

1 **Community algorithms reveal song type themes in**  
2 **Adelaide's warbler song type sequence networks**

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18

19 **Abstract**

20 Some New World Warblers (Family: Parulidae) sing with immediate variety during the dawn chorus and  
21 eventual variety during daytime song. We used network analysis, including a community clustering  
22 algorithm, to further characterize song type sequences during the dawn chorus and daytime song in male  
23 Adelaide’s warblers (*Setophaga adelaidae*). Networks had longer path lengths than expected by chance,  
24 indicating that song type transitions were constrained. Community analysis revealed the presence of  
25 “themes,” or groups of song types that individuals deliver in close sequential proximity. To our  
26 knowledge, this is the first report of song type themes in Parulidae. Males did not cycle through their  
27 repertoires efficiently, as would be expected if large repertoires were attractive to females. Themes might  
28 emerge from the learning process or from interactions with neighbors. Themes may function to improve  
29 vocal performance or organize song types with similar functions. Relative to dawn chorus networks,  
30 daytime song networks had longer paths and stronger community structure. We hypothesize that song  
31 type networks are more structured during daytime song because song delivery is optimized for vocal  
32 warm-up during the dawn chorus, males frequently switch among intended receivers during the dawn  
33 chorus, or females prefer extended themes during daytime song.

34

35 **Keywords**

36 Bird song, community analysis, dawn chorus, network analysis, Parulidae

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39 The sequential order with which songbirds (Suborder: Passeri) deliver their song types can vary by  
40 context (Hedley 2016a; Hedley et al. 2018; Suzuki et al. 2019). This variation has been shown to affect  
41 receivers' behavior, suggesting that song order can have functional consequences (e.g., Taylor et al.  
42 2017). A classic example of contextual variation in song delivery occurs in certain New World warblers  
43 (Family: Parulidae) that deliver songs differently during the dawn chorus than they do during daytime  
44 song (Spector 1992). Previous studies have used traditional song type delivery metrics like switch rate  
45 and diversity to characterize differences in song type delivery between these two singing modes. While  
46 useful, these metrics ignore potentially important axes of variation, such as the orderliness of song type  
47 sequences and the tendency of certain song types to be delivered in close sequential proximity. We  
48 addressed this gap in knowledge by using network analysis to characterize and compare song type  
49 delivery during dawn chorus and daytime singing in a New World Warbler.

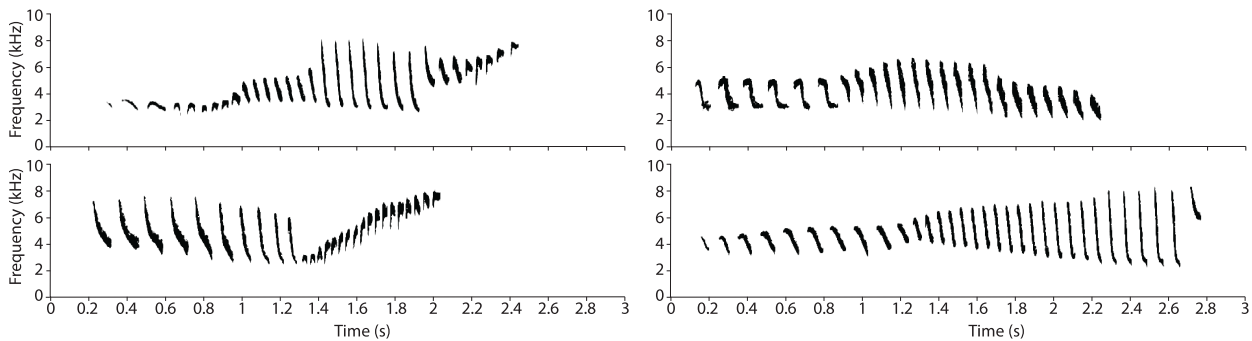
50 Network analysis has proven to be a powerful tool for the analysis of song type sequences (Allen et al.  
51 2019; Deslandes et al. 2014; Hedley 2016b; Kaluthota et al. 2020; Sasahara et al. 2012; Taylor et al.  
52 2016; Weiss et al. 2014; Zsebök et al. 2021). In a typical song type sequence network, song types are  
53 represented by nodes (objects in the network) and first-order transitions between song types are  
54 represented as directed edges (arrows connecting nodes). Metrics developed for network analysis can be  
55 used to quantify the properties of song type sequences. For example, the network metric “minimum  
56 average path length” (hereafter, “path length”) measures the mean distance in number of edges between  
57 pairs of nodes. Applied to song type sequence networks, a long path length implies structure borne of  
58 constraint: birds choose certain transitions and avoid others (Kaluthota et al. 2020). In addition to  
59 generating metrics like path length, song type sequence networks can also reveal whether groups of song  
60 types tend to cluster together in sequences.

61 Community clustering algorithms assign the nodes of a network to subgroups called “communities”  
62 (Agrawal and Patel 2020; Yang et al. 2016). In song type sequence networks, these algorithms identify  
63 clusters of song types that tend to be delivered in ordinal proximity to one another (Opaev and  
64 Kolesnikova 2022). We use the term “themes” to describe these clusters (following Cody et al. 2016;  
65 Ivanitskii and Marova 2022; Pandolfino and Hedley 2019). Other authors have called sequentially  
66 associated song types “packages” (e.g., Todt and Hultsch 1998). We view these terms as synonyms. The  
67 probability of transitioning to a song type within the same community, theme, or package exceeds the  
68 probability of transitioning to a song type that belongs to a different one.

69 We analyzed communities in male Adelaide's warbler (*Setophaga adelaidae*) song type sequence  
70 networks. Males in our study population sing repertoires of  $29.0 \pm 4.0$  discrete song types, each of which  
71 is a frequency modulated trill (Fig. 1; Kaluthota et al. 2019a). Patterns of song type delivery vary by  
72 context. During the breeding season, males participate in a dawn chorus, during which they sing at high  
73 rates in switch mode. Most males deliver their dawn chorus from high up in one or two tall trees on their  
74 territory. For mated males, the dawn chorus ends when the female joins the male (unpublished data).  
75 Members of our group have observed the end of many dawn choruses, but we have never seen pair mates  
76 copulate, so copulation is probably not common at that time. After the female joins the male, the pair  
77 typically patrols the territory borders and engages in border conflicts with neighbours. After the dawn  
78 chorus, song rates are lower, and males sing in repeat mode. Unmated males, which we excluded from the  
79 present study, continue dawn-like singing throughout the morning (Staicer 1996b).

80

81 Like many New World warblers, Adelaide’s warblers’ repertoires comprise two song categories –  
 82 Category A and Category B (sometimes called Type 1 and Type 2, respectively; Kaluthota et al. 2019a;  
 83 Spector 1992; Staicer 1996a). The defining differences between the categories are patterns of song  
 84 delivery. Males sing Category A songs throughout the year, in repeat mode, with long latencies between  
 85 songs. In contrast, they sing Category B songs only in the breeding season, in switch mode, and with  
 86 short latencies between songs. The dawn chorus, which occurs only during the breeding season,  
 87 comprises almost entirely Category B songs. After the dawn chorus males sing a mix of Category A and  
 88 B songs. Two studies defined song categories based on these differences in song delivery and then  
 89 compared their acoustic structures. One study reported that relative to Category B songs, Category A  
 90 songs tend to be longer, with more notes (Kaluthota et al. 2019a; b), while the other found Category A  
 91 songs have a less complex structure, higher overall frequency, and broader frequency bandwidth (Staicer  
 92 1996a). Both studies reported that a given song type might be used in Category A by one male, but in  
 93 Category B by another. Further complicating matters, Kaluthota et al. (2019) concluded that category  
 94 membership may be a continuous property (such that a given song type might fall on a spectrum from A  
 95 to B) rather than a discrete one. In the present study, we sidestep these complications by focusing on the  
 96 distinction between the dawn chorus and daytime singing (everything after the end of the dawn chorus),  
 97 rather than song categories.  
 98



99  
 100 **Figure 1.** Sound spectrograms of four song types from male Adelaide’s warblers (Hann window, 512 points  
 101 / sample). Copied from Vazquez-Cardona et al. (2023) with permission from the authors.

102  
 103 The goals of this descriptive study are to characterize and compare individuals’ song type sequence  
 104 networks during the dawn chorus and daytime song. We analyzed networks based on natural singing from  
 105 individually marked male Adelaide’s warblers. We then used the results to generate hypotheses about the  
 106 proximate and functional constraints that might have generated the observed differences between song  
 107 type sequence networks from the dawn chorus and daytime song.

108  
 109 **Materials and Methods**

110 **Field work**

111 Mated male Adelaide’s warblers were recorded at the Cabo Rojo National Wildlife Refuge, Puerto Rico  
 112 (17°59’N, 67°100’W) in 2012, 2017, and 2018. All birds used in this study were captured with mist nets  
 113 and acoustic lures and marked with a unique combination of plastic colored leg bands and a numbered

114 metal band prior to recording. Recordings were made with Marantz PMD-661 digital recorders (Marantz,  
115 Sagami-hara, Japan) and Sennheiser ME66 “shotgun” microphones (Sennheiser electronic GmbH & Co.  
116 KG, Wedemark, Germany) and saved as .wav files (sampling rate 44.1 kHz; bit depth 16 bits). In 2012,  
117 nine males were recorded for 4 days each. Recordings began 45min before sunrise and ended 2h 45min  
118 after sunrise. In 2017 and 2018, birds were recorded for  $4.2 \pm 2.02$  days (avg.  $\pm$  SD), from the first song  
119 of the day until approximately two hours after sunrise.

120 Field work was conducted with permission from the U.S. Fish and Wildlife Service (permits 2012-01,  
121 41521-2016-11), the Departamento de Recursos Naturales y Ambientales de Puerto Rico (permit 2016-  
122 IC-068-1), the University of Puerto Rico at Mayagüez Animal Care and Use Committee (September 17,  
123 2010), and University of Lethbridge Animal Welfare Committee (protocol #1605). Bird handling was  
124 conducted under D.M.L.’s master bird banding license (no. 23969).

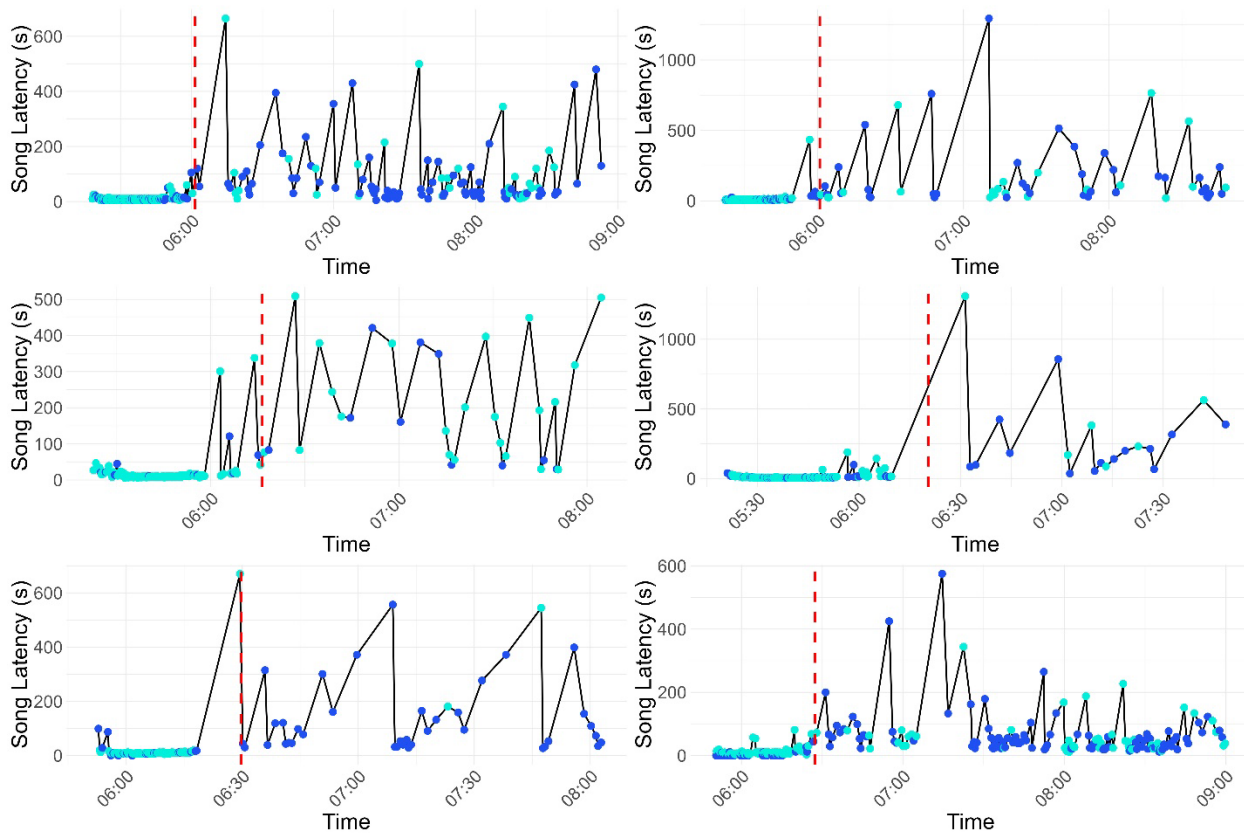
### 125 Scoring and analysis

126 Adelaide’s warblers’ sing repertoires of discrete song types, but there is also some variation within types.  
127 The main sources of within-type variation in our population are the number of notes in each part  
128 (syllable) of the song, and the presence or absence of short introductory, or more commonly, terminal  
129 elements. The goal of our song type analysis was to split types and lump variants within a type. For all  
130 years, two songs were considered to belong to the same type if they were judged to be 80% similar with  
131 respect to overall frequency contour (the shape of the outline of the song on a spectrogram) and note  
132 shape. Although less common, consistent, large differences in the number of notes in each phrase were  
133 also grounds for splitting song types. The presence or absence of short introductory or terminal elements  
134 was not used to separate types. Hybrid songs, comprising part or all of two song types without a silent gap  
135 between them, were treated as unique song types, but these were rare (< 1% of songs). Using these  
136 criteria, it was straightforward to assign songs to song types within an individual’s repertoire. Assigning  
137 songs to types among individuals is more challenging, but we did not need to do that for the present  
138 study. Annotators visualized 2012 recordings in Syrinx PC v.2.6 (Burt 1995-2006) and entered data into a  
139 spreadsheet. After all scoring was complete, one observer (D.M.L.) reviewed all song types. The  
140 recordings from 2017 and 2018 were annotated in Raven Pro 1.6.1 (Center for Conservation Bioacoustics  
141 2019). After scoring was complete, one person (P.C.M. for 2017, S.W.K. for 2018) reviewed all song  
142 types.

143 We used song type sequences to generate song type sequence networks. We first removed sequential  
144 repetitions of song types. For example, we would have converted the song type sequence “A-A-A-B-B-A-  
145 A-C-C” to “A-B-A-C.” We omitted sequential repetitions because (1) differences in repetitions between  
146 dawn chorus and daytime song have already been characterized in this population, as we discussed above  
147 (Kaluthota et al. 2019a; C Staicer 1991; Staicer 1996a), (2) repetitions have no effect on the metrics path  
148 length or reciprocity, as they are typically calculated, and (3) repetitions distort community clustering,  
149 because they are always within-cluster transitions. The third point merits elaboration. If we had included  
150 repetitions, clusters would be defined primarily by birds’ tendency to repeat song types (which is already  
151 known to differ between the dawn chorus and daytime song) rather than their tendency to sing sets of  
152 song types in sequential proximity (which is not yet known). Because birds sing repetitively during  
153 daytime song, the modularity (strength of clustering) would be much higher during daytime song than  
154 during the dawn chorus if we included repetitions, but we would not know whether that difference

155 indicated a difference in their tendency to sing sets of song types in sequential proximity during those  
156 time periods.

157 The time that the dawn chorus ends varies by day and individual. We therefore wrote an algorithm to  
158 define the end of the dawn chorus in a way that was consistent and repeatable. We developed this  
159 algorithm by experimenting with different policies until we found one that produced reasonable results for  
160 almost all our recordings. The winning policy ignored the first ten songs, because song is often sporadic  
161 when birds begin singing. After that point, the cut-off was placed at the midpoint of the silent gap just  
162 before either of the following conditions were met: (1) three consecutive silent gaps between songs were  
163 all  $\geq 45$  s, or (2) there were  $\geq 10$  consecutive songs without a song type switch (Fig 2.). Song type  
164 sequences before this cut-off were labelled “dawn chorus” and song type sequences after the cut-off were  
165 labelled “daytime song.”



166

167

168 **Figure 2.** Example plots based recordings of male Adelaide’s warblers from each year of the study (top  
169 row: 2012, middle row: 2017, bottom row: 2018). Dark blue dots represent songs that belong to the same  
170 song type as the previous song, and light blue dots represent songs that do not. The red dotted line  
171 indicates the cutoff between the dawn chorus and daytime singing. See text for details.

172

173 We used these sequences to construct directed, weighted song type sequence networks. The word  
174 “directed” means that each edge describes one or more transitions *from* a particular song type *to* another

175 song type (in a non-directed network, edges do not specify a direction). Any two nodes in a network could  
176 be directly connected by zero edges (no transitions), one edge (transitions from A-to-B only), or two  
177 edges (transitions in both directions). Edges were weighted by the observed number of transitions. Each  
178 network comprised all the song types and song type transitions (regardless of the presence of silent gaps)  
179 recorded from one individual, on one day, during one time period (dawn chorus or daytime song).

180 Network analysis can, in principle, be applied to networks with any number of nodes (song types)  $> 1$ .  
181 However, variation in the number of nodes will bias some network metrics. We statistically account for  
182 the effects this variation in our analyses (below). It is important to construct networks from a sufficient  
183 number of samples (songs), because network structure is less stable when samples are small. We therefore  
184 omitted networks with fewer than 100 songs from the analysis ( $n < 100$  networks). We were left with 125  
185 networks to analyze (Table 1). Most individuals contributed more than one network to our analyses.

186 We chose the walktrap clustering algorithm because it is effective for a variety of cluster densities and  
187 network sizes (de Sousa and Zhao 2014; Pons and Latapy 2006; Yang et al. 2016). The walktrap  
188 algorithm identifies communities from random “walks” through the network. Beginning at one node,  
189 which we call the “home node,” the algorithm takes a short random walk of predetermined length (walk  
190 length = 4 steps in the present study) and records which node it lands on (we call this node the  
191 “destination”). It repeats this process many times, then moves on to the next home node and does it again,  
192 until it has generated a distribution of destinations from random walks from each node. Frequent  
193 occurrences of a node as a destination are taken as evidence that it is in close proximity to the home node.  
194 The algorithm then uses hierarchical clustering to identify communities.

195 We scored the following metrics from each song type sequence network: path length, reciprocity, number  
196 of communities, and modularity. As described above, path length is the mean number of steps required to  
197 connect any two nodes in the network. In a song type sequence network, high values indicate structure  
198 born of constraint – certain sequence are more common, and others are less common, than would be  
199 expected in a random network (Kaluthota et al. 2020). Reciprocity describes the probability that the  
200 reciprocal of a directed edge (that is, an edge that connects the same two nodes in the opposite direction)  
201 is also present in the graph. In song type sequence networks, reciprocity measures the bidirectionality of  
202 song type transitions. The number of communities is simply a count of communities identified by the  
203 walktrap algorithm. Modularity measures the strength of community structure. A high score indicates a  
204 high ratio of intra-community connections to inter-community connections.

205  
206 We ran Monte Carlo simulations to test whether observed network properties differed from null  
207 expectations. We first averaged the variable of interest over all networks for a given period (dawn chorus,  
208 daytime song), for each individual (e.g., the average reciprocity of male DgDgY’s dawn chorus  
209 networks). This step ensured that all individuals were weighted equally. We then averaged these within-  
210 individual averages over all individuals for a given period to arrive at the observed test statistic (e.g., the  
211 observed mean path length of dawn chorus networks). Next, we randomized the order of song type  
212 sequences (after eliminating sequential repeats) to generate 10,000 random sequences. We designed our  
213 randomization algorithm to avoid generating song type sequences with sequential repetitions, because the  
214 observed edited sequences did not have repetitions. We used each random sequence to make a song type  
215 sequence network, which we subjected to the walktrap algorithm. Our randomization procedure preserved  
216 the number of song types (nodes) and song type transitions from the observed data while randomly  
217 redistributing the transitions. This approach did not always preserve the number of edges from the

218 observed networks, because the number of edges does not necessarily correspond to the total number of  
219 transitions in a weighted song type transition network. Finally, we used the random song type sequence  
220 networks to generate a null distribution of test statistics (i.e., network metrics), which we compared to the  
221 observed test statistic to calculate a realized p-value.

222 We built generalized linear mixed models (GLMMs) to test whether network properties vary by time of  
223 day. Data were the raw (unaveraged) network parameters. Models used Gaussian error distributions and  
224 estimated parameters with maximum likelihood. Each model included time period, number of songs, and  
225 number of song types as independent variables. The number of songs and song types were included as  
226 covariates because they can affect network metrics (e.g., the number of song types limits the path length).  
227 Individual and day (nested within individual) were included as random variables to account for the non-  
228 independence of networks from the same individual as well as those from a given individual in the same  
229 day. We tested whether time period influenced network metrics by looking at the bootstrapped confidence  
230 intervals from the GLMM output. We also conducted likelihood ratio tests by removing the variable of  
231 interest from each model and comparing the full model to the reduced model with the *anova* function. To  
232 be conservative, we concluded that there were contextual differences for variables in which both the  
233 confidence intervals and the likelihood ratio tests indicated a difference.

234 All analyses were conducted in R x64 4.1.0. (R Core Team 2018), running the R Studio development  
235 environment (RStudio Team 2021). Network analyses relied on the *igraph* package (Csardi and Nepusz  
236 2006). We used *lme4* for linear modeling. Data and code are available at [\(put data repository information  
237 here\)](#).

## 238 Results

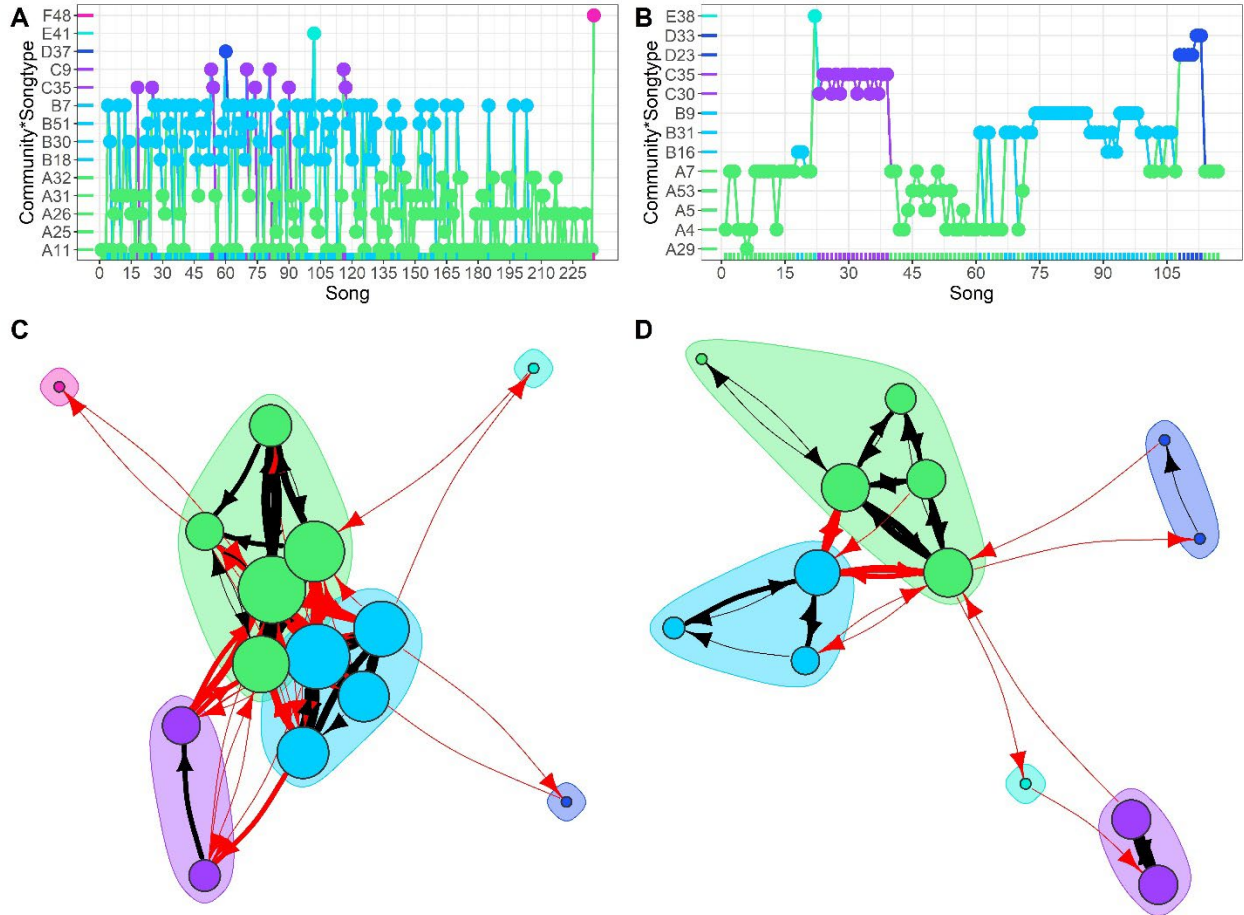
239 Our networks included 22,236 songs from 28 males (Table 1). The walktrap algorithm divided networks  
240 into communities, each of which contained a set of song types that the focal male tended to deliver in  
241 ordinal proximity to one another (Fig. 3). Two recordings did not meet either of our cut-off conditions,  
242 but visual analysis indicated they included both a dawn chorus and daytime song. We set the dawn chorus  
243 cut-offs manually for those recordings.

244 **Table 1.** Descriptive statistics from Adelaide’s warbler song type sequence networks.

	Males	Networks	Duration (min)*	Latency (s)*	Songs*	Transitions*	Song Types*
Dawn Chorus	28	91	39.4 ± 20.7	13.0 ± 5.5	181.8 ± 47.6	59.5 ± 15.5	14.8 ± 3.2
Daytime Song	17	34	158.1 ± 36.3	70.4 ± 25.4	145.7 ± 37.2	24.6 ± 12.9	10.7 ± 3.7

245 \* Data represent avg. ± SD of within-individual averages.

246



247  
 248 **Figure 3.** Scatterplots (A & B) and networks (C & D), representing one song type sequence from the  
 249 dawn chorus (A & C) and another from daytime song (B & D). These two sequences are from different  
 250 males. They were chosen because their modularity scores were close to the average modularity scores for  
 251 the dawn chorus (A & C), and daytime song (B & D) networks, respectively. In A and B, colors represent  
 252 communities identified by the walktrap community clustering algorithm. In C and D, nodes (circles)  
 253 represent song types, and edges (arrows) represent first-order transitions between song types. Node size  
 254 indicates the number of songs of each type and edge weight (thickness) indicates the number of  
 255 transitions. The translucent shapes describe communities and the colors of these shapes and the nodes  
 256 correspond to community ID. Black edges show transitions within communities and red edges show  
 257 transitions among communities. The placement of nodes and communities is intended to make  
 258 connections easy to discern. Community proximity is not a proxy for modularity.

259

260 **Table 2.** Summary of network metrics from Adelaide’s warbler song type sequence networks. Values  
 261 were first averaged within individual, then averaged among individuals. Values based on randomized data  
 262 are in parentheses.

	<b>Path Length</b>	<b>Reciprocity</b>	<b>Communities</b>	<b>Modularity</b>
Dawn Chorus	1.16 ± 0.27 (0.94 ± 0.0037)	0.62 ± 0.10 (0.59 ± 0.0057)	3.43 ± 1.48 (1.76 ± 0.098)	0.13 ± 0.10 (0.048 ± 0.004650)
Daytime Song	1.64 ± 0.53 (0.70 ± 0.0053)	0.68 ± 0.12 (0.72 ± 0.0090)	2.90 ± 1.00 (1.39 ± 0.12)	0.31 ± 0.14 (0.025 ± 0.0067)

263  
 264 The Monte Carlo analyses indicated that all network variables differed significantly from null  
 265 expectations (all  $p < 0.0001$ ). For both dawn chorus and daytime song networks, observed values of path  
 266 length, number of communities, and modularity, exceeded null expectations. The observed reciprocity  
 267 greater than expected during the dawn chorus, but lower than expected during daytime song (Table 2).  
 268 The effect sizes for reciprocity were small.

269 The confidence intervals produced by the GLMMs indicated that path length and modularity were  
 270 significantly higher during daytime song than they were during the dawn chorus (Tables 2, 3; Fig. 4). The  
 271 confidence intervals for reciprocity and number of communities straddled zero, indicating no significant  
 272 difference. The likelihood ratio tests, however, indicated significant differences in all four network  
 273 parameters (path length:  $\chi^2 = 106.03$ ,  $df = 1$ ,  $p < 0.0001$ ; reciprocity:  $\chi^2 = 0.023$ ,  $df = 1$ ,  $p < 0.0001$ ;  
 274 communities:  $\chi^2 = 1.218$ ,  $df = 1$ ,  $p = 0.0001$ ; modularity:  $\chi^2 = 63.031$ ,  $df = 1$ ,  $p < 0.0001$ ).

275 We combined the results of these two tests with our evaluation of group means and distributions to  
 276 interpret our findings. We concluded that, compared to the dawn chorus networks, daytime song networks  
 277 were characterized by moderately higher path length and much higher modularity. We did not interpret  
 278 the differences in reciprocity or number of communities across time periods because the effect sizes were  
 279 small, and the significance tests were equivocal.

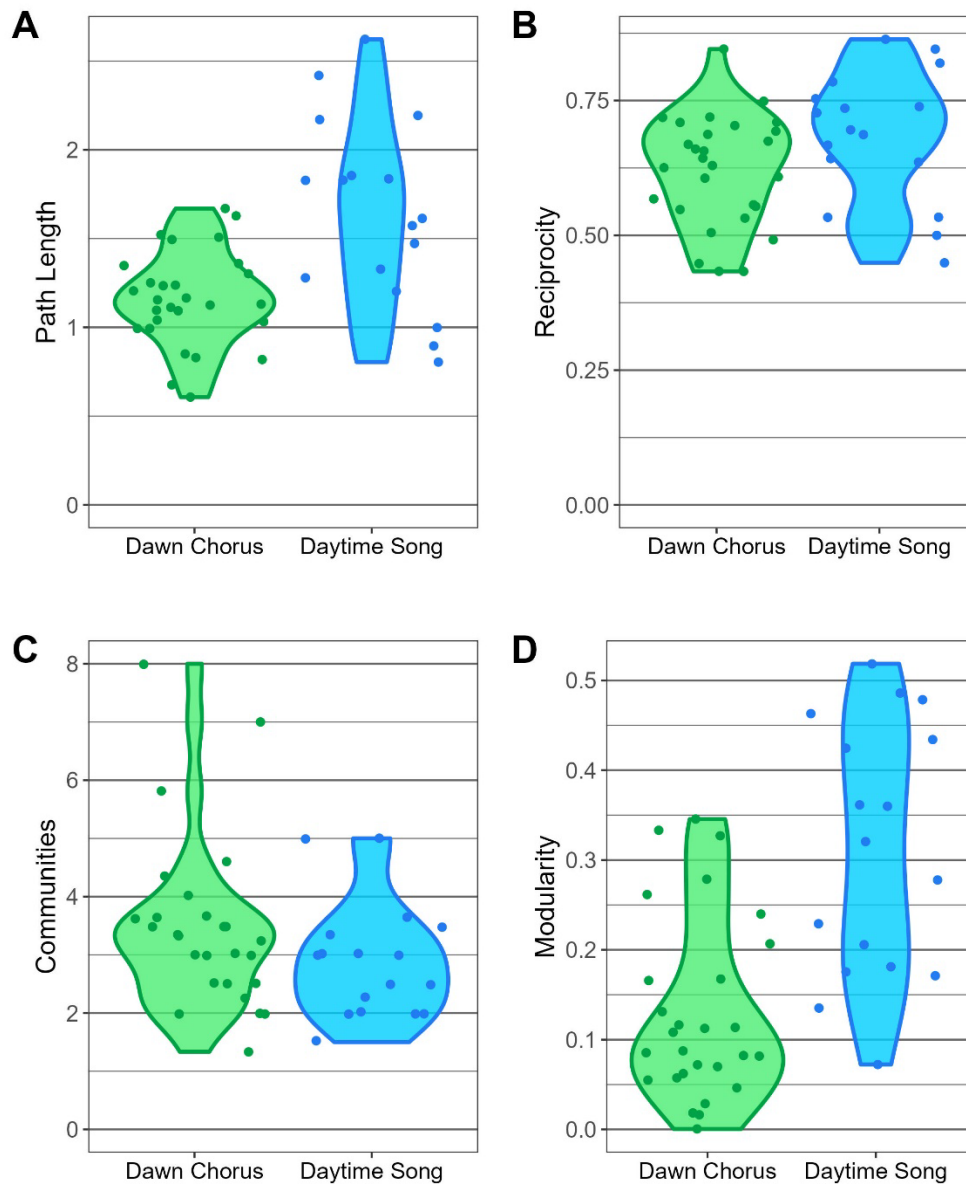
280 We included number of songs and number of song types as covariates in our GLMMs (Table 3). The  
 281 number of songs covaried negatively with path length and positively with reciprocity. The number of  
 282 song types scaled positively with path length, communities, and modularity, and negatively with  
 283 reciprocity.

284  
 285 **Table 3.** Parameter estimates and 95% confidence intervals (in parentheses) from GLMM’s that test the  
 286 effect of time of day on Adelaide’s warbler song type sequence networks. See text for details.

	<b>Path length</b>	<b>Reciprocity</b>	<b>Communities</b>	<b>Modularity</b>
Intercept	1.20 (1.045, 1.35)	0.79 (0.73, 0.84)	1.50 (0.55, 2.35)	0.15 (0.069, 0.23)
Period (relative to daytime song)	-0.69 (-0.80, -0.60)	-0.0027 (-0.044, 0.036)	-0.32 (-0.85, 0.21)	-0.23 (-0.27, -0.18)
# songs	-0.0030 (-0.0037, -0.0024)	0.00093 (0.00067, 0.0011)	-0.0025 (-0.0068, 0.0021)	-0.00031 (-0.00066, 0.000032)

# Song Types	0.082 (0.071, 0.094)	-0.022 (-0.026, -0.019)	0.18 (0.12, 0.24)	0.018 (0.013, 0.023)
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287



288

289 **Figure 4.** Violin plots comparing network metrics derived from male Adelaide’s warblers’ song type sequences recorded during the dawn chorus and daytime song.  
290

291 **Discussion**

292 We used network analysis to characterize and compare male Adelaide’s warblers’ song type sequences  
293 during the dawn chorus and daytime song. Our analyses revealed stronger evidence of structure (i.e.,  
294 longer path lengths, more communities, and higher modularity) than would be expected from random  
295 sequences. We interpret this finding to mean that song transitions are constrained, such that individuals

296 tend to favor certain transitions and avoid others. The network metric reciprocity was slightly, but  
297 significantly, higher than expected by chance. Walktrap community analysis revealed the existence of  
298 distinct communities. Collectively, these findings indicate that male Adelaide's warbler song type  
299 sequences are structured into themes, rather than being delivered randomly, or linearly as in some other  
300 species (Hedley 2016a; Kroodsmma 1979).

301 We propose four non-exclusive hypotheses to explain why Adelaide's warblers deliver song types as  
302 themes. First, song learning could underlie the emergence of themes. Vocal units that are learned together  
303 tend to cluster together during song delivery in nightingales (*Luscinia megarhynchos*; Hultsch and Todt  
304 2004) and zebra finches (*Taeniopygia guttata*; Williams and Staples 1992). Second, organizing songs into  
305 clusters may be an adaptation to facilitate efficient recall. It would be interesting to test whether birds sing  
306 with higher vocal performance when transitioning within versus between themes (Logue et al. 2020;  
307 Sierro et al. 2023). A third hypothesis is that vocal interactions among countersinging males, like song  
308 type matching and song advancing, interact with male's endogenous song type sequencing rules such that  
309 themes emerge (Logue 2021). This appears to be the case during the dawn chorus, when multiple  
310 neighbouring males converge on song type themes (Logue et al. unpublished data). Our fourth hypothesis  
311 is that community structure emerges from the adaptive clustering of song types into functionally distinct  
312 themes. If different song types function differently (e.g., Trillo and Vehrencamp 2005), it may be adaptive  
313 for birds to group songs with similar functions into themes. If certain song types function in aggressive  
314 interactions, for example, we would expect many transitions among those types during agonistic  
315 encounters.

316 Our results allow us to reject the hypothesis that male Adelaide's warblers efficiently showcase the size of  
317 their song type repertoires. Although males deliver songs with immediate variety during the dawn chorus,  
318 they do not run through their full repertoire quickly in a way that might impress female receivers who  
319 prefer large repertoires (as in Searcy et al. 2022). Rather, they sing from one theme for a while before  
320 moving on to another theme (Fig. 3). As further evidence against this hypothesis, some song types are  
321 only sung rarely (unpublished data).

### 322 [Why does song delivery differ between the dawn chorus and daytime song?](#)

323 There are many hypotheses about the functions of the dawn chorus, but little in the way of consensus (Gil  
324 and Llusia 2020; Schlicht et al. 2023; Staicer et al. 1996; Vazquez-Cardona et al. 2023). Our findings add  
325 to a long list of differences between song delivery during the dawn chorus and daytime song. Relative to  
326 daytime singing, the dawn chorus has a much higher song rate and song type switch rate, less pronounced  
327 structure (shorter path length and lower modularity), and uses a different part of the song type repertoire  
328 (Kaluthota et al. 2019a; CA Staicer 1991; present study). Any coherent hypothesis about dawn chorus  
329 function in Adelaide's warbler must be compatible with all these differences.

330 One potential explanation for the observed contextual differences relates to the finding that male  
331 Adelaide's warblers warm up their voices during the dawn chorus (Schraft et al. 2017; Vazquez-Cardona  
332 et al. 2023). Perhaps rapidly switching between themes warms up the voice more efficiently than singing  
333 one theme for a long time. The social environment also differs between the dawn chorus, when males are  
334 alone and relatively stationary, and daytime song, when they patrol the borders of their territory with their  
335 mates. Based on the hypothesis that males use different song types to communicate with different  
336 neighbours, they may rapidly switch from one intended receiver to another during the dawn chorus but  
337 communicate at length with one receiver before moving on to the next during daytime song. Finally, it  
338 may be the case that males sing in repeat mode with extended themes during daytime song because that is

339 what females prefer. This hypothesis is consistent with the recent findings that repetitive singing  
340 improves consistency in male Eurasian blue tits (*Cyanistes caeruleus*), and females prefer songs with high  
341 vocal consistency (Sierro et al. 2023).

342 The differences we observed between song type sequence networks from the dawn chorus and daytime  
343 song cannot be explained by the direct effects of higher song type switch rates during the dawn chorus  
344 because we eliminated sequential repetitions before generating networks. There may, however, be indirect  
345 effects of song type switch rates on song type sequences. For example, the number of sequential  
346 repetitions of a song type could influence the time lag until a singer returns to that type (Searcy et al.  
347 2019). The finding that modularity was higher during daytime song does not necessarily mean that birds  
348 adhere more strictly to themes during daytime song. Theme switching generates between-cluster  
349 transitions that reduce modularity scores, so high levels of theme switching, rather than low adherence to  
350 themes, may explain why modularity was lower in the dawn chorus.

### 351 [Comparable studies](#)

352 This is the latest in a string of recent studies that use community clustering to identify themes in song type  
353 sequence networks in California thrashers (*Toxostoma redivivum*; Cody et al. 2016; Taylor et al. 2017),  
354 grey-crowned warblers (*Phylloscopus tephrocephalus*; Opaev and Kolesnikova 2022), and now  
355 Adelaide's warblers (present study). It appears that song type themes are widespread and common in  
356 songbirds with medium and large song type repertoires.

357 It is instructive to consider the different ways that community clustering algorithms have been applied to  
358 animal signal sequences. We used the walktrap community algorithm, but other studies used the Newman  
359 algorithm (Cody et al. 2016; Sánchez Castellanos et al. 2015), the spinglass algorithm (Paul et al. 2021),  
360 or an unspecified algorithm (Allen et al. 2019; Opaev and Kolesnikova 2022). We chose the walktrap  
361 algorithm because of its simplicity and robustness. We found that it was easy to implement, the results  
362 were straightforward to interpret and visualize, and the clusters corresponded to groups of songs that were  
363 delivered together in song type sequences (e.g., Fig. 3). One limitation of the walktrap approach,  
364 however, is that a node (song type) cannot be assigned to more than one cluster. Some studies of signal  
365 sequence networks might benefit from a community algorithm that allows nodes to occur in more than  
366 one cluster.

367 Another important difference among studies that apply community analysis to acoustic signal sequence  
368 networks is the scale of analysis. Some analyses apply clustering algorithms to a smaller scale to identify  
369 clusters of acoustic subunits (e.g., syllables) within songs (Allen et al. 2019; Paul et al. 2021). It is also  
370 possible to apply community analysis at a broader scale, as in Opaev and Kolesnikova (2022), which  
371 combined song sequences of individual grey-crowned warblers to identify themes at the population level.

372  
373 We found the number of songs and song types covaried with several network metrics. Had we not  
374 included these covariates, our results would have been biased by uncontrolled variation in the number of  
375 songs and song type. We recommend including the number of songs and song types as covariates in most  
376 studies of song type sequence networks.

377 One limitation of our study is that we only examined first-order transitions in song type sequences. Our  
378 networks show the frequency with which a song type at position  $X$  is followed by another song type at  
379 position  $X + 1$ . They do not show the frequency with which a song type at position  $X$  is followed by  
380 another song type at position  $X + Y$ , where  $Y > 1$ . Similarly, our analysis does not show how

381 combinations of song types might influence subsequent song type choices. We can imagine, for example,  
382 that song type C is more likely to follow the song type sequence A-B, than it is to follow D-B, but our  
383 analysis does not address this possibility. There is evidence of such “higher-order dependencies” in bird  
384 song sequences (Hedley 2016b; Searcy et al. 2022). Although we did not directly examine higher order  
385 dependencies, our application of community clustering algorithms to first-order signal sequence network  
386 models is a simple way of asking which song types are associated with one another, whether or not first-  
387 order transitions generate that association.

388 We used song type sequence networks to describe patterns of song type delivery, but we do not view  
389 them as Markov models of the process that generates song type sequences. We reject the generative  
390 interpretation because Markov chains seem to be poor models of signal choice in animals (Kershenbaum  
391 et al. 2014). One reason for this mismatch is that sequences are probably influenced by exogenous factors  
392 in addition to internal rules. In particular, it is likely that neighbours’ songs influence individuals’ song  
393 type sequences (Logue 2021; CA Staicer 1991). A full accounting of song type sequences probably  
394 requires a communication network approach in which multiple signalers are recorded simultaneously.

## 395 Conclusion

396 The finding that male Adelaide’s warbler song type sequences are characterized by themes improves our  
397 understanding of acoustic communication in this species and opens avenues for additional research on the  
398 origin and function(s) of song type themes. Song type sequences were more structured (constrained)  
399 during daytime song than they were during the dawn chorus. This finding is one of several differences  
400 between dawn chorus and post-dawn singing, all of which must be accounted for by a coherent theory of  
401 song function in this species. We believe this is the first study to show evidence of themes in New World  
402 Warblers’ song type sequences, and the first to show that the community structure of song type sequences  
403 varies across contexts.

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411

## 412 Declaration of interest statement

413 The authors declare that they have no known competing financial interests or personal relationships that  
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415

## 416 AI Statement

417 We used ChatGPT to assist with syntax and debugging in R.

418

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