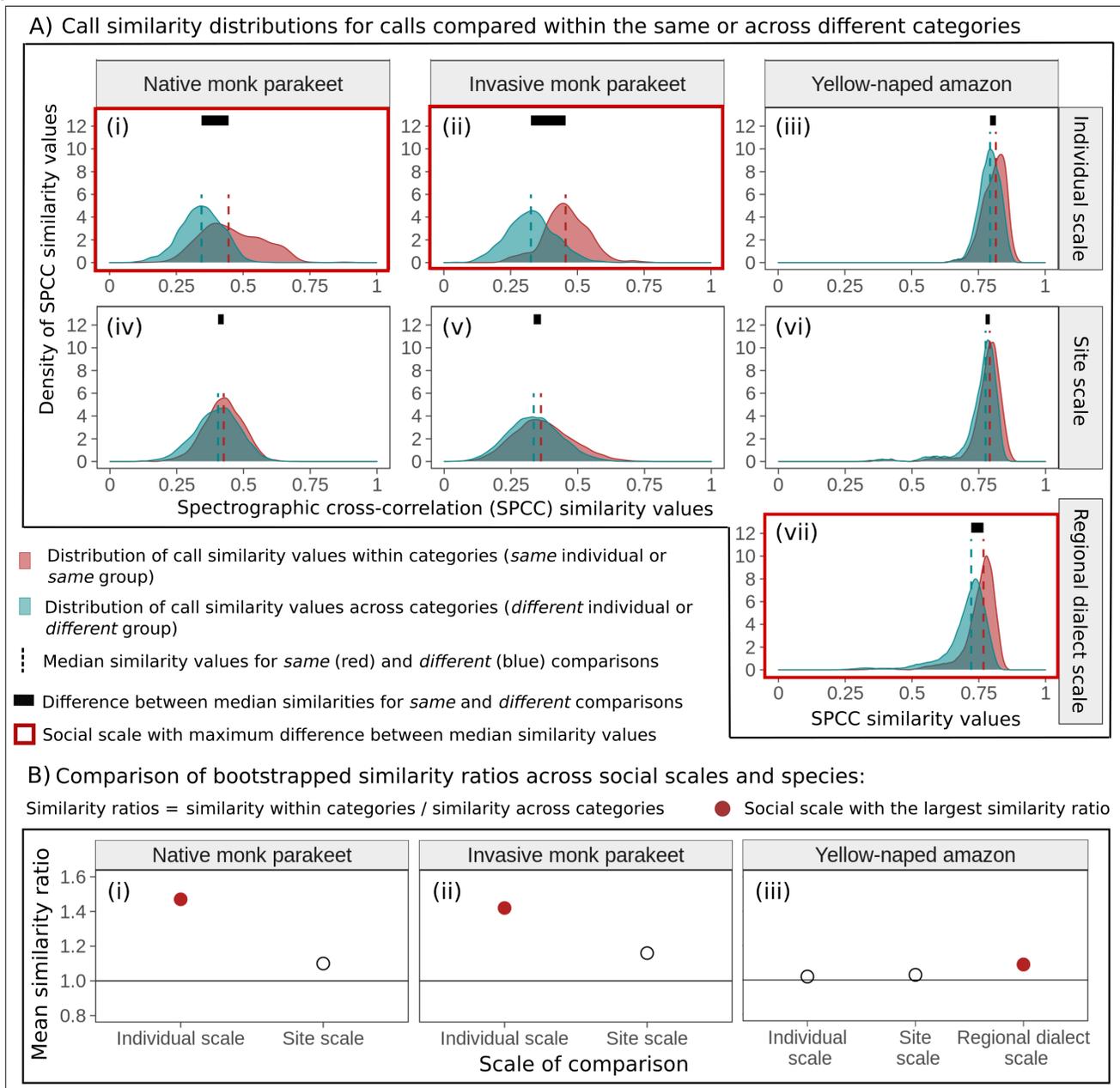
508

509 *3.5 Benchmarking hierarchical mapping patterns with another species*

510 The hierarchical mapping patterns that we identified for both native and invasive range monk  
511 parakeet calls differed from the hierarchical mapping patterns that we recapitulated in yellow-  
512 naped amazon calls. Our benchmarking results showed that the individual scale was the  
513 social scale with the strongest acoustic convergence in native and invasive range monk  
514 parakeet calls, while the regional dialect scale displayed the strongest convergence in yellow-  
515 naped amazon calls. We found that the greatest separation between the median similarity  
516 values of the two categories of comparison per social scale (e.g. same or different individual  
517 or group) occurred at the individual scale for native and invasive range monk parakeets  
518 (Figure 4A, panels i and ii). For yellow-naped amazons, we detected the greatest separation  
519 between categories at the regional dialect scale (Figure 4A, panel vii). In addition, the  
520 bootstrapped similarity ratios that we used to assess the strength of acoustic convergence  
521 were greatest at the individual scale for monk parakeets in each of the native and invasive  
522 ranges (Figure 4B, panels i and ii). In contrast, the largest similarity ratio for yellow-naped  
523 amazons occurred at the regional dialect scale (Figure 4B, panel iii).

524

Figure 4:



528 **Figure 4 Legend:** We benchmarked hierarchical mapping patterns in native and invasive  
 529 range monk parakeet calls against yellow-naped amazon calls. Panel A shows density curves  
 530 for the distributions of spectrographic cross-correlation (SPCC) similarity values that  
 531 represent comparisons of calls within or among categories in red and blue shading,  
 532 respectively. The dashed lines represent the median similarity values per distribution. In Panel  
 533 B, we show the mean similarity ratios calculated from bootstrapped SPCC values. The solid  
 534 line at 1 represents no convergence within a given category. For both native and invasive  
 535 range monk parakeets, we show site scale results obtained from the full dataset of calls.  
 536 Across both panels, the social scale at which the strongest convergence occurred is shown in  
 537 red.  
 538

539 **4. Discussion**

540 We asked whether the type of identity information that is important to communicate in learned  
541 signals changes after the social environment is perturbed over the ecological timescale of a  
542 biological invasion. We found that individual identity remained the most important type of  
543 identity information to communicate in learned monk parakeet vocalizations. We discuss this  
544 new insight into the resilience of identity information encoded in learned communication  
545 signals, and point to possible directions for future work over ecological and evolutionary  
546 timescales.

547

548 *4.1 Hierarchical mapping patterns were similar between native and invasive range monk*  
549 *parakeet populations*

550 Monk parakeets in native range populations in Uruguay and invasive range populations in the  
551 U.S. emphasized individual identity information in learned vocalizations. In each range, the  
552 hierarchical mapping patterns that we quantified in contact calls showed the strongest  
553 convergence at the individual scale and weaker convergence within sites. These results were  
554 robust to the greater degree of repeated individual sampling that we identified in our invasive  
555 range site scale dataset (supplementary section 16). In addition, the low convergence that we  
556 identified at the site scale in two cities sampled over time, which represented independent  
557 introduction events, suggested that these hierarchical mapping patterns were unlikely to have  
558 changed in the broader U.S. invasive range over the timespan of this study. We also  
559 recapitulated the structural differences between native and invasive range calls that reflected  
560 the simplification of individual vocal signatures associated with smaller local populations in the  
561 U.S. (see the separation in acoustic space among native and invasive range calls in Figure  
562 2B and Figure 3B) (Smith-Vidaurre et al., 2021).

563 Our analyses indicate that despite invasion, individual identity remained the most  
564 important type of identity information to communicate to receivers. In other words, we inferred  
565 that the type of identity information emphasized in learned calls was resilient to the social  
566 disruption that is expected to occur during the early stages of a biological invasion. Our  
567 findings also indicate that although some features of the social environment changed after  
568 invasion, such as the smaller local population sizes that we identified in previous work (Smith-  
569 Vidaurre et al., 2021), monk parakeets' social environments may have been generally resilient  
570 to invasion or were re-established after initial perturbations. If the individually distinctive  
571 contact calls that we identified in the native and invasive ranges are used for individual vocal  
572 recognition, then parakeets in each range should be engaging in social interactions that favor  
573 signaling individual identity in learned communication signals. Our quantitative approaches  
574 with vocal signals allowed us to reach this inference about monk parakeets' social  
575 environments without depending on the time- and resource-intensive collection of social data.  
576 However, future work could directly address whether native and invasive range monk  
577 parakeets are engaging in similar types of social interactions that require individual vocal  
578 recognition, such as repeated interactions and differentiated relationships with many other  
579 individuals (Bergman & Beehner, 2015; Tibbetts et al., 2007).

580

#### 581 *4.2 Benchmarking our results against a parrot species that exhibits regional vocal dialects*

582 We performed a comparative analysis with yellow-naped amazon contact calls to place our  
583 ecological comparison of native and invasive range monk parakeet calls in an evolutionary  
584 context. If invasive range monk parakeets switched to emphasizing group membership  
585 information in contact calls, then hierarchical mapping patterns in invasive range monk  
586 parakeet calls should have been more similar to yellow-naped amazons, which exhibit  
587 regional vocal dialects that are audibly and visibly distinctive to humans (Salinas-Melgoza et

588 al., 2012; Sewall et al., 2016; Wright, 1996; Wright & Dahlin, 2018). Instead, we found that  
589 hierarchical mapping patterns were similar between native and invasive range monk  
590 parakeets, confirming that identity information in monk parakeet contact calls was resilient to  
591 the invasion process over ecological timescales.

592 Our benchmarking analysis also highlighted the importance of using quantitative tools  
593 to complement human perception of audible and visible variation in avian vocalizations. When  
594 relying on the human ear and eye, the variation among regional dialects in yellow-naped  
595 amazon calls is far more perceptible than individually distinctive monk parakeet calls. For  
596 example, the regional dialects that we recapitulated in the amazon calls are distinctive to the  
597 human ear (Wright, 1996), including North dialect calls that sound like “wah-wah”, and  
598 variants of the South dialect that sound like “weeup”. In contrast, patterns of individual  
599 variation in monk parakeet contact calls are difficult to distinguish by the human ear, and calls  
600 of different individuals sound no different than “chees”. However, when we used quantitative  
601 methods to compare hierarchical mapping patterns between species, we found that individual  
602 scale convergence in native and invasive range monk parakeet calls was stronger than  
603 regional dialect convergence for yellow-naped amazons (Figure 4A: panels i, ii, and vii).

604 Amazon vocal dialects may be more perceptible to humans than monk parakeet  
605 individual vocal signatures because of humans’ limited abilities to perceive fine-scale temporal  
606 variation at higher frequencies (Dooling, Leek, Gleich, & Dent, 2002; Lohr, Dooling, &  
607 Bartone, 2006). Parrots’ auditory perception abilities appear tuned for higher frequencies,  
608 such as orange-fronted conures (*Eupsittula canicularis*), which display the greatest auditory  
609 sensitivity in a frequency band that overlaps with the greatest spectral energies in contact  
610 calls (Wright, Cortopassi, Bradbury, & Dooling, 2003). In addition, yellow-naped amazon calls  
611 exhibit slower frequency modulation patterns that are more perceptible to humans, and can  
612 also be arranged into fewer categories (e.g. a few regional dialects), a task that should pose

613 lower cognitive challenges compared to categorizing monk parakeet calls by many different  
614 individuals (Bradbury et al., 1998; Wiley, 2013). Overall, our benchmarking results point to the  
615 importance of using computational approaches to identify information in animal signals that is  
616 difficult for humans to perceive but may be critical in animal communication systems.

617

#### 618 *4.3 Future research considerations with hierarchical mapping patterns*

619 We combined computational tools with a conceptual framework of how hierarchical mapping  
620 patterns are connected to identity signaling in animal vocal signals. This combined approach  
621 allowed us to quantify hierarchical mapping patterns and then infer the most salient social  
622 information encoded in vocal signals. Similar computational approaches could be applied to  
623 quantify hierarchical mapping patterns with existing datasets of animal signals to learn more  
624 about the social environments in which individuals communicate across a broader range of  
625 taxa, without depending on the time-intensive collection of social data from marked  
626 individuals. The hierarchical mapping patterns identified for a particular population or species  
627 can also be used as a foundation for designing biologically relevant playback experiments,  
628 which can be more time-consuming than recording communication signals, and are  
629 fundamental to understand how receivers use the social information that signalers  
630 communicate. Playback experiments are important because mismatches can occur between  
631 the social information encoded in signals and the information that receivers use for social  
632 recognition, especially when it is cognitively costly to track certain types of information  
633 (Bergman, 2010; Bergman et al., 2015).

634         Researchers using hierarchical mapping patterns to make inferences about identity  
635 signaling and the social environment should take additional considerations into account. For  
636 instance, recording unmarked individuals in natural populations provides only a snapshot of  
637 dynamic social interactions, as well as the social information conveyed in signals that is

638 important in a given social environment. Some species may exhibit variation within a single  
639 signal type that should be considered carefully when quantifying hierarchical mapping  
640 patterns, such as parrots that use multiple contact call variants, including budgerigars and  
641 orange-fronted conures (*Eupsittula canicularis*) (Bradbury et al., 2001; Dahlin, Young, Cordier,  
642 Mundry, & Wright, 2014; Farabaugh, Linzenbold, & Dooling, 1994). Furthermore, sampling  
643 one or a few vocalizations per individual over a short time frame makes it difficult to assess  
644 how social information changes during dynamic social interactions, such as the rapid vocal  
645 matching exhibited by wild orange-fronted conures and rose-breasted cockatoos (*Eolophus*  
646 *roseicapillus*) (Balsby et al., 2009; Scarl et al., 2009). Finally, while the literature has focused  
647 on explaining how social signals arise in more complex social environments with frequent and  
648 repeated interactions among many individuals (Bergman et al., 2015; Pollard et al., 2011;  
649 Ramos-Fernandez et al., 2018; Sewall et al., 2016; Tibbetts et al., 2007), there is less of a  
650 conceptual foundation for how identity information in learned communication signals should  
651 change in social environments characterized by fewer individuals and differentiated  
652 relationships overall.

653

654 **Data Accessibility:** Annotated code and knitted RMarkdown files supporting this  
655 article will be made available on GitHub. Data that can be used to reproduce results will be  
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657

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668 G.S.V. and V.P.M. performed fieldwork in 2019. G.S.V. and T.F.W. designed the study, and  
669 G.S.V. took the lead on analyses with support from V.P.M., E.A.H., A.S.M., and T.F.W.  
670 Manuscript writing was led by G.S.V. and T.F.W, and all authors contributed to reviewing and  
671 editing the manuscript.

672

673 **Ethics:** This research was conducted under an approved Institutional Animal Care and Use  
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## 691 **References**

- 692 Aplin, L. M. (2019). Culture and cultural evolution in birds: A review of the evidence. *Animal*  
693 *Behaviour*, *147*, 179–187. <https://doi.org/10.1016/j.anbehav.2018.05.001>
- 694 Araya-Salas, M., & Smith-Vidaurre, G. (2017). warbleR: An R package to streamline analysis  
695 of animal acoustic signals. *Methods in Ecology and Evolution*, *8*(2), 184–191.  
696 <https://doi.org/10.1111/2041-210X.12624>
- 697 Balsby, T. J. S., & Bradbury, J. W. (2009). Vocal matching by orange-fronted conures  
698 (*Aratinga canicularis*). *Behavioural Processes*, *82*(2), 133–139.  
699 <https://doi.org/10.1016/j.beproc.2009.05.005>
- 700 Berg, K. S., Delgado, S., Cortopassi, K. A., Beissinger, S. R., & Bradbury, J. W. (2012).  
701 Vertical transmission of learned signatures in a wild parrot. *Proceedings of the Royal*  
702 *Society B: Biological Sciences*, *279*(1728), 585–591.  
703 <https://doi.org/10.1098/rspb.2011.0932>
- 704 Berg, K. S., Delgado, S., Okawa, R., Beissinger, S. R., & Bradbury, J. W. (2011). Contact calls  
705 are used for individual mate recognition in free-ranging green-rumped parrotlets, *Forpus*  
706 *passerinus*. *Animal Behaviour*, *81*(1), 241–248.  
707 <https://doi.org/10.1016/j.anbehav.2010.10.012>
- 708 Bergman, T. J. (2010). Experimental evidence for limited vocal recognition in a wild primate:  
709 Implications for the social complexity hypothesis. *Proceedings of the Royal Society B:*  
710 *Biological Sciences*, *277*(1696), 3045–3053. <https://doi.org/10.1098/rspb.2010.0580>
- 711 Bergman, T. J., & Beehner, J. C. (2015). Measuring social complexity. *Animal Behaviour*, *103*,  
712 203–209. <https://doi.org/10.1016/j.anbehav.2015.02.018>
- 713 Blackburn, T. M., Pysek, P., Bacher, S., Carlton, J. T., Duncan, R. P., Jarosik, V., Wilson, J. R.  
714 U., & Richardson, D. M. (2011). A proposed unified framework for biological invasions.  
715 *Trends in Ecology and Evolution*, *26*(7), 333–339.  
716 <https://doi.org/10.1016/j.tree.2011.03.023>
- 717 Boughman, J. W. (1998). Vocal learning by greater spear-nosed bats. *Proceedings of the*  
718 *Royal Society B: Biological Sciences*, *265*(1392), 227–233.  
719 <https://doi.org/10.1098/rspb.1998.0286>

- 720 Boughman, J. W., & Wilkinson, G. S. (1998). Greater spear-nosed bats discriminate group  
721 mates by vocalizations. *Animal Behaviour*, *55*(6), 1717–1732.  
722 <https://doi.org/10.1006/anbe.1997.0721>
- 723 Bradbury, J. W., & Balsby, T. J. S. (2016). The functions of vocal learning in parrots.  
724 *Behavioral Ecology and Sociobiology*, *70*, 293–312. [https://doi.org/10.1007/s00265-016-](https://doi.org/10.1007/s00265-016-2068-4)  
725 [2068-4](https://doi.org/10.1007/s00265-016-2068-4)
- 726 Bradbury, J. W., Cortopassi, K. A., & Clemmons, J. R. (2001). Geographical variation in the  
727 contact calls of orange-fronted parakeets. *The Auk*, *118*(4), 958–972.  
728 <https://doi.org/10.1093/auk/118.4.958>
- 729 Bradbury, J. W., & Vehrencamp, S. L. (1998). *Principles of Animal Communication*.  
730 Sunderland, MA, USA: Sinauer Associates, Inc.
- 731 Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5–32.  
732 <https://doi.org/10.1023/A:1010933404324>
- 733 Buhrman-Deever, S. C., Rappaport, A. R., & Bradbury, J. W. (2007). Geographic variation in  
734 contact calls of feral North American populations of the monk parakeet. *The Condor*,  
735 *109*(2), 389–398. <https://doi.org/10.1093/condor/109.2.389>
- 736 Clark, C. W., Marler, P., & Beeman, K. (1987). Quantitative analysis of animal vocal  
737 phonology: An application to swamp sparrow song. *Ethology*, *76*, 101–115.  
738 <https://doi.org/10.1111/j.1439-0310.1987.tb00676.x>
- 739 Dahlin, C. R., Young, A. M., Cordier, B., Mundry, R., & Wright, T. F. (2014). A test of multiple  
740 hypotheses for the function of call sharing in female budgerigars, *Melopsittacus*  
741 *undulatus*. *Behavioral Ecology and Sociobiology*, *68*(1), 145–161. [https://doi.org/10.1007/](https://doi.org/10.1007/s00265-013-1631-5)  
742 [s00265-013-1631-5](https://doi.org/10.1007/s00265-013-1631-5)
- 743 Dlugosch, K. M., & Parker, I. M. (2008). Founding events in species invasions: Genetic  
744 variation, adaptive evolution, and the role of multiple introductions. *Molecular Ecology*,  
745 *17*(1), 431–449. <https://doi.org/10.1111/j.1365-294X.2007.03538.x>
- 746 Dooling, R. J., Leek, M. R., Gleich, O., & Dent, M. L. (2002). Auditory temporal resolution in  
747 birds: discrimination of harmonic complexes. *The Journal of the Acoustical Society of*  
748 *America*, *112*(2), 748–759. <https://doi.org/10.1121/1.1494447>
- 749 Eberhard, J. R. (1998). Breeding biology of the monk parakeet. *The Wilson Bulletin*, *110*(4),  
750 463–473.
- 751 Eberhard, J. R., Zager, I., Ferrer-Paris, J. R., & Rodríguez-Clark, K. (2022). Contact calls of  
752 island Brown-throated Parakeets exhibit both character and variance shifts compared to  
753 calls of their mainland relatives. *Ornithology*, *139*, 1–18.  
754 <https://doi.org/10.1093/ornithology/ukab076>

- 755 Edelaar, P., Roques, S., Hobson, E. A., Goncalves Da Silva, A., Avery, M. L., Russello, M. A.,  
756 Senar, J. C., Wright, T. F., Carrete, M., & Tella, J. L. (2015). Shared genetic diversity  
757 across the global invasive range of the monk parakeet suggests a common restricted  
758 geographic origin and the possibility of convergent selection. *Molecular Ecology*, *24*(9),  
759 2164–2176. <https://doi.org/10.1111/mec.13157>
- 760 Farabaugh, S. M., Linzenbold, A., & Dooling, R. J. (1994). Vocal plasticity in budgerigars  
761 (*Melopsittacus undulatus*): Evidence for social factors in the learning of contact calls.  
762 *Journal of Comparative Psychology*, *108*(1), 81–92. [https://doi.org/10.1037/0735-](https://doi.org/10.1037/0735-7036.108.1.81)  
763 [7036.108.1.81](https://doi.org/10.1037/0735-7036.108.1.81)
- 764 Furuyama, T., Kobayasi, K. I., & Riquimaroux, H. (2016). Role of vocal tract characteristics in  
765 individual discrimination by Japanese macaques (*Macaca fuscata*). *Scientific Reports*,  
766 *6*(January), 32042. <https://doi.org/10.1038/srep32042>
- 767 Guerra, J. E., Cruz-Nieto, J., Ortiz-Maciel, S. G., & Wright, T. F. (2008). Limited geographic  
768 variation in the vocalizations of the endangered thick-billed parrot: Implications for  
769 conservation strategies. *Condor*, *110*(4), 639–647.  
770 <https://doi.org/10.1525/cond.2008.8609>
- 771 Hobson, E. A. (2020). Differences in social information are critical to understanding  
772 aggressive behavior in animal dominance hierarchies. *Current Opinion in Psychology*,  
773 *33*, 209–215. <https://doi.org/10.1016/j.copsyc.2019.09.010>
- 774 Hobson, E. A., Avery, M. L., & Wright, T. F. (2014). The socioecology of monk parakeets:  
775 insights into parrot social complexity. *The Auk*, *131*, 756–775.  
776 <https://doi.org/10.1642/AUK-14-14.1>
- 777 Hobson, E. A., Mønster, D., & DeDeo, S. (2021). Aggression heuristics underlie animal  
778 dominance hierarchies and provide evidence of group-level social information.  
779 *Proceedings of the National Academy of Sciences of the United States of America*,  
780 *118*(10), e2022912118. <https://doi.org/10.1073/pnas.2022912118>
- 781 Hobson, E. A., Smith-Vidaurre, G., & Salinas-Melgoza, A. (2017). History of nonnative monk  
782 parakeets in Mexico. *PLoS ONE*, *12*(9), e0184771.  
783 <https://doi.org/10.1371/journal.pone.0184771>
- 784 Humphries, G. R. W., Buxton, R. T., & Jones, I. L. (2018). Machine learning techniques for  
785 quantifying geographic variation in Leach's storm-petrel (*Hydrobates leucorhous*). In G.  
786 R. W. Humphries, D. R. Magness, & F. Huettmann (Eds.), *Machine Learning for Ecology*  
787 *and Sustainable Natural Resource Management* (pp. 295–312). Cham, Switzerland:  
788 Springer Nature. [https://doi.org/10.1007/978-3-319-96978-7\\_15](https://doi.org/10.1007/978-3-319-96978-7_15)
- 789 Janik, V. M., Sayigh, L. S., & Wells, R. S. (2006). Signature whistle shape conveys identity  
790 information to bottlenose dolphins. *Proceedings of the National Academy of Sciences of*

791 *the United States of America*, 103(21), 8293–8297.  
792 <https://doi.org/10.1073/pnas.0509918103>

793 Janik, V. M., & Slater, P. J. B. (1998). Context-specific use suggests that bottlenose dolphin  
794 signature whistles are cohesion calls. *Animal Behaviour*, 56(4), 829–838.  
795 <https://doi.org/10.1006/anbe.1998.0881>

796 Jones, B. L., Daniels, R., Tufano, S., & Ridgway, S. (2020). Five members of a mixed-sex  
797 group of bottlenose dolphins share a stereotyped whistle contour in addition to  
798 maintaining their individually distinctive signature whistles. *PLoS ONE*, 15(5), e0233658.  
799 <https://doi.org/10.1371/journal.pone.0233658>

800 Keen, S. C., Odom, K. J., Webster, M. S., Kohn, G. M., Wright, T. F., & Araya-Salas, M.  
801 (2021). A machine learning approach for classifying and quantifying acoustic diversity.  
802 *Methods in Ecology and Evolution*, 12(7), 1213–1225. [https://doi.org/10.1111/2041-](https://doi.org/10.1111/2041-210x.13599)  
803 [210x.13599](https://doi.org/10.1111/2041-210x.13599)

804 Keen, S., Ross, J. C., Griffiths, E. T., Lanzone, M., & Farnsworth, A. (2014). A comparison of  
805 similarity-based approaches in the classification of flight calls of four species of North  
806 American wood-warblers (Parulidae). *Ecological Informatics*, 21, 25–33.  
807 <https://doi.org/10.1016/j.ecoinf.2014.01.001>

808 Kershenbaum, A., Sayigh, L. S., & Janik, V. M. (2013). The encoding of individual identity in  
809 dolphin signature whistles: how much information is needed? *PLoS ONE*, 8(10), e77671.  
810 <https://doi.org/10.1371/journal.pone.0077671>

811 Lohr, B., Dooling, R. J., & Bartone, S. (2006). The discrimination of temporal fine structure in  
812 call-like harmonic sounds by birds. *Journal of Comparative Psychology*, 120(3), 239–251.  
813 <https://doi.org/10.1037/0735-7036.120.3.239>

814 Mammen, D. L., & Nowicki, S. (1981). Individual differences and within-flock convergence in  
815 chickadee calls. *Behavioral Ecology and Sociobiology*, 9(3), 179–186.  
816 <https://doi.org/10.1007/BF00302935>

817 Martinez, T. M., & Logue, D. M. (2020). Conservation practices and the formation of vocal  
818 dialects in the endangered Puerto Rican parrot, *Amazona vittata*. *Animal Behaviour*, 166,  
819 261–271. <https://doi.org/10.1016/j.anbehav.2020.06.004>

820 Nousek, A. E., Slater, P. J. B., Wang, C., & Miller, P. J. O. (2006). The influence of social  
821 affiliation on individual vocal signatures of northern resident killer whales (*Orcinus orca*).  
822 *Biology Letters*, 2(4), 481–484. <https://doi.org/10.1098/rsbl.2006.0517>

823 Nowicki, S., & Searcy, W. A. (2014). The evolution of vocal learning. *Current Opinion in*  
824 *Neurobiology*, 28, 48–53. <https://doi.org/10.1016/j.conb.2014.06.007>

825 Odom, K. J., Araya-Salas, M., Morano, J. L., Ligon, R. A., Leighton, G. M., Taff, C. C., Dalziell,  
826 A. H., Billings, A. C., Germain, R. R., Pardo, M., Guimaraes de Andrade, L., Hedwig, D.,

- 827 Keen, S. C., Shiu, Y., Charif, R. A., Webster, M. S., & Rice, A. N. (2021). Comparative  
828 bioacoustics: A roadmap for quantifying and comparing animal sounds across diverse  
829 taxa. *Biological Reviews*, 96(4), 1135–1159. <https://doi.org/10.1111/brv.12695>
- 830 Pollard, K. A., & Blumstein, D. T. (2011). Social group size predicts the evolution of  
831 individuality. *Current Biology*, 21(5), 413–417. <https://doi.org/10.1016/j.cub.2011.01.051>
- 832 Prior, N. H., Smith, E., Lawson, S., Ball, G. F., & Dooling, R. J. (2018). Acoustic fine structure  
833 may encode biologically relevant information for zebra finches. *Scientific Reports*, 8(1),  
834 6212. <https://doi.org/10.1038/s41598-018-24307-0>
- 835 Ramos-Fernandez, G., King, A. J., Beehner, J. C., Bergman, T. J., Crofoot, M. C., Di Fiore, A.,  
836 Lehmann, J., Schaffner, C. M., Snyder-Mackler, N., Zuberbuhler, K., Aureli, F., & Boyer,  
837 D. (2018). Quantifying uncertainty due to fission–fusion dynamics as a component of  
838 social complexity. *Proceedings of the Royal Society B: Biological Sciences*, 285(1879),  
839 20180532. <https://doi.org/10.1098/rspb.2018.0532>
- 840 Rendall, D., Owren, M. J., & Rodman, P. S. (1998). The role of vocal tract filtering in identity  
841 cueing in rhesus monkey (*Macaca mulatta*) vocalizations. *The Journal of the Acoustical*  
842 *Society of America*, 103(1), 602–614. <https://doi.org/10.1121/1.421104>
- 843 Rendell, L. E., & Whitehead, H. (2003). Vocal clans in sperm whales (*Physeter*  
844 *macrocephalus*). *Proceedings of the Royal Society B: Biological Sciences*, 270(1512),  
845 225–231. <https://doi.org/10.1098/rspb.2002.2239>
- 846 Russello, M. A., Avery, M. L., & Wright, T. F. (2008). Genetic evidence links invasive monk  
847 parakeet populations in the United States to the international pet trade. *BMC*  
848 *Evolutionary Biology*, 8, 217. <https://doi.org/10.1186/1471-2148-8-217>
- 849 Salinas-Melgoza, A., & Renton, K. (2021). Geographic variation in vocalisations of the Military  
850 Macaw in western Mexico. *Bioacoustics*, 30(2), 197–214.  
851 <https://doi.org/10.1080/09524622.2020.1714479>
- 852 Salinas-Melgoza, A., & Wright, T. F. (2012). Evidence for vocal learning and limited dispersal  
853 as dual mechanisms for dialect maintenance in a parrot. *PLoS ONE*, 7(11), e48667.  
854 <https://doi.org/10.1371/journal.pone.0048667>
- 855 Scarl, J. C., & Bradbury, J. W. (2009). Rapid vocal convergence in an Australian cockatoo, the  
856 galah *Eolophus roseicapillus*. *Animal Behaviour*, 77(5), 1019–1026.  
857 <https://doi.org/10.1016/j.anbehav.2008.11.024>
- 858 Sewall, K. B. (2009). Limited adult vocal learning maintains call dialects but permits pair-  
859 distinctive calls in red crossbills. *Animal Behaviour*, 77(5), 1303–1311.  
860 <https://doi.org/10.1016/j.anbehav.2009.01.033>

- 861 Sewall, K. B. (2011). Early learning of discrete call variants in red crossbills: Implications for  
862 reliable signaling. *Behavioral Ecology and Sociobiology*, *65*(2), 157–166.  
863 <https://doi.org/10.1007/s00265-010-1022-0>
- 864 Sewall, K. B., Young, A. M., & Wright, T. F. (2016). Social calls provide novel insights into the  
865 evolution of vocal learning. *Animal Behaviour*, *120*, 163–172.  
866 <https://doi.org/10.1016/j.anbehav.2016.07.031>
- 867 Seyfarth, R. M., Cheney, D. L., Bergman, T., Fischer, J., Zuberbühler, K., & Hammerschmidt,  
868 K. (2010). The central importance of information in studies of animal communication.  
869 *Animal Behaviour*, *80*(1), 3–8. <https://doi.org/10.1016/j.anbehav.2010.04.012>
- 870 Smith-Vidaurre, G. (2020). *Patterns of genetic and acoustic variation in a biological invader*.  
871 New Mexico State University.
- 872 Smith-Vidaurre, G., Araya-Salas, M., & Wright, T. F. (2020). Individual signatures outweigh  
873 social group identity in contact calls of a communally nesting parrot. *Behavioral Ecology*,  
874 *31*(2), 448–458. <https://doi.org/10.1093/beheco/arz202>
- 875 Smith-Vidaurre, G., Perez-Marrufo, V., & Wright, T. F. (2021). Individual vocal signatures show  
876 reduced complexity following invasion. *Animal Behavior*, *179*, 15–39.  
877 <https://doi.org/10.1016/j.anbehav.2021.06.020>
- 878 The Cornell Lab of Ornithology Bioacoustics Research Program. (2014). Raven Pro:  
879 Interactive sound analysis software. Ithaca, NY: The Cornell Lab of Ornithology.
- 880 Tibbetts, E. A., & Dale, J. (2007). Individual recognition: It is good to be different. *Trends in*  
881 *Ecology and Evolution*, *22*(10), 529–537. <https://doi.org/10.1016/j.tree.2007.09.001>
- 882 Watwood, S. L., Tyack, P. L., & Wells, R. S. (2004). Whistle sharing in paired male bottlenose  
883 dolphins, *Tursiops truncatus*. *Behavioral Ecology and Sociobiology*, *55*(6), 531–543.  
884 <https://doi.org/10.1007/s00265-003-0724-y>
- 885 Wiley, R. H. (2013). Specificity and multiplicity in the recognition of individuals: Implications for  
886 the evolution of social behaviour. *Biological Reviews*, *88*(1), 179–195.  
887 <https://doi.org/10.1111/j.1469-185X.2012.00246.x>
- 888 Wright, T. F. (1996). Regional dialects in the contact call of a parrot. *Proceedings of the Royal*  
889 *Society of London, B*, *263*, 867–872. <https://doi.org/10.1098/rspb.1996.0128>
- 890 Wright, T. F., Cortopassi, K. A., Bradbury, J. W., & Dooling, R. J. (2003). Hearing and  
891 vocalizations in the orange-fronted conure (*Aratinga canicularis*). *Journal of Comparative*  
892 *Psychology*, *117*(1), 87–95. <https://doi.org/10.1037/0735-7036.117.1.87>
- 893 Wright, T. F., & Dahlin, C. R. (2018). Vocal dialects in parrots: patterns and processes of  
894 cultural evolution. *Emu - Austral Ornithology*, *118*(1), 50–66.  
895 <https://doi.org/10.1080/01584197.2017.1379356>

896 Wright, T. F., Dahlin, C. R., & Salinas-Melgoza, A. (2008). Stability and change in vocal  
897 dialects of the yellow-naped amazon. *Animal Behavior*, 76(3), 1017–1027.  
898 <https://doi.org/10.1016/j.anbehav.2008.03.025>