

1 **A novel method for using bioacoustics to monitor post-**
2 **translocation behaviour in an endangered passerine.**

3 Authors: Oliver C. Metcalf¹, John G. Ewen², Mhairi McCready^{2, 3}, Emma M. Williams^{4, 5}, J.
4 Marcus Rowcliffe².

5 *1. Department of Life Sciences, Imperial College London, Silwood Park Campus, Buckhurst Road,*
6 *Ascot, Berkshire, SL5 7PY, UK; 2. ZSL Institute of Zoology, Regent's Park, London NW1 4 RY, UK; 3.*
7 *Rotokare Scenic Reserve, 365 Sangster Rd, Eltham, New Zealand, 4. Matuku Ecology, 7 Kowhai*
8 *Terrace, Christchurch, New Zealand, 8022; 4. Wildlife Ecology Group, Massey University, Private Bag*
9 *11-222, Palmerston North, New Zealand*

10 *Short running title:* Bioacoustics to monitor dispersal behaviour

11 *Word count (including references, tables and figure legends):* 6,553

12 **Correspondence author. oliver.metcalf@stu.mmu.ac.uk, current address: Department of*
13 *Science and Engineering, Manchester Metropolitan University, John Dalton East Building, All*
14 *Saints, Manchester, M15 6BU*

15

16 **ABSTRACT**

17 **1.** Conservation translocations are an important tool in wildlife management, but have
18 traditionally suffered from a low success rate. Increasing understanding of animal behaviour
19 is vital in improving the success of translocations, but few methods exist to efficiently monitor
20 highly mobile and cryptic species post-release.

21 **2.** We present a novel approach to using dynamic occupancy modelling in
22 combination with data derived from autonomous acoustic recording units to monitor the post-
23 release behaviour of hihi (*Notiomystis cincta*), a threatened endemic bird, at a translocation
24 site in New Zealand. The process of analysing large quantities of acoustic data was
25 facilitated by using automated classifiers and manual validation, an approach that was both
26 accurate and efficient.

27 **3.** We find that this approach detects behavioural change consistent with the
28 transition from exploration of a new site to territory formation. We identify that hihi territories
29 at the study site were closely linked to watercourses, but were not related to distance from
30 release site.

31 **4.** We find that this method is able to effectively monitor post-release dispersal, and
32 could provide a cost-efficient and less invasive alternative to radio-tracking for monitoring of
33 vocal species.

34

35

36

37

38

39 **Keywords:** Reintroduction, Hihi, Bioacoustics, Occupancy Modelling, Ecoacoustics,
40 Translocation, Monitoring.

41

42 **INTRODUCTION**

43 Conservation translocations have become an important tool for wildlife management
44 (Fischer & Lindenmayer 2000). The number of species moved globally is substantial, for
45 example 279 animal species in North America, (Bricchieri-Colombi & Moehrenschrager 2016),
46 and over 242 species in the world's oceans (Swan et al. 2016). Publications of translocation
47 studies continue to increase near exponentially (Seddon & Armstrong 2016). Despite this
48 popularity, a series of reviews have shown that conservation translocations often fail to
49 establish populations (Griffith et al. 1989; Fischer & Lindenmayer 2000; Soorae 2016). There
50 is also often a lack of adequate monitoring to ascertain reasons for translocation success or
51 failure (Seddon et al. 2012), and this has led to numerous calls to improve post-translocation
52 monitoring (e.g. Scott et al. 2010; Sutherland et al. 2010; Ewen et al. 2014; Bricchieri-Colombi
53 & Moehrenschrager 2016).

54

55 Post-release dispersal is a poorly monitored aspect of animal conservation
56 translocations, despite its known importance in successfully establishing populations (Le
57 Gouar et al 2012; Osborne & Seddon 2012). Learning about possible causes of increased
58 mortality during post-release dispersal (a component of cost of release; Tavecchia et al.
59 2009) could provide guidance on important translocation decisions, for example, appropriate
60 release group sizes to compensate for early losses and selection of appropriate release sites
61 to reduce cost of release. Furthermore, as animal settlement in to home ranges can be used
62 as a proxy for translocation success, monitoring post-release dispersal can be useful in
63 translocation evaluations (Flanagan et al. 2016).

64

65 Monitoring post-release dispersal, however, is frequently challenging and expensive.
66 In small passerine species this often requires expensive radio-transmitters and antenna
67 arrays, or dedicated staff tracking individually marked birds (Dougill et al. 2000; Bain et al.
68 2012; Fountain et al. 2016). These high-cost methods often only provide a brief window of
69 monitoring data, and can be intrusive for the animals, even leading to injuries and increased

70 mortality (Pierce et al. 2007; Barron et al. 2010). However, advances in statistical
71 techniques, particularly the advent of dynamic (or multi-season) occupancy modelling
72 (DOM), mean that it is now possible to infer changes in behaviour of populations across both
73 spatial and temporal dimensions (Kéry & Chandler 2016) without needing to track known
74 individual animals.

75

76 Occupancy modelling estimates the probability of occupancy of a target species at a
77 sample location based on supplied presence-absence data, while accounting for imperfect
78 detection of the target species (MacKenzie et al. 2006). This allows inferences to be made
79 about habitat preferences and post-release behaviour based on occupancy probability.
80 DOMs allow estimates of occupancy to vary over time by modelling extinction and
81 colonisation probabilities at sampling locations (Kéry & Chandler 2016). This approach can
82 model dispersal behaviour of the target species over time by calculating changes in
83 occupancy probability between seasons within which closure is assumed (i.e. occupancy
84 status does not change). To control for the effect of imperfect detection on apparent
85 occupancy, a number of repeat visits within each closed season are required. However,
86 collecting data over enough seasons to model behaviour change, with the necessary repeat
87 visits, can require a prohibitive amount of effort in the field using traditional survey
88 techniques such as transects or point counts.

89

90 When the target species is vocal, one method for achieving repeated presence-
91 absence records efficiently is the use of autonomous acoustic recording units (ARUs)
92 (Shonfield & Bayne 2017). Using multiple recorders, multiple locations can be monitored
93 simultaneously, and over time-frames that capture different daily or seasonal behaviours
94 (Tegeler et al. 2012). ARUs can record for extended periods of time without human
95 interaction after initial set-up (Hobson et al. 2002; Tegeler et al. 2012) which means that

96 ARUs can be used even in terrain that would normally make repeat visits problematic
97 (Klingbeil & Willig. 2015; Williams 2016). Furthermore ARUs reduce detection bias because
98 data collection is independent of observer skill levels (Klingbeil & Willig. 2015), and does not
99 require the presence of humans – a factor that can alter avian behaviour (Digby et al. 2013).

100

101 DOMs have been used to model seasonal occupancy changes at large spatial and
102 temporal scales (Brambilla et al. 2012; Gow & Stutchbury 2013; Frey et al. 2016), and
103 several studies utilise autonomous, acoustically derived data combined with single-season
104 occupancy modelling (Furnas & Callas 2015; Campos-Cerqueira & Aide 2016). As far as we
105 are aware, however, no previous study has combined temporally detailed data collected by
106 ARUs with DOMs to efficiently model post-translocation dispersal and settlement behaviour
107 at a local scale. Here we test the utility of combining acoustic data from ARUs and DOMs
108 using a conservation translocation of hihi (*Notiomystis cincta*) in New Zealand as a case
109 study. Noting that previous successful hihi translocations have shown an initial exploratory
110 phase with wide distribution across the site, followed by settlement in territories associated
111 with particular environmental features (Richardson & Ewen 2016), we use this novel
112 approach to answer the following questions:

113 1) Is it possible to detect hihi transitioning from an initial exploratory phase to a
114 settlement phase, characterised by an increase in extinction probability and a corresponding
115 decrease in colonisation probability?

116 2) Is it possible to detect the emergence of preferred environmental features as
117 settlement progresses, characterised by effects of environmental predictors on final hihi
118 occupancy probability?

119

120 **METHODS**

121 **Species Description and Study Site**

122 The hihi is a small passerine endemic to New Zealand and classified as vulnerable in
123 the IUCN Red List (BirdLife International 2016). Hihi went extinct on mainland New Zealand
124 in the 1880s and survived solely on Te Hauturu-o-Toi/Little Barrier Island, due to the
125 predator-free environment. Successful reintroduction programmes established another 5
126 populations on two further islands - Tiritiri Matangi and Kapiti - and three predator-free
127 mainland reserves; Karori Wildlife Sanctuary, Maungatautari Ecological Island (MEI) and
128 Bushy Park (Richardson et al. 2015). All populations are dependent on the maintenance of a
129 predator-free environment, and additionally the reintroduced populations rely on
130 supplementary feeding stations (Chauvenet et al. 2012) and nest boxes (Richardson et al.
131 2015) with the exception of MEI and Kapiti. The inability of hihi to disperse over long
132 distances and high dependence on heavily managed predator-free environments mean that
133 further increases in hihi population require further translocations, so that post-translocation
134 monitoring, and understanding behaviour after release, is of particular importance in this
135 species.

136 There are several traits that make hihi an ideal candidate species for this study. Hihi
137 breed annually between September and March, and the majority breed in their first year
138 (Richardson et al. 2015). Previous monitoring following radio-transmitter tagged hihi
139 released at MEI found hihi disperse quickly after release, prior to eventual breeding site
140 selection being primarily guided by the movements of female hihi in the first weeks post-
141 release (Richardson 2015). There was a strong correlation between female hihi location after
142 4 weeks and their eventual breeding location, with the same, but weaker effect also present
143 in males. Further, MEI post-release monitoring found that hihi preferred to settle on sites
144 within 150m of a watercourse (Richardson & Ewen 2016). A further predictor of habitat
145 selection in released hihi at MEI was proximity to both the release site and the
146 supplementary feeders, but it was not possible to disentangle these effects due to the

147 feeders being located at the release site. These behavioural traits, in combination with hihi
148 being highly vocal but difficult to resight by fieldworkers, mean that monitoring using acoustic
149 recorders and DOMs should be an effective method.

150

151 The translocation of hihi to Rotokare Scenic Reserve (RSR) provided an ideal
152 opportunity to test this method of monitoring. On 1st April 2017, 40 juvenile hihi (with an
153 even sex ratio) were translocated from Tiritiri Matangi and released at two locations within
154 Rotokare (Fig.1). Artificial feeders were provided at 5 locations (Fig.1). Rotokare is located at
155 -39.448259°S, 174.414640°E, in the Taranaki region of North Island, New Zealand. RSR
156 comprises 230 hectares of primary forest, wetland and lake (Scrimgeour & Pickett 2011),
157 with 12.5 hectares of scrub, regenerating from high grazing-pressure that occurred up to
158 2008. The site, a basin, drains into a 17.8-hectare natural lake in the centre. It is a 'mainland
159 island' reserve - the perimeter of the site is enclosed with predator-exclusion fencing and 12
160 pest species were eradicated between 2009 and 2011. The reserve is surrounded by
161 pasture, creating a habitat barrier to dispersal beyond the reserve, with the closest suitable
162 neighbouring habitat c1km to the east. The steep slopes and dense vegetation covering the
163 reserve make re-sighting hihi challenging, whilst the relatively small size of the reserve
164 allowed for comprehensive coverage with audio-recorders, therefore making RSR an
165 excellent study site.

166

167 **Autonomous Recording and Survey Design**

168 We used omni-directional ARUs developed by the New Zealand Department of
169 Conservation, and previously used to survey kiwi (*Apteryx* species) and Australasian bittern
170 (*Botaurus poiciloptilus*) (Digby et al. 2013; Williams 2016). We deployed ARUs at 31
171 locations across the site in a 270 m grid created using QGIS v2.18.10 (QGIS Development
172 Team 2015). Due to the inaccessible nature of much of the forest on the reserve, we placed
173 ARUs along the closest existing predator monitoring lines, which are spaced at 50 m

174 intervals across the reserve, on suitable vegetation 1.5 m above ground (Fig.1). The ARUs
175 were deployed for a total of 32 days between 18 April (18 days after the release date) and
176 19 May 2017, to cover the expected exploration and settlement phases. Each ARU was
177 programmed to record for two daily recording periods, lasting 2 hr each; the first being from
178 08:00-10:00, and the second from 15:00-17:00 (sunrise was 06:53 and sunset 17:50 on 18th
179 April 2017). This provided 64 recording periods and 128 hr of recordings per ARU.
180 Recording periods were divided into eight 32 kHz sound files, each being 15 min in length.
181 This resulted in the collection of 15,872 15 min recording periods across the study.

182

183 **Semi-automated Call Recognition**

184 We assessed the presence or absence of hihi calls in each 15 min recording using a
185 process of semi-automated call recognition (SACR). An hour-long recording was made at
186 RSR using the same model of ARU, during which we spoke immediately after all visually
187 confirmed hihi vocalisations (hereafter the narrated recordings), to use as training data for
188 the automated call recognition models. The most frequent vocalisation heard was the 'stitch'
189 call (Higgins et al. 2001). Other vocalisations consisted of irregular squeaks and whistles
190 comprising sub-song, and two high-pitched squeak-like calls; these vocalisations were either
191 infrequent or were at a frequency that was problematic for the recorders, and we discounted
192 them from further analysis.

193

194 We created automated call recognition models (ACRMs) using SongScope v4.1.5
195 (Wildlife Acoustics 2011). SongScope is a freely available software utilising Hidden Markov
196 Models and spectral feature vectors to detect call structures (Wildlife Acoustics 2011b). It
197 was chosen over other freely or cheaply available call detection programmes as it produces
198 a higher number of true detections than Raven Pro (Bioacoustics Research Program

199 2010)(Duan et al. 2013), and has a relatively user-friendly interface compared to R-based
200 packages such as 'warbleR' (Araya-Salas & Smith-Vidaurre 2017).

201

202 We collected training data for ACRMs from the narrated recording and identified
203 further calls by visual inspection of spectrograms of recordings made at Rotokare prior to the
204 commencement of the study period, using Raven Pro. We made annotations to the identified
205 vocalisations in SongScope. Automated call recognition model parameters were guided by
206 recommendations for the detection of 'click' type calls in Duan et al (2013) and the
207 SongScope 4.0 User's Manual (2011). We tested an initial subset of call recognition models,
208 containing large variations in parameters, against a 15 min recording containing 72 hihi calls
209 which had been manually identified using visual inspection of spectrograms in Raven Pro.
210 Once the most successful models had been identified, we made further refinement to the
211 parameters of the classification models in an ad hoc manner. It was apparent that no single
212 model would be adequate as models with high levels of true positives also had
213 correspondingly high false positive rates, to the extent that manually checking the number of
214 false positives would be hugely time consuming. Instead, a 2 model approach was adopted,
215 an initial model with low false positive rate to detect the majority of calls, and a second
216 model with a higher false positive rate to be used on the sound files in which hihi had not
217 already been detected. We tested the candidate models against a subset of the study data -
218 the recordings from a single recorder from 18th April - 3rd May 2017- in which we manually
219 identified hihi presence or absence for each 15 min recording by visual inspection of
220 spectrograms in Raven Pro. All models that identified less than 50% of the recordings with
221 hihi present were rejected, and of the remaining models, the one with the lowest number of
222 false positives was selected as the first model. Further candidate models were then tested
223 against the recordings from the subset of study data which the first model had identified as
224 absent of hihi vocalisations. We selected the second model with the highest number of true

225 detections, having rejected any model that returned over 6,000 false positives (roughly 3
226 hours work to manually validate).

227

228 We used SongScope to search all 15 min recordings for candidate vocalisations
229 using the first model resulting in a list of all candidate detections linked to a spectrogram of
230 the sound. As any false positives produced by the ACRMs violate an assumption of
231 occupancy modelling, these spectrograms were manually validated to remove false-positives
232 following the methods set out in a previous study (Campos-Cerqueira & Aide 2016).

233

234 During the validation process, the SongScope spectrograms associated with
235 candidate vocalisations were displayed with a fast Fourier transform (FFT) size of 256, FFT
236 overlap 7/8 and 0 decibel gain. To ensure all false detections were ruled out, we discounted
237 candidate vocalisations visually, whilst all positive detections were confirmed visually and
238 aurally. All 15 min recordings that contained one or more hihi vocalisation were coded as
239 present in a presence-absence matrix. All 15 min recordings in which hihi were not detected
240 by Model 1 were then searched for candidate vocalisations using Model 2, and the validation
241 process repeated. For Model 2 spectrograms, we used a 15 decibel gain to detect quieter or
242 more distant vocalisations (except in cases with high background noise, such as periods of
243 heavy rain). The presence/absence database was then updated with all hihi presence
244 detected by Model 2, with the remaining recordings coded as absence. Additionally, we
245 coded all 15 min recording periods in which recordings were not obtained through hardware
246 failure or human error as missing. To complete the matrix, we coded any 15 min period in
247 which the ARU were being serviced, or when background noise blocked all bird calls for the
248 entire recording period, as missing.

249

250 **Dynamic Occupancy Modelling**

251 The matrix of presence/absence data was then used to generate a single-species
252 dynamic occupancy model using the package Unmarked in R ver3.3.1 (Fiske & Chandler
253 2011; R Core Team 2017). To model the probability of occupancy, a period of 'closure' is
254 required to ascertain the probability of detection (MacKenzie 2006; Kéry & Chandler 2016).
255 During the closure season, replicate observations of the site are made and occupancy
256 status, either present or absent, is assumed to remain constant throughout. In addition to the
257 assumption of closure, DOMs also require the assumption that sites are independent from
258 each other during a closed season. Violations of the closure assumption typically lead to
259 over-estimation of occupancy (Rota et al. 2009), and this can be a particularly inhibiting
260 factor in the use of DOMs for mobile species. A solution to this problem, made viable by
261 using ARUs to collect repeat surveys without needing to return to a site multiple times, is to
262 set the closure season to a short duration. We assumed seasons of closure to be 2 hours.
263 Each 15 min recording was designated as a replicate visit, so that each season had 8
264 replicate visits.

265 Covariates were selected for all 4 parameters of the model; initial probability of
266 occupancy (occupancy), probability of colonisation (colonisation), probability of extinction
267 (extinction), and probability of detection (detection). Covariates were selected on a
268 hypothesis driven basis, informed by prior research on the species and a single model set
269 was defined *a priori*. Date was selected as a predictor of colonisation and extinction, as
270 female hihi at MEI had been found to settle on breeding territories four weeks after
271 translocation, thus changes in behaviour around this period could provide important insight
272 in to the settlement process and final territory location at RSR. The study was designed so
273 that the fourth week after release fell roughly in the middle of the survey period, giving the
274 best opportunity to detect behavioural change in this period. Date was coded as a
275 categorical variable with four levels, each level representing 8 days. It was also included as

276 a predictor of detection to account for possible changes in vocalisations during territory
277 formation. Distance from water (DfW) and distance from release (DfR) were included as
278 predictors of initial occupancy, colonisation, and extinction, as these were found to be the
279 most significant environmental predictors of hihi territory presence at MEI by Richardson and
280 Ewen (2016). Distance from water included watercourses on the Land Information New
281 Zealand river centrelines map plus the RSR lake edge. The interactions between Date and
282 DfR and DfW respectively were also included as predictors of initial occupancy, colonisation,
283 and extinction. Aspect (a categorical variable with 4 levels centred between cardinal points),
284 and Topographical Position Index (TPI) (Weiss 2000) (a measure of exposure indexed by
285 cell elevation relative to the average of neighbouring cells' elevation), were included as
286 covariates for detection as proxies for the effect of wind on the recorders, to capture the
287 increased likelihood of target vocalisations being masked by wind noise at exposed locations
288 or facing the prevailing wind. The interaction between Aspect and TPI were also included in
289 detection. Time was included as a categorical predictor of detection with 4 levels (hours 1 to
290 4), to account for possible change in vocalisation rate across the day.

291

292 Covariates to retain for each parameter in the final model were selected
293 successively, using Akaike's information criterion (AIC) following an adapted version of the
294 method set out by Kéry et al. (2013). Firstly, detection was optimised by successively fitting
295 models with increasing complexity following the rules of marginality (McCullagh & Nelder
296 1989), from a starting model with all parameters constant. For each covariate or interaction,
297 the AIC weight from each model was summed, and any covariate or interaction with a
298 summed AIC weight of ≥ 0.8 was retained. Once covariates with AIC weight of > 0.8 had been
299 identified for detection, the detection structure was maintained, and initial occupancy was
300 optimised following the same process. Next, colonisation and then extinction were optimised,
301 and covariates identified for each parameter. Then covariates were again identified for
302 extinction and colonisation, this time optimising extinction first. The two sets of covariate AIC

303 weights for extinction and colonisation were then averaged, and all covariates with a
304 summed AIC weight of ≥ 0.8 were retained.

305 Predicted occupancy patterns from the model were ascertained using the 'predict'
306 function in Unmarked, and the effects of the variables on colonisation and extinction were
307 plotted following the methods set out in Kéry & Chandler (2016). A map of RSR with
308 predicted hihi occupancy values was generated in R.

309 **RESULTS**

310 **Semi-automated Call Recognition**

311 After manual validation to remove false positives, Model 1 correctly detected the
312 presence of hihi in 79 of the 256 15 min recordings used as a test subsample. A further 98
313 recording periods were correctly identified as absent of hihi vocalisations, giving Model 1 a
314 69.1% accuracy rate against the visual analysis of the test data. Model 2 correctly detected
315 an additional 35 recordings with hihi vocalisations present, so that in combination the two
316 models correctly identified recordings with hihi present in 75% of cases compared to visual
317 analysis. When added to the correctly identified absences, the two models combined
318 correctly identified hihi presence or absence in 99.2% of recordings in comparison to the
319 visual analysis of the test data (SACR additionally detected 2 hihi calls missed by visual
320 analysis).

321

322 When applied to the full dataset, Model 1 produced 16,633 candidate vocalisations,
323 whilst Model 2 produced 266,768 candidate vocalisations. After manual validation, Model 1
324 detected 713 15 min recordings in which hihi were present, and Model 2 detected a further
325 382 from recordings in which Model 1 failed to detect hihi presence. The final
326 presence/absence matrix contained 1,015 presences, as some of the 15 min recording
327 periods were later recategorized as missing data. Overall, missing data accounted for 1,256
328 of recording periods or 7.9% of the total.

329

330 **Dynamic Occupancy Modelling**

331 The optimised model showed a strong negative correlation between date and
332 colonisation and a strong positive correlation between date and extinction (Table 1, Fig 3),
333 consistent with territory formation. Similarly, distance from water was found to be positively
334 correlated with extinction and negatively correlated with colonisation (Table 1, Fig 4). Both
335 TPI and Aspect had a strong negative effect on detection rates (Table 1). After initially even
336 probability of occupancy across the site, a strong preference for proximity to water
337 developed rapidly over the first week, followed by a decelerating overall reduction in
338 occupancy while retaining the preference for proximity to water. (Table 1, Fig 5). The
339 decrease in overall occupancy can be attributed to either mortality during the study period
340 causing a decrease in the overall population, or hihi presence becoming intensified in
341 preferred areas. Additional monitoring surveys conducted outside of this study using
342 traditional transect methodology identified a minimum of 22 individual hihi between 1st and
343 5th May 2017 (a total of 36 individuals were identified throughout May when including *ad hoc*
344 sightings) (McCready 2017a, unpublished) and 26 individuals were identified during the June
345 survey from 30th May to 3rd June (McCready 2017b, unpublished). This suggests that the
346 population remained relatively stable during the study period, suggesting that reduced
347 overall occupancy can be attributed to more intensive use of preferred areas and territory
348 consolidation. The preference for proximity to watercourses is illustrated in Figure 6, with the
349 highest probability of hihi occupancy clearly following the edge of the lake and shadowing
350 the streams, with areas of high ground furthest from flowing water the least likely to be
351 occupied.

352

353 **DISCUSSION**

354 Dynamic occupancy modelling using sound recordings collected by ARUs and
355 processed using SACR was able to model spatial and temporal variations in hihi behaviour,
356 answering both questions 1 and 2 effectively. We found a pattern of increasing extinction
357 and decreasing colonisation over the duration of the study period (Fig 3) indicating that hihi
358 were reducing their movement around the site and increasingly staying within preferred
359 areas, behaviour suggestive of territory formation. The areas that hihi chose to settle in were
360 strongly predicted by distance from water. We have found that ARUs were able to capture
361 the sound recordings required for DOMs, and that SACR is an effective method to analyse
362 large datasets to remove false positives, allowing the study to be conducted at spatial and
363 temporal scales that facilitate a detailed analysis of occupancy not previously attempted.

364

365 **Semi-automated Call Recognition**

366 Detection of hihi presence or absence over a 15 min recording was successful. After
367 the manual elimination of false-positives, SACR was as accurate as visual checking of
368 sonograms, whilst being approximately 10 times faster. SACR successfully produced the
369 data necessary for DOMs using free, openly available software and much faster than visual
370 analysis of spectrograms. Although no attempt was made to quantify the percentage of calls
371 detected against those present on the recordings, we estimate that both the chosen models
372 detected <10% of the total number of calls that could have been detected by a visual
373 inspection of the sonograms, emphasising the benefits of using presence or absence over a
374 15 minute period, rather than attempting to quantify the number of calls. The models also
375 produced a large number of false positives, particularly Model 2. This was anticipated, as
376 'click' type calls, such as the hihi stitch call, show up as simple vertical lines on sonograms,
377 which are easily mistaken for a variety of non-target sounds. This potential problem is largely
378 overcome by the SACR method, with visual verification of even such large numbers of false
379 positives taking less time than visual inspection of the entire dataset. Further research into

380 the impacts of varying detection rates on occupancy modelling would be useful, as using
381 automated recognition models that detect fewer calls but benefit from lower rates of false
382 positives would greatly reduce the time required to analyse the recordings.

383

384 **Dynamic Occupancy Modelling**

385 These findings demonstrate the ability of this approach to detect not only behavioural
386 change, but also the environmental factors that underpin habitat selection. Furthermore, the
387 results of this study are supported by previous research conducted at MEI using radio-
388 tracking methods. Richardson and Ewen (2016) found hihi settling on to territories over a
389 similar timescale, and also found that distance from water was the most important factor in
390 habitat selection. However, the methods described here have several advantages over
391 radio-tracking, namely that they are passive, involving no disturbance to the subject, studies
392 an entire population rather than selected individuals, and is potentially more cost-effective
393 given the dramatic decline in cost of ARUs.

394

395 The models of hihi occupancy presented here are heavily simplified, and many more
396 variables could impact on hihi occupancy than are considered here. The intention of such a
397 pared down model was to establish whether this modelling technique could be used at such
398 fine scale to identify behaviour already supported from previous studies, in which we were
399 successful. However, these techniques could also be used for translocation monitoring of
400 species about which we have little or no *a priori* knowledge of their habits in the wild, by
401 fitting a model with all hypothesised covariates and examining the effects of each on the
402 model. Further research in to the effects of varying the duration of closure seasons would be
403 beneficial to establish if there is an optimal duration to avoid any possible violations of the
404 DOM assumptions, whilst minimising the effort required to gather data.

405

406 **Conclusion**

407 Effective monitoring of post-release dispersal is necessary to evaluate conservation
408 translocations and to inform future translocation planning, but it presents a range of
409 logistical, financial and technological challenges to practitioners. This novel combination of
410 ARUs and dynamic occupancy modelling has proved a powerful tool, able to temporally and
411 spatially model hihi behaviour at scales that previously required expensive, intrusive and
412 logistically challenging transmitter technology. The acoustic analysis was able to effectively
413 detect hihi stitch calls sufficiently well to enable dynamic occupancy modelling, despite being
414 one of the least suitable vocalisations for this method, indicating this method could be
415 applied to a wide range of vocal species. This method allows translocation monitoring to be
416 conducted effectively and efficiently across a range of areas and species that would
417 previously have proven too challenging, improving understanding of the factors that lead to
418 successful conservation translocations. Furthermore, this method could be readily applied to
419 a range of scenarios beyond translocation ecology where monitoring of animal behaviour is
420 desirable but currently challenging. For instance, it would make an excellent tool for
421 monitoring behavioural change and area-avoidance post-construction of wind farms, or for
422 monitoring conservation actions designed to alter the habitat use of target species, giving
423 this novel monitoring method a truly broad range of possible applications.

424

425

426 **ACKNOWLEDGEMENTS**

427

428 We are extremely grateful for the support of Rotokare Scenic Reserve Trust, particularly
429 Simon Collins, Fiona Gordon, Tricia Jamieson and Aaron Jacobson. We would also like to
430 thank Kate Richardson, Kevin Parker, Andrew Knight and Morena Mills for providing advice
431 and guidance throughout the project, and to Simon McKeogh, Montana McLeod and Caitlin
432 Andrews without whom much of the fieldwork would not have been possible.

433

434 **DATA ACCESSABILITY**

435 It is the intention of the authors to make the relevant data available on Dryad.

436

437 **LITERATURE CITED**

- 438 Araya-Salas M, Smith-Vidaurre G. 2017. warbleR: an r package to streamline analysis of
439 animal acoustic signals. *Methods in Ecology and Evolution* 8:184–191. Available from
440 <http://doi.wiley.com/10.1111/2041-210X.12624> (accessed August 7, 2017).
- 441 Bain D, French K, Baker J, Clarke J. 2012. Translocation of the Eastern Bristlebird 1: radio-
442 tracking of post-release movements. *Ecological Management & Restoration* 13:153–158.
443 Blackwell Publishing Ltd.
- 444 Barron DG, Brawn JD, Weatherhead PJ. 2010. Meta-analysis of transmitter effects on avian
445 behaviour and ecology. *Methods in Ecology and Evolution* 1:180–187. Blackwell Publishing
446 Ltd.
- 447 Bioacoustics Research Program. 2010. Raven Pro: Interactive Sound Analysis Software
448 (Version 1.4) [Computer software]. The Cornell Lab of Ornithology, Ithaca, NY. Available
449 from <http://www.birds.cornell.edu/raven>.
- 450 BirdLife International. 2016. IUCN Red List for birds. Available from <http://www.birdlife.org>
451 (accessed November 20, 2016).
- 452 Brambilla M, Falco R, Negri I. 2012. A spatially explicit assessment of within-season
453 changes in environmental suitability for farmland birds along an altitudinal gradient. *Animal*
454 *Conservation* 15:638–647.
- 455 Brichieri-Colombi TA, Moehrensclager A. 2016. Alignment of threat, effort, and perceived
456 success in North American conservation translocations. *Conservation Biology* 30:1159–
457 1172.
- 458 Campos-Cerqueira M, Aide TM. 2016. Improving distribution data of threatened species by
459 combining acoustic monitoring and occupancy modelling. *Methods in Ecology and Evolution*
460 7:1340–1348.
- 461 Castro I. 1995. Behavioural ecology and management of Hihi (*Notiomystis cincta*), an
462 endemic New Zealand honeyeater. Unpublished PhD thesis, Massey University, New
463 Zealand. Available from: <https://mro.massey.ac.nz/handle/10179/4115>.
- 464 Chauvenet ALM, Ewen JG, Armstrong DP, Coulson T, Blackburn TM, Adams L, Walker LK,
465 Pettorelli N. 2012. Does supplemental feeding affect the viability of translocated
466 populations? The example of the hihi. *Animal Conservation* 15:337–350.
- 467 Digby A, Towsey M, Bell BD, Teal PD. 2013. A practical comparison of manual and
468 autonomous methods for acoustic monitoring. *Methods in Ecology and Evolution* 4:675–683.
- 469 Doerr LR, Richardson KM, Ewen JG, Armstrong DP. 2017. Effect of supplementary feeding
470 on reproductive success of hihi (stitchbird, *Notiomystis cincta*) at a mature forest
471 reintroduction site. *New Zealand Journal of Ecology* 41:34–40.
- 472 Dougill SJ, Johnson L, Banko PC, Goltz DM, Wiley MR, Semones JD. 2000. Consequences
473 of antenna design in telemetry studies of small passerines. *Journal of Field Ornithology*
474 71:385–388.
- 475 Duan S, Zhang J, Roe P, Wimmer J, Dong X, Truskinger A, Towsey M. 2013. Timed
476 Probabilistic Automaton : a Bridge between Raven and Song Scope for Automatic Species
477 Recognition. In Muñoz-Avila, H., & Stracuzzi, D.J. (Eds.) *Proceedings of the Twenty-Fifth*

478 Innovative Applications of Artificial Intelligence Conference, AAAI, Bellevue, Washington,
479 USA, pp. 1519-1524..

480 Ewen JG, Soorae PS, Canessa S. 2014. Reintroduction objectives, decisions and outcomes:
481 global perspectives from the herpetofauna. *Animal Conservation* 17:74–81.

482 Fischer J, Lindenmayer D. 2000. An assessment of the published results of animal
483 relocations. *Biological Conservation* 96:1–11.

484 Fiske IJ, Chandler RB. 2011. unmarked : An R Package for Fitting Hierarchical Models of
485 Wildlife Occurrence and Abundance 43.

486 Flanagan SE, Brown MB, Fennessy J, Bolger DT. 2016. Use of home range behaviour to
487 assess establishment in translocated giraffes. *African Journal of Ecology* 54:365–374.

488 Fountain K, Jeffs C, Croft S, Gregson J, Lister J, Evans A, Carter I, Chang YM, Sainsbury
489 AW. 2016. The influence of risk factors associated with captive rearing on post-release
490 survival in translocated ciril buntings *Emberiza cirilus* in the UK. *Oryx* 51, 332-338.

491 Frey SJK, Hadley AS, Betts MG. 2016. Microclimate predicts within-season distribution
492 dynamics of montane forest birds. *Diversity and Distributions* 22:944–959.
493 DOI:wiley.com/10.1111/ddi.12456

494 Furnas BJ, Callas RL. 2015. Using automated recorders and occupancy models to monitor
495 common forest birds across a large geographic region. *Journal of Wildlife Management*
496 79:325–337.

497 Gow EA, Stutchbury BJM. 2013. Within-season nesting dispersal and molt dispersal are
498 linked to habitat shifts in a Neotropical migratory songbird. *The Wilson Journal of Ornithology*
499 125:696–708.

500 Griffith B, Scott JM, Carpenter JW, Reed C. 1989. Translocation as a Species Conservation
501 Tool: Status and Strategy. American Association for the Advancement of Science. Available
502 from <http://www.jstor.org/stable/1704075> (accessed August 22, 2017).

503 Higgins PJ, Peter JM, Steele WK. 2001. Handbook of Australian, New Zealand & Antarctic
504 birds. Oxford University Press, Melbourne, Australia.

505 Hobson K a., Rempel RS, Greenwood H, Turnbull B, Van Wilgenburg SL. 2002. Acoustic
506 surveys of birds using electronic recordings: New potential from an omnidirectional
507 microphone system. *Wildlife Society Bulletin* 30:709–720.

508 Kéry M, Chandler R. 2016. Dynamic occupancy models in unmarked. Available
509 at:<http://cran.r-project.org/web/packages/unmarked/vignettes/colect.pdf>. [Accessed 12 July
510 2017].

511 Klingbeil BT, Willig MR. 2015. Bird biodiversity assessments in temperate forest : The value
512 of point count versus acoustic monitoring protocols Bird biodiversity assessments in
513 temperate forest : the value of point count versus acoustic monitoring protocols. *PeerJ*.
514 (3:e973) DOI:10.7717/peerj.973.

515 Le Gouar, P. Mihoub, J-B. Sarrazin F. 2012. Dispersal and habitat selection: behavioural
516 and spatial constraints for animal translocations. Pages 138-164 in: Ewen JG, Armstrong
517 DP, Parker KA, & Seddon PJ, editors. *Reintroduction Biology: Integrating Science and
518 Management*. Blackwell Publishing Ltd, Chichester..

519 MacKenzie DI. 2006. Modeling the probability of resource use: The effect of, and dealing
520 with, detecting a species imperfectly. *Journal of Wildlife Management* 70:367–374.

521 MacKenzie DI, Nichols J, Royle J, Pollock K, Bailey L, Hines J. 2006. *Occupancy estimation
522 and modeling : inferring patterns and dynamics of species occurrence*. Elsevier/Academic
523 Press.

524 McCready, M. 2017(a). Hihi post release monitoring report: May 2017. Unpublished.

525 McCready, M. 2017(b). Hihi post release monitoring report: June 2017. Unpublished.

526 Osborne P, Seddon P. 2012. Selecting suitable habitats for reintroductions. Pages 73-104
527 in: Ewen JG, Armstrong DP, Parker KA, & Seddon PJ, editors. *Reintroduction Biology:
528 Integrating Science and Management*. Blackwell Publishing Ltd, Chichester.

529 Pettorelli N, Vik JO, Mysterud A, Gaillard J, Tucker CJ, Stenseth NC, Lyon CB. 2005. Using
530 the satellite-derived NDVI to assess ecological responses to environmental change *Trends
531 in Ecology and Evolution*. 20:503-510.

532 Pierce AJ, Stevens DK, Mulder R, Salewski V. 2007. Plastic colour rings and the incidence
533 of leg injury in flycatchers (Muscicapidae, Monarchidae). *Ringling & Migration* 23:205–210.

534 Richardson KM. 2015. *Dispersal: the Effects of Phenotype and Habitat Selection in
535 Reintroduced Populations*. Unpublished PhD thesis, Massey University, New Zealand.
536 Available from: <https://mro.massey.ac.nz/handle/10179/10177>.

537 Richardson KM, Ewen JG. 2016. Habitat selection in a reintroduced population: social
538 effects differ between natal and post-release dispersal. *Animal Conservation* 19:413–421.

539 Richardson KM, Ewen JG, Brekke P, Doerr LR, Parker KA, Armstrong DP. 2015. Behaviour
540 during handling predicts male natal dispersal distances in an establishing reintroduced hihi (*541
Notiomystis cincta*) population. *Animal Conservation*. 11:135-143.

542 Rota CT, Fletcher Jr RJ, Dorazio RM, Betts MG. 2009. Occupancy estimation and the
543 closure assumption. *Journal of Applied Ecology* 46:1173–1181.

544 Scott JM, Goble DD, Haines AM, Wiens JA, Neel MC. 2010. Conservation-reliant species
545 and the future of conservation. *Conservation Letters* 3:91–97.

546 Scrimgeour J, Pickett AJ. 2011. Taxon plan for western brown kiwi (*Apteryx mantelli*):46.
547 Available from [http://www.doc.govt.nz/Documents/conservation/native-animals/birds/taxon-
548 plan-for-western-brown-kiwi.pdf](http://www.doc.govt.nz/Documents/conservation/native-animals/birds/taxon-plan-for-western-brown-kiwi.pdf) (accessed July 24, 2017).

549 Seddon P, Maartin Strauss W, Innes J. 2012. *Animal Translocations: What Are They and
550 Why Do We Do Them?* Page 1-32 in Ewen JG, Armstrong DP, Parker K A, & Seddon PJ,
551 editors. *Reintroduction Biology: Integrating Science and Management*. Backwell Publishing
552 Ltd, . Chichester.

553 Seddon PJ, Armstrong DP, Maloney RF. 2007. Developing the Science of Reintroduction
554 *Biology*. *Conservation Biology* 21:303–312.

555 Shonfield J, Bayne EM. 2017. Autonomous recording units in avian ecological research:
556 current use and future applications. *Avian Conservation and Ecology* 12:art14. DOI:
557 10.5751/ACE-00974-120114.

558 Soorae PS 2016. Introduction. Page i-ix in Soorae PS , editor Global Re-introduction
559 Perspectives: 2016. Case-studies from around the globe. IUCN/SSC Reintroduction
560 Specialist Group; Environment Agency Abu Dhabi, Gland, Switzerland:Abu Dhabi, UAE.

561 Sutherland WJ et al. 2010. Standards for documenting and monitoring bird reintroduction
562 projects. Conservation Letters 3:229–235.

563 Swan KD, McPherson JM, Seddon PJ, Moehrensclager A. 2016. Managing Marine
564 Biodiversity: The Rising Diversity and Prevalence of Marine Conservation Translocations.
565 Conservation Letters 9:239–251.

566 Tavecchia G, Viedma C, Martínez-Abraín A, Bartolomé M-A, Gómez JA, Oro D. 2009.
567 Maximizing re-introduction success: Assessing the immediate cost of release in a threatened
568 waterfowl. Biological Conservation **142**:3005–3012.

569 Tegeler AK, Morrison ML, Szewczak JM. 2012. Using extended-duration audio recordings to
570 survey avian species. Wildlife Society Bulletin 36:21–29.

571 Tveite H. 2015. NNJoin QGIS Plugin 1.2.2. Available from:
572 <https://plugins.qgis.org/plugins/NNJoin/>. [Accessed: 15 July 2017].

573 Weiss AD, Conservancy TN. 2000. Topographic Position and Landforms Analysis. Available
574 from: http://www.jennessent.com/downloads/TPI-poster-TNC_18x22.pdf. [Accessed: 14 July
575 2017]

576 Wildlife Acoustics. 2011a. Song Scope: Bioacoustics Software (Version 4.1.5). [Computer
577 Software]. Available from: <https://www.wildlifeacoustics.com/download/song-scope-software>
578 . [Accessed on 12 March 2017].

579 Wildlife Acoustics. 2011b. Song Scope Manual. Available from:
580 <https://www.wildlifeacoustics.com/download/song-scope-software> . [Accessed on 12 March
581 2017].

582 Williams EM. 2016. Developing monitoring methods for cryptic species: A case study of the
583 Australasian bittern *Botaurus poiciloptilus*. Unpublished PhD thesis, Massey University, New
584 Zealand. Available from: <https://mro.massey.ac.nz/handle/10179/10830>.

585

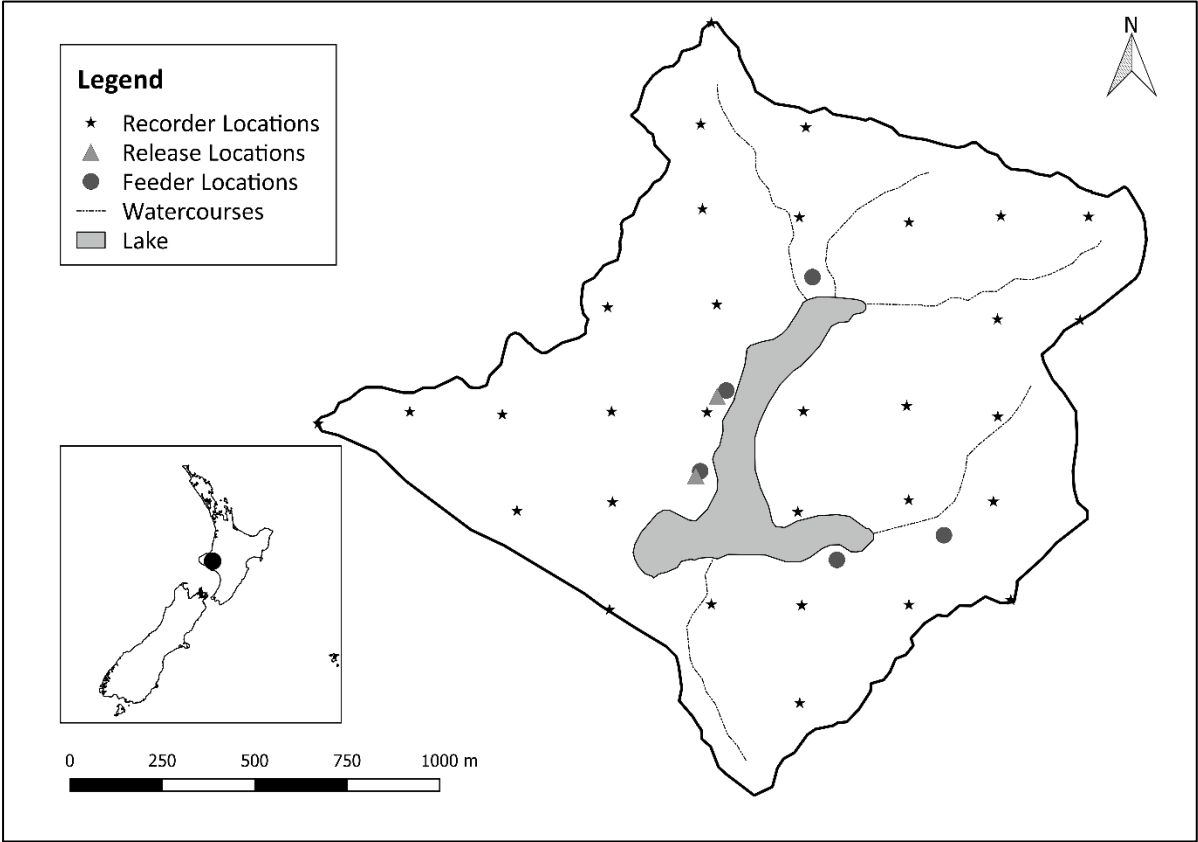
586 **TABLES**

587 **Table 1: Model parameters and variables used in the dynamic occupancy model of**
 588 **hihi (*Notiomystis cincta*) dispersal behaviour at Rotokare Scenic Reserve, North**
 589 **Island, New Zealand. Note numbers relate as follows: 1. Environmental variable**
 590 **predicted to have an impact on hihi distribution; 2. Temporal, categorical variable predicted**
 591 **to have an impact on hihi distribution; 3. Temporal variable predicted to have an impact on**
 592 **hihi detection; 4. Environmental variable predicted to have an impact on hihi call detection.**

593

Model parameters	Covariates	Summed AIC weight	Covariate Coefficients in Optimised Model (SE)
Initial probability of occupancy (ψ)	Distance from water (DfW) ¹	0.585	
	Distance from Release (DfR) ¹	0.284	
Colonisation (γ)	Date ²	0.992	Date1: contrast baseline Date2: -0.789 (0.260) Date3: -0.294 (0.250) Date4: -0.800 (0.257)
	DfW ¹	0.890	-0.175 (0.086)
	DfR ¹	0.192	
	Date*DfW	0.124	
	Date*DfR	0.026	
Extinction (ϵ)	Date ²	0.895	Date1: contrast baseline Date2: 0.227 (0.314) Date3: 0.749 (0.313) Date4: 0.784 (0.373)

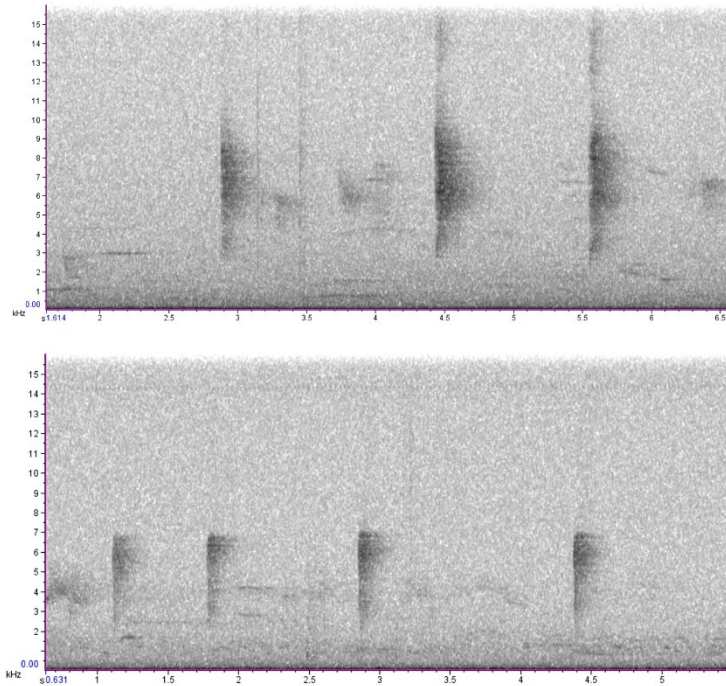
	DfW ¹	0.999	0.656 (0.171)
	DfR ¹	0.609	
	Date*DfW	0.173	
	Date*DfR	0.101	
Probability of detection (p)	Date ³	0.63	
	Aspect ⁴	1.00	E-S: contrast baseline S-W: -0.6951 (0.1433) W-N: -0.9804 (0.1416) N-E: -0.0211 (0.1069)
	Topographical Position Index ⁴	1.00	-0.3448 (0.0411)
	Time ³	0.46	
	Aspect*TPI	0.079	
Optimised model parameters: $\psi = \sim 1$ $\gamma = \sim \text{DfW} + \text{date}$, $\varepsilon = \sim \text{DfW} + \text{date}$, $\rho = \sim \text{Aspect} + \text{TPI}$			



596

597 **Figure 1: Locations of 32 autonomous recording units (Stars) deployed at Rotokare**
598 **Scenic Reserve, North island, New Zealand to monitor dispersal of 40 translocated**
599 **hihi post release. Recorders were deployed between 18th April and 19th May 2017.**
600 **Triangles denote release sites and circles are feeder locations.**

601



602

603 **Figure 2: An example of spectrograms detected on autonomous recording devices**

604 **deployed at Rotokare scenic reserve, North island, New Zealand. Top: Three hihi**

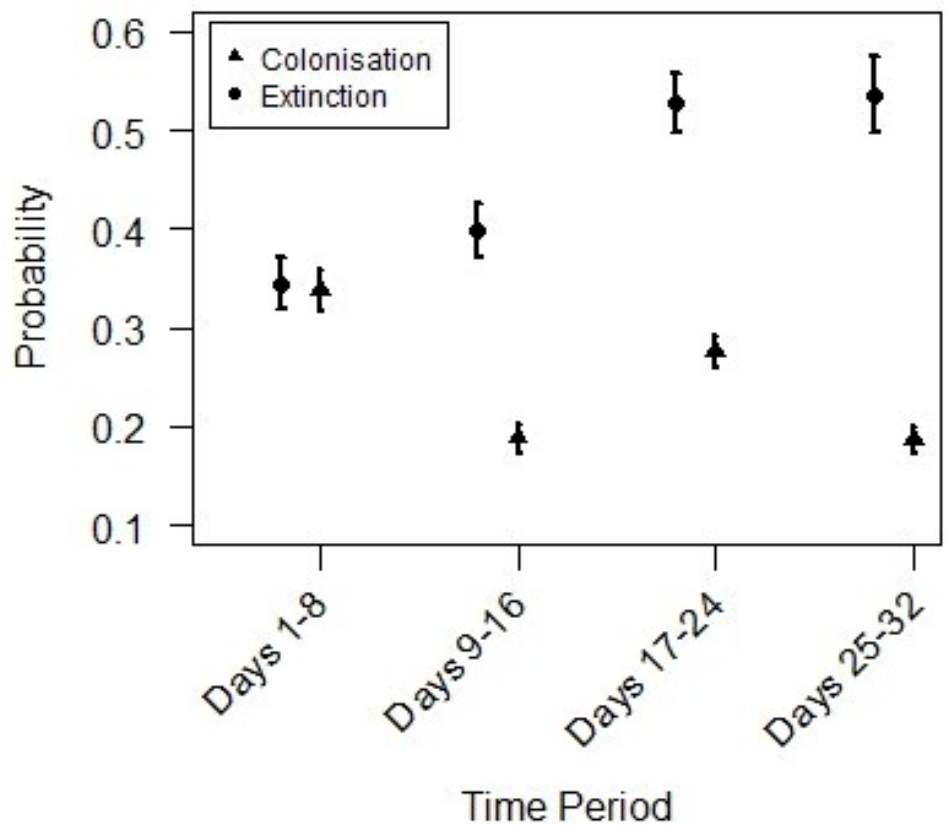
605 **(*Notiomystis cincta*) 'stitch' vocalisations, recorded during the study with FFT at 512**

606 **points, a 50% overlap, and Hann windowBottom: A spectrogram of New Zealand**

607 **fernbird (*Megalurus punctatus*) showing how these calls are similar to those of hihi**

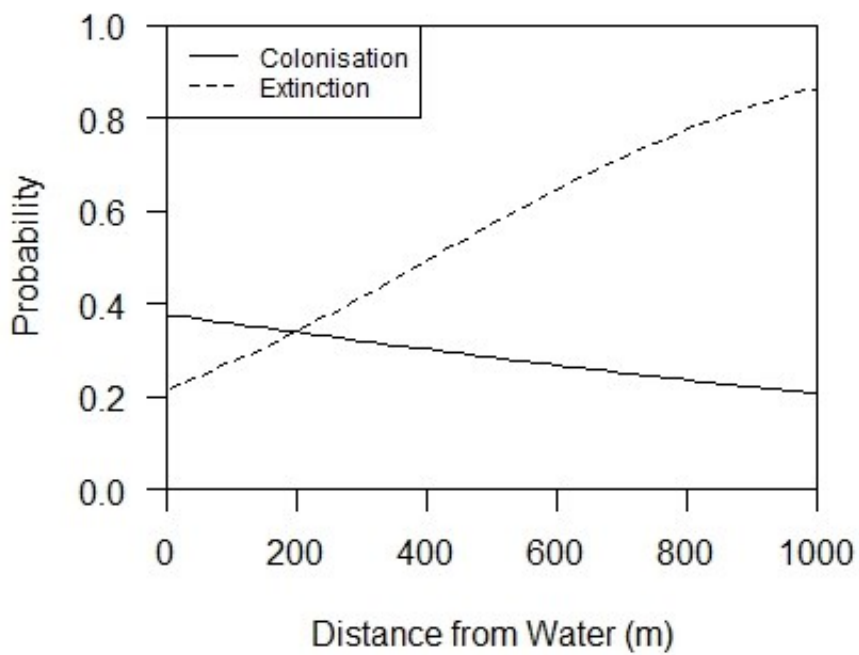
608 **and therefore likely to be detected as false positives by automated call recognition**

609 **models.**



610

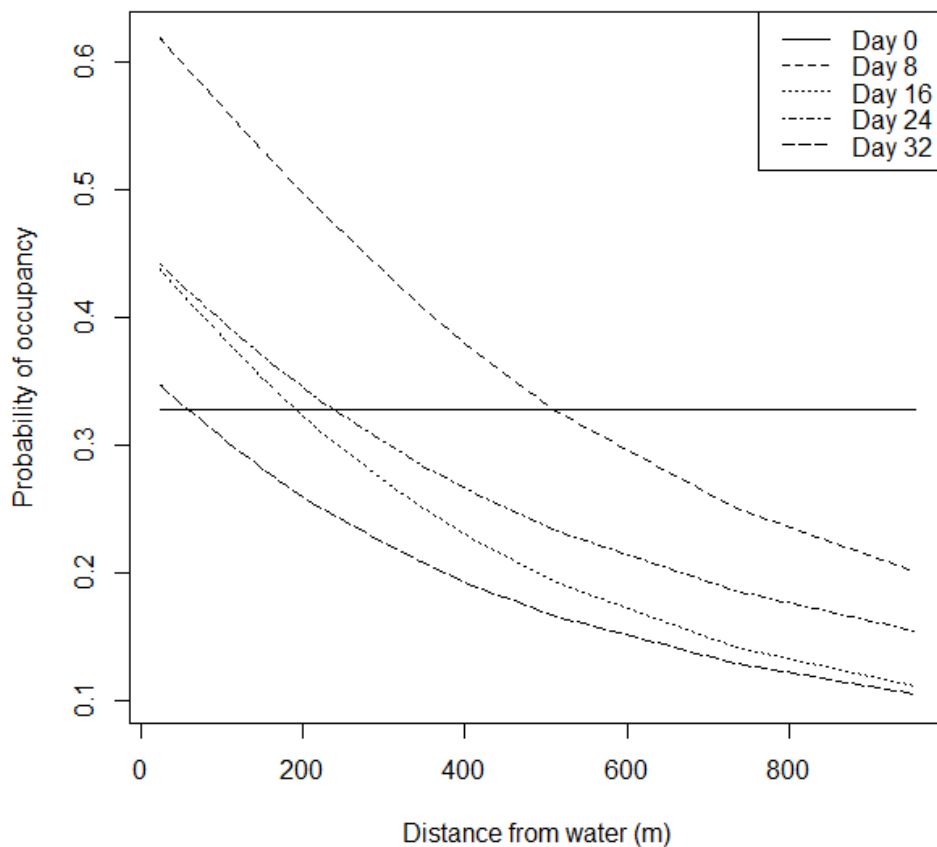
611 **Figure 3: The effect of time after release on the probability of hihi colonisation and**
 612 **extinction at any given point in Rotokare Scenic Reserve.**



613

614 **Figure 4: The effect of distance from water on hihi colonisation and extinction**
615 **probability at Rotokare Scenic Reserve.**

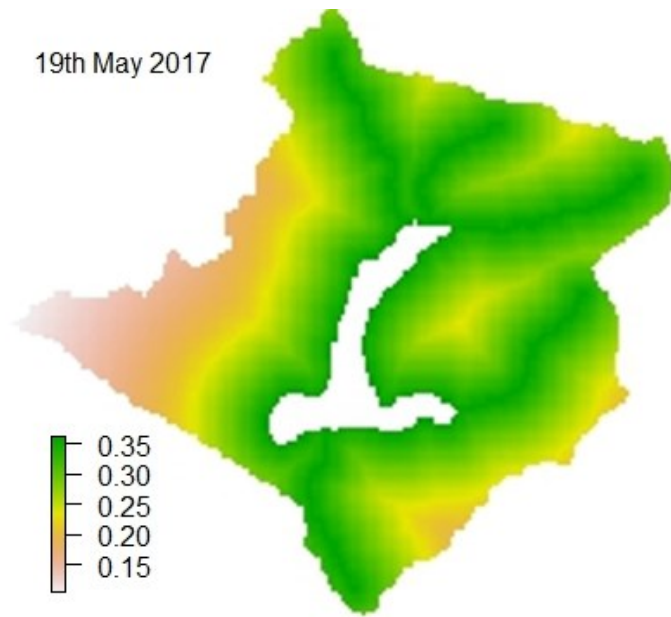
616



617

618 **Figure 5: The effect of distance from water on the probability of hihi occurrence on**
619 **19th May 2017 at Rotokare Scenic Reserve.**

620



621

622 **Figure 6: Map of hihi occurrence probability at Rotokare Scenic Reserve at the end of**
623 **the study period.**

624

625