

1 **Supplemental Information**

2 **Habitat loss on the breeding grounds is a major contributor to population declines in a**  
3 **long-distance migratory songbird**

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## 15 **Supplemental Methods**

### 16 *Light-level geolocation*

17           We defined twilight (sunrise and sunset events) using the `findTwilights` function with a  
18 threshold of 1. Sunrise and sunset times were assigned as the time the ambient light-levels  
19 recorded by the geolocator rose above and fell below the threshold value, respectively. We set a  
20 minimum dark period of six hours to remove spurious twilight events. Once twilights were  
21 determined with used the `changeLight` function available in the `GeoLight` package [1] to identify  
22 migratory phenology using a stationary duration of two days. We subsequently merged  
23 stationary locations that were closer than 300 km. We used informative behavioral priors in our  
24 analysis to help refine location estimates. We used two distinct flight speed models within our  
25 behavioral model, one corresponding to stationary periods and another to migratory periods ([2],  
26 [Fig. S2](#)). In addition to using different flight speed parameters we used different zenith angles  
27 throughout the year [3,4]. We determined the zenith angle associated with each identified  
28 stationary period using the `findHEzenith` function available in the `GeoLight` package [1].  
29 Geographic coordinates estimated while including uncertainty inherent in light-level geolocation  
30 [5] were derived by combining a model describing the difference between observed and expected  
31 twilight times, a behavioral movement model and a land mask which restricted stationary periods  
32 of the annual cycle to land masses while allowing flights to occur over water [6,7]. We ran the  
33 MCMC analysis using a Metropolis sampler. We made our geographic inference from 5000  
34 draws from the posterior distribution following an initial burn-in phase of 1000 draws.

### 35 *Habitat loss & fragmentation*

36 Habitat loss was summarized from the Global Forest Change data set (version 1.6; [8]) using  
37 Google Earth Engine [9]. We summarized the area of habitat loss in each year between 2000 and  
38 2017 within each 500km x 500km target location (see *Migratory Connectivity*) and calculated  
39 the cumulative loss across years. For each population we derived a weighted average of habitat  
40 loss that accounts for location uncertainty. We used the estimated probability that a population  
41 used a particular 500km x 500km region derived from the MC metric to calculate a weighted  
42 average [Fig. S1](#)). We present the annual rate of change as a summary statistic because the area of  
43 inference differed between breeding ( $\sim 7850 \text{ km}^2$ ) and non-breeding seasons ( $250,000 \text{ km}^2$ ).  
44 Within our analysis we used the cumulative habitat loss. In addition to habitat loss, we derived  
45 several metrics that describe habitat fragmentation within each landscape. We calculated the  
46 percentage of forest cover (PLAND), edge density (ED), patch density (PD), nearest patch (NP),  
47 largest patch index (LPI), total core area (TCA), and core area index (CAI) metrics [10] using the  
48 LandscapeMetrics R package [11]. Several of the metrics were highly correlated ( $r > 0.75$ , Fig.  
49 S3) and were removed from the analysis to reduce redundancy. We included the largest patch  
50 index (LPI) which is an area to edge metric that approaches 0 when the largest patch becomes  
51 small and approaches 100 when the landscape is comprised of a single patch, number of patches  
52 (NP) which is an aggregation metric that describes the number of patches within the landscape  
53 but does not contain information about how patches are configured within the landscape. Finally,  
54 we included total core area (TCA) which is a configuration metric that describes the amount of  
55 core area (non-edge habitat) within a landscape [11]. For each metric we used 8 neighbors  
56 (queen's case) and did not consider pixels at the edge of the landscape boundary as core area. For  
57 fragmentation metrics that calculated edge we used 90m or 3 raster cells (30m x 30m resolution)  
58 as the distance from edge to be considered core.

59 Supplemental Results

60 *Habitat loss & fragmentation*

61 The amount of core forested habitat (total core area) declined at the greatest rate at stopover  
62 regions prior to making long-distance over water flights (mean = -124.71, range = -228.29 - -  
63 65.49 thousand ha<sup>-yr</sup>) followed by the stationary non-breeding landscapes (mean = -28.45, range  
64 = -38.98 - -2.57 thousand ha<sup>-yr</sup>), stopover regions post Atlantic crossing (mean = -49.79, range =  
65 -79.41 - -15.13 thousand ha<sup>-yr</sup>) and finally the breeding grounds (mean = -14.01, range = -21.57  
66 - -7.29 thousand ha<sup>-yr</sup>).

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68 **Supplemental Tables**

69 Table S1. Mean abundance and 95% credible interval of Connecticut warblers along breeding  
 70 bird survey routes within each of the ‘natural’ populations.

Year	Quebec	Great Lakes	Northern U.S.	Ontario W.	Alberta W.	Alberta E.	Saskatchewan	Manitoba
2000	0.09 (0.00 : 0.48)	0.56 (0.16 : 1.27)	1.40 (0.92 : 1.97)	1.66 (1.16 : 2.37)	1.19 (0.61 : 2.02)	1.08 (0.72 : 1.51)	1.28 (0.72 : 2.04)	3.29 (1.22 : 7.82)
2001	0.09 (0.00 : 0.44)	0.27 (0.06 : 0.72)	1.60 (1.08 : 2.23)	1.55 (1.13 : 2.05)	2.42 (1.31 : 4.43)	1.03 (0.63 : 1.64)	3.07 (1.71 : 5.98)	0.48 (0.21 : 0.90)
2002	0.07 (0.00 : 0.39)	0.04 (0.01 : 0.14)	1.00 (0.63 : 1.48)	1.17 (0.85 : 1.56)	1.78 (1.01 : 2.82)	0.98 (0.64 : 1.43)	4.08 (2.93 : 5.44)	2.16 (0.67 : 5.53)
2003	0.05 (0.00 : 0.32)	0.20 (0.03 : 0.75)	0.87 (0.54 : 1.30)	1.49 (0.98 : 2.49)	1.96 (1.15 : 3.04)	1.22 (0.78 : 2.02)	2.76 (1.83 : 3.86)	1.50 (0.91 : 2.24)
2004	0.04 (0.00 : 0.27)	0.03 (0.00 : 0.11)	1.08 (0.61 : 2.03)	0.75 (0.48 : 1.14)	3.05 (1.71 : 5.57)	1.41 (0.89 : 2.45)	1.38 (0.33 : 4.34)	0.16 (0.06 : 0.33)
2005	0.03 (0.00 : 0.19)	0.03 (0.00 : 0.10)	1.01 (0.66 : 1.47)	1.38 (0.75 : 2.61)	1.30 (0.68 : 2.16)	1.54 (1.11 : 2.06)	1.02 (0.55 : 1.68)	1.68 (0.58 : 4.12)
2006	1.69 (0.09 : 8.27)	0.13 (0.02 : 0.52)	0.65 (0.40 : 0.98)	1.78 (1.26 : 2.63)	0.61 (0.28 : 1.13)	0.67 (0.41 : 1.02)	0.92 (0.46 : 1.59)	2.58 (1.55 : 4.40)
2007	2.17 (0.53 : 5.28)	0.16 (0.04 : 0.44)	0.94 (0.54 : 1.65)	2.39 (1.87 : 2.97)	0.88 (0.41 : 1.58)	1.40 (0.82 : 2.72)	0.79 (0.39 : 1.36)	1.24 (0.42 : 3.10)
2008	4.45 (1.60 : 8.97)	0.15 (0.03 : 0.41)	0.74 (0.45 : 1.15)	2.02 (1.57 : 2.53)	0.66 (0.29 : 1.24)	1.47 (1.02 : 2.08)	1.29 (0.71 : 2.07)	1.67 (0.73 : 3.64)
2009	0.01 (0.00 : 0.07)	0.30 (0.09 : 0.74)	0.61 (0.36 : 0.95)	1.79 (1.39 : 2.25)	0.76 (0.32 : 1.63)	1.45 (1.04 : 1.94)	0.40 (0.15 : 0.82)	2.00 (1.33 : 2.86)
2010	1.66 (0.21 : 6.37)	0.44 (0.15 : 0.98)	0.34 (0.18 : 0.56)	1.33 (0.99 : 1.75)	0.88 (0.39 : 1.67)	1.37 (0.97 : 1.84)	0.25 (0.06 : 0.82)	2.54 (1.72 : 3.55)
2011	0.75 (0.14 : 2.19)	0.37 (0.13 : 0.79)	0.46 (0.22 : 0.90)	1.05 (0.76 : 1.41)	0.69 (0.32 : 1.24)	0.64 (0.42 : 0.94)	0.37 (0.12 : 0.95)	0.08 (0.02 : 0.20)
2012	0.96 (0.18 : 2.70)	0.44 (0.17 : 0.93)	0.40 (0.22 : 0.66)	1.25 (0.93 : 1.65)	0.93 (0.38 : 2.17)	0.74 (0.48 : 1.09)	0.08 (0.02 : 0.19)	0.07 (0.02 : 0.17)
2013	1.21 (0.24 : 3.31)	0.47 (0.18 : 0.97)	0.46 (0.25 : 0.76)	0.99 (0.72 : 1.32)	0.47 (0.20 : 0.90)	0.67 (0.43 : 0.98)	0.74 (0.18 : 2.18)	0.08 (0.02 : 0.20)
2014	0.75 (0.11 : 2.31)	0.40 (0.14 : 0.84)	0.23 (0.12 : 0.41)	0.94 (0.67 : 1.28)	0.57 (0.24 : 1.08)	0.86 (0.57 : 1.24)	0.69 (0.26 : 1.31)	0.05 (0.01 : 0.16)
2015	0.45 (0.05 : 1.50)	0.29 (0.09 : 0.68)	0.35 (0.16 : 0.67)	1.24 (0.86 : 1.82)	0.39 (0.15 : 0.78)	0.30 (0.16 : 0.50)	0.64 (0.27 : 1.17)	0.81 (0.24 : 2.13)
2016	0.40 (0.03 : 1.40)	0.25 (0.07 : 0.60)	0.22 (0.10 : 0.42)	1.28 (0.93 : 1.68)	0.34 (0.13 : 0.70)	0.63 (0.31 : 1.32)	0.68 (0.24 : 1.61)	1.67 (0.93 : 2.94)
2017	0.35 (0.02 : 1.34)	0.12 (0.02 : 0.35)	0.26 (0.12 : 0.50)	1.16 (0.83 : 1.55)	0.43 (0.16 : 0.88)	0.65 (0.39 : 0.97)	0.72 (0.34 : 1.26)	0.42 (0.18 : 0.79)

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73 **Supplemental Figures**

74 **Fig. S1** The target regions (500km x 500km) used to estimate the strength of migratory  
75 connectivity (MC) for Connecticut warblers between breeding and significant stopover locations  
76 (A. pre Atlantic crossing, B. post Atlantic crossing) and the stationary non-breeding season (C).  
77 The target regions outlined in black were the regions with a transition probability greater than 0  
78 identified in the migratory connectivity analysis. The target regions outlined in white were  
79 included as possible target regions but were not used by populations in our analysis. The lines  
80 connect the breeding location with the target regions used by a population. The width of the line  
81 represents that transition probability from the breeding site to the target regions - wide lines  
82 represent a greater probability a given population used that target region. Figure S1 D shows an  
83 enlarged region in South America where Connecticut warblers spent the stationary non-breeding  
84 season.

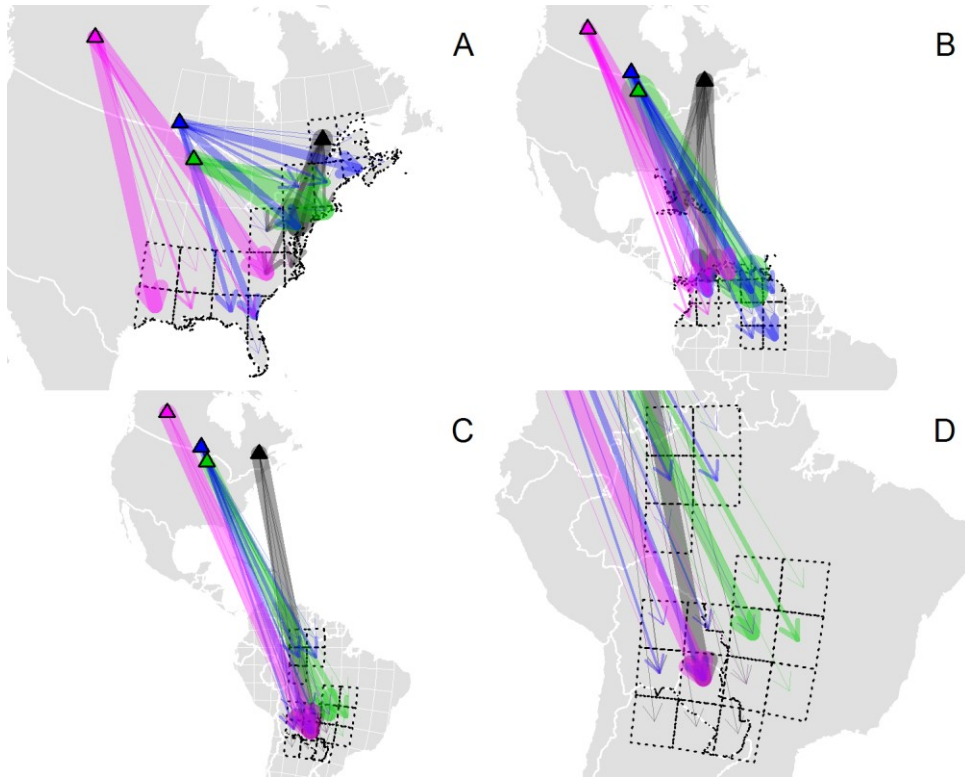
85 **Fig. S2** The flight behavior mask used for stationary (solid line) and migratory (dotted) phases of  
86 the annual cycle. We allowed for a greater flight speed during migratory periods than during  
87 stationary periods.

88 **Fig. S3** A scatterplot matrix showing the correlation and correlation coefficients between  
89 landscape fragmentation metrics. For each landscape we derived the percentage of forest cover  
90 (PLAND), edge density (ED), patch density (PD), nearest patch (NP), largest patch index (LPI),  
91 total core area (TCA), and core area index (CAI\_mn) using the LandscapeMetrics package [11].

92 **Fig. S4** Posterior predictive diagnostic of model fit for habitat loss (A) and habitat fragmentation  
93 (B) using Chi-square goodness of fit test statistic.

94 **Fig. S5** Connecticut warbler observation locations submitted to eBird.org by community  
95 scientists (also referred to as citizen scientists). Observations are color coded by season and size  
96 of the locations is representative of the number of individuals seen at that location. While spring  
97 migration routes of individuals are unknown, eBird checklists suggest that the geographic  
98 regions used by Connecticut warblers during spring and fall migration are similar.

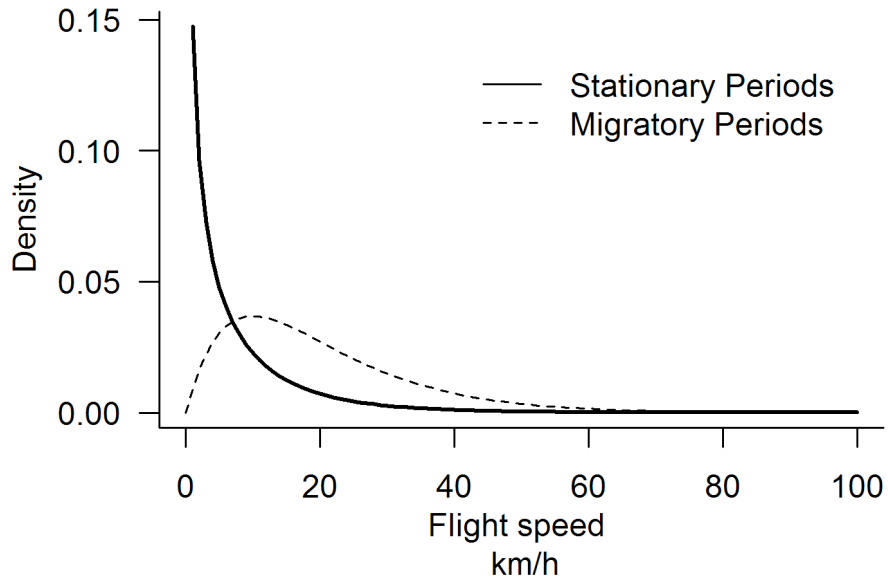
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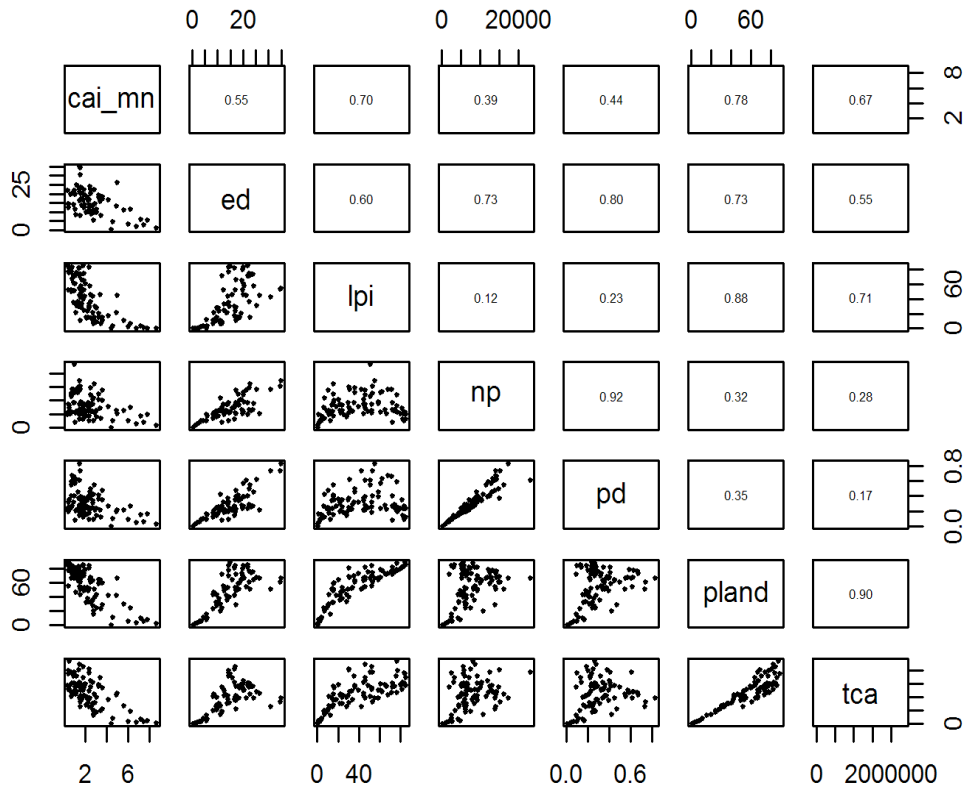


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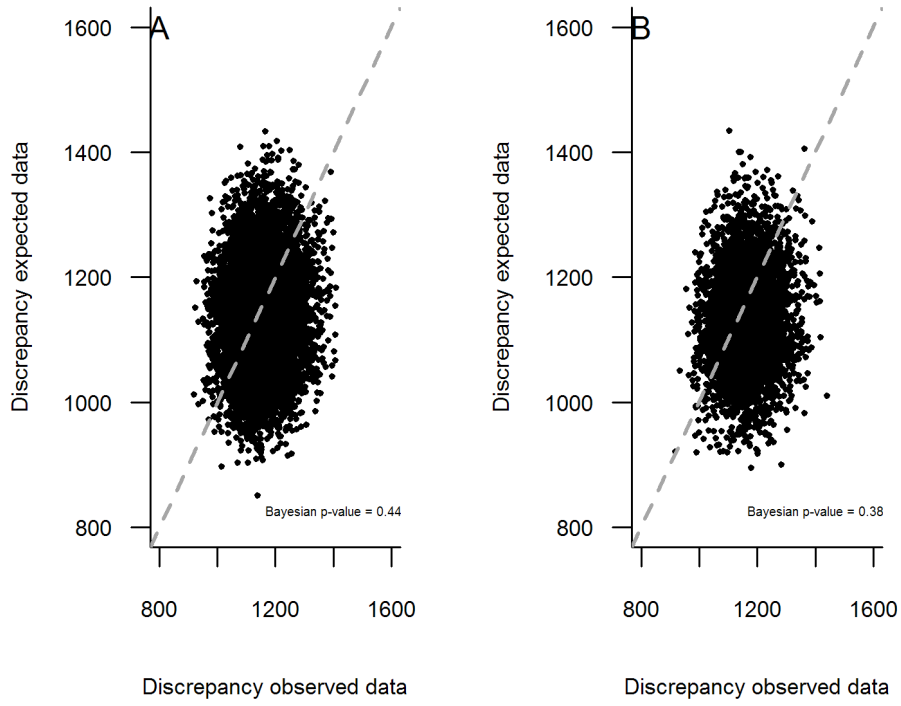






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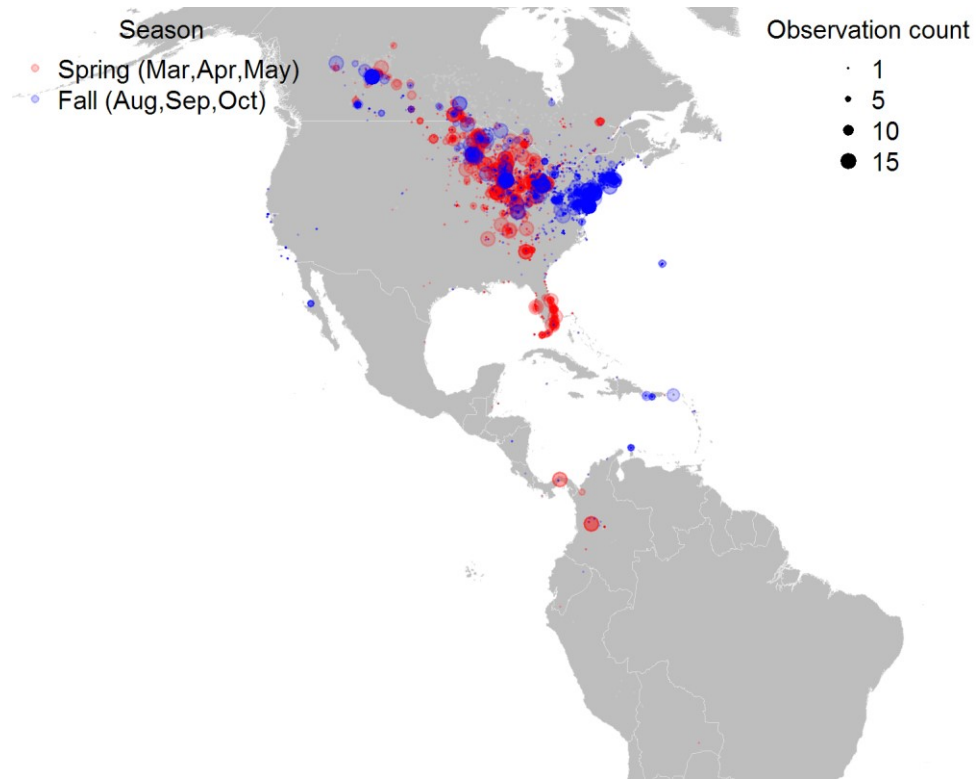
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112 **Fig. S5**



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115 **Supplemental References**

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147

148

149 **Appendix 1. JAGS model**

```
150 ## model{
151 ## # THIS IS A POISSON REGRESSION TO ESTIMATE CONNECTICUT WARBLER ABUNDANCE
152 ## # USING BBS ROUTE LEVEL TOTALS FOLLOWING RUSHING ET AL. 2016 JAE
153 ##
154 ## # model indicator variable as joint distribution to facilitate mixing
155 ## # Hooten & Hobbs 2015, AHM vol 1. Kery & Royle pg 342
156 ##
157 ## # Priors
158 ## HyperTrend ~ dnorm(0,0.01)
159 ## HyperAlpha ~ dnorm(0,0.01)
160 ## # forest loss hyper priors #
161 ## Hyper_cumbreed ~ dnorm(0,0.01)
162 ## Hyper_cumwinter ~ dnorm(0,0.01)
163 ## Hyper_cumpre ~ dnorm(0,0.01)
164 ## Hyper_cumpost ~ dnorm(0,0.01)
165 ## Hyper_cumloss ~ dnorm(0,0.01)
166 ## # fragmentation priors
167 ## Hyper_lpi ~ dnorm(0,0.01)
168 ## Hyper_np ~ dnorm(0,0.01)
169 ## Hyper_tca ~ dnorm(0,0.01)
170 ## Hyper_npwinter ~ dnorm(0,0.01)
171 ## Hyper_nppre ~ dnorm(0,0.01)
172 ## Hyper_nppost ~ dnorm(0,0.01)
173 ## Hyper_lpiwinter ~ dnorm(0,0.01)
174 ## Hyper_lpipre ~ dnorm(0,0.01)
175 ## Hyper_lpipost ~ dnorm(0,0.01)
176 ## Hyper_tcawinter ~ dnorm(0,0.01)
177 ## Hyper_tcapre ~ dnorm(0,0.01)
178 ## Hyper_tcapost ~ dnorm(0,0.01)
179 ## Hyper_obs ~ dnorm(0,0.01)
180 ## Hyper_eps ~ dnorm(0,0.001)
181 ##
182 ## # Priors for population-level intercept
183 ## # and indicator variable for cumulative breeding
184 ## # forest loss
185 ##
186 ## for(p in 1:npopulations){
187 ## # intercept
188 ## alpha[p] ~ dnorm(HyperAlpha,tau.alpha)
189 ## beta.trend[p] ~ dnorm(HyperTrend,tau.trend)
190 ##
191 ## # prior indicators #
```

```

192  ## pop.breed.ind[p] ~ dbeta(5,5)
193  ## pop.lpi.ind[p] ~ dbeta(5,5)
194  ## pop.np.ind[p] ~ dbeta(5,5)
195  ## pop.tca.ind[p] ~ dbeta(5,5)
196  ##
197  ## # realized indicators #
198  ## breed.ind[p] ~ dbern(pop.breed.ind[p])
199  ## breed.lpi.ind[p] ~ dbern(pop.lpi.ind[p])
200  ## breed.np.ind[p] ~ dbern(pop.np.ind[p])
201  ## breed.tca.ind[p] ~ dbern(pop.tca.ind[p])
202  ##
203  ## # joint beta & indicator #
204  ## beta_cumbreed[p] ~ dnorm(Hyper_cumbreed, tau.cumBreed)
205  ## beta.cumbreed[p] <- breed.ind[p]*beta_cumbreed[p]
206  ##
207  ## beta_breed_lpi[p] ~ dnorm(Hyper_lpi, tau.breedLPI)
208  ## beta.breed.lpi[p] <- breed.lpi.ind[p]*beta_breed_lpi[p]
209  ##
210  ## beta_breed_np[p] ~ dnorm(Hyper_np, tau.breedNP)
211  ## beta.breed.np[p] <- breed.np.ind[p]*beta_breed_np[p]
212  ##
213  ## beta_breed_tca[p] ~ dnorm(Hyper_tca, tau.breedTCA)
214  ## beta.breed.tca[p] <- breed.tca.ind[p]*beta_breed_tca[p]
215  ## }
216  ##
217  ## # HARD CODE BETA ESTIMATES FOR WINTER, PRE AND POST FLIGHT LOSS TO 0
218  ## # FOR POPULATIONS WHERE WE DON'T HAVE TRACKING INFORMATION FOR
219  ## # we have info from 1,3,4,6
220  ## for(tp in c(1,3,4,6)){ # tp = tracked population
221  ## # Cumulative loss during winter
222  ## pop.winter.ind[tp] ~ dbeta(5,5)
223  ## winter.ind[tp] ~ dbern(pop.winter.ind[tp])
224  ## beta_cumwinter[tp] ~ dnorm(Hyper_cumwinter, tau.cumWinter)
225  ## beta.cumwinter[tp] <- winter.ind[tp]*beta_cumwinter[tp]
226  ##
227  ## # Cumulative loss pre flight
228  ## pop.pre.ind[tp] ~ dbeta(5,5)
229  ## pre.ind[tp] ~ dbern(pop.pre.ind[tp])
230  ## beta_cumpre[tp] ~ dnorm(Hyper_cumpre, tau.cumPre)
231  ## beta.cumpre[tp] <- pre.ind[tp]*beta_cumpre[tp]
232  ##
233  ## # Cumulative loss post flight
234  ## pop.post.ind[tp] ~ dbeta(5,5)
235  ## post.ind[tp] ~ dbern(pop.post.ind[tp])
236  ## beta_cumpost[tp] ~ dnorm(Hyper_cumpost, tau.cumPost)

```

```

237  ## beta.cumpost[tp] <- post.ind[tp]*beta_cumpost[tp]
238  ##
239  ## # Cumulative loss post flight
240  ## pop.cumloss.ind[tp] ~ dbeta(5,5)
241  ## cumloss.ind[tp] ~ dbern(pop.cumloss.ind[tp])
242  ## beta_cumloss[tp] ~ dnorm(Hyper_cumloss, tau.cumLoss)
243  ## beta.cumloss[tp] <- cumloss.ind[tp]*beta_cumloss[tp]
244  ##
245  ## # lpi
246  ## # winter
247  ## lpi.winter.ind[tp] ~ dbeta(5,5)
248  ## winter.lpi.ind[tp] ~ dbern(lpi.winter.ind[tp])
249  ## beta_winter_lpi[tp] ~ dnorm(Hyper_lpiwinter, tau.lpiWinter)
250  ## beta.winter.lpi[tp] <- winter.lpi.ind[tp]*beta_winter_lpi[tp]
251  ## # pre
252  ## lpi.pre.ind[tp] ~ dbeta(5,5)
253  ## pre.lpi.ind[tp] ~ dbern(lpi.pre.ind[tp])
254  ## beta_pre_lpi[tp] ~ dnorm(Hyper_lpipre, tau.lpiPre)
255  ## beta.pre.lpi[tp] <- pre.lpi.ind[tp]*beta_pre_lpi[tp]
256  ## # post
257  ## lpi.post.ind[tp] ~ dbeta(5,5)
258  ## post.lpi.ind[tp] ~ dbern(lpi.post.ind[tp])
259  ## beta_post_lpi[tp] ~ dnorm(Hyper_lpipost, tau.lpiPost)
260  ## beta.post.lpi[tp] <- post.lpi.ind[tp]*beta_post_lpi[tp]
261  ##
262  ## # tca
263  ## # winter
264  ## tca.winter.ind[tp] ~ dbeta(5,5)
265  ## winter.tca.ind[tp] ~ dbern(tca.winter.ind[tp])
266  ## beta_winter_tca[tp] ~ dnorm(Hyper_tcawinter, tau.tcaWinter)
267  ## beta.winter.tca[tp] <- winter.tca.ind[tp]*beta_winter_tca[tp]
268  ## # pre
269  ## tca.pre.ind[tp] ~ dbeta(5,5)
270  ## pre.tca.ind[tp] ~ dbern(tca.pre.ind[tp])
271  ## beta_pre_tca[tp] ~ dnorm(Hyper_tcapre, tau.tcaPre)
272  ## beta.pre.tca[tp] <- pre.tca.ind[tp]*beta_pre_tca[tp]
273  ## # post
274  ## tca.post.ind[tp] ~ dbeta(5,5)
275  ## post.tca.ind[tp] ~ dbern(tca.post.ind[tp])
276  ## beta_post_tca[tp] ~ dnorm(Hyper_tcapost, tau.tcaPost)
277  ## beta.post.tca[tp] <- post.tca.ind[tp]*beta_post_tca[tp]
278  ##
279  ## # np
280  ## # winter
281  ## np.winter.ind[tp] ~ dbeta(5,5)

```



```

282  ## winter.np.ind[tp] ~ dbern(np.winter.ind[tp])
283  ## beta_winter_np[tp] ~ dnorm(Hyper_npwinter, tau.npWinter)
284  ## beta.winter.np[tp] <- winter.np.ind[tp]*beta_winter_np[tp]
285  ## # pre
286  ## np.pre.ind[tp] ~ dbeta(5,5)
287  ## pre.np.ind[tp] ~ dbern(np.pre.ind[tp])
288  ## beta_pre_np[tp] ~ dnorm(Hyper_nppre, tau.npPre)
289  ## beta.pre.np[tp] <- pre.np.ind[tp]*beta_pre_np[tp]
290  ## # post
291  ## np.post.ind[tp] ~ dbeta(5,5)
292  ## post.np.ind[tp] ~ dbern(np.post.ind[tp])
293  ## beta_post_np[tp] ~ dnorm(Hyper_nppost, tau.npPost)
294  ## beta.post.np[tp] <- post.np.ind[tp]*beta_post_np[tp]
295  ##
296  ## }
297  ##
298  ## # HARD CODE BETA ESTIMATES NOT IN MODEL TO ZERO #
299  ## beta.cumwinter[2] <- 0
300  ## beta.cumwinter[5] <- 0
301  ## beta.cumwinter[7] <- 0
302  ## beta.cumwinter[8] <- 0
303  ## beta.cumpre[2] <- 0
304  ## beta.cumpre[5] <- 0
305  ## beta.cumpre[7] <- 0
306  ## beta.cumpre[8] <- 0
307  ## beta.cumpost[2] <- 0
308  ## beta.cumpost[5] <- 0
309  ## beta.cumpost[7] <- 0
310  ## beta.cumpost[8] <- 0
311  ## beta.cumloss[2] <- 0
312  ## beta.cumloss[5] <- 0
313  ## beta.cumloss[7] <- 0
314  ## beta.cumloss[8] <- 0
315  ## beta.winter.lpi[2] <- 0
316  ## beta.winter.lpi[5] <- 0
317  ## beta.winter.lpi[7] <- 0
318  ## beta.winter.lpi[8] <- 0
319  ## beta.pre.lpi[2] <- 0
320  ## beta.pre.lpi[5] <- 0
321  ## beta.pre.lpi[7] <- 0
322  ## beta.pre.lpi[8] <- 0
323  ## beta.post.lpi[2] <- 0
324  ## beta.post.lpi[5] <- 0
325  ## beta.post.lpi[7] <- 0
326  ## beta.post.lpi[8] <- 0

```

```
327 ## beta.winter.tca[2] <- 0
328 ## beta.winter.tca[5] <- 0
329 ## beta.winter.tca[7] <- 0
330 ## beta.winter.tca[8] <- 0
331 ## beta.pre.tca[2] <- 0
332 ## beta.pre.tca[5] <- 0
333 ## beta.pre.tca[7] <- 0
334 ## beta.pre.tca[8] <- 0
335 ## beta.post.tca[2] <- 0
336 ## beta.post.tca[5] <- 0
337 ## beta.post.tca[7] <- 0
338 ## beta.post.tca[8] <- 0
339 ## beta.winter.np[2] <- 0
340 ## beta.winter.np[5] <- 0
341 ## beta.winter.np[7] <- 0
342 ## beta.winter.np[8] <- 0
343 ## beta.pre.np[2] <- 0
344 ## beta.pre.np[5] <- 0
345 ## beta.pre.np[7] <- 0
346 ## beta.pre.np[8] <- 0
347 ## beta.post.np[2] <- 0
348 ## beta.post.np[5] <- 0
349 ## beta.post.np[7] <- 0
350 ## beta.post.np[8] <- 0
351 ##
352 ## # beta coefficients
353 ## beta.naive ~ dnorm(0, tau.naive)
354 ##
355 ## # precision terms
356 ## tau.naive ~ dgamma(0.001,0.001)
357 ## tau.alpha ~ dgamma(0.001,0.001)
358 ## tau.alpha.trend ~ dgamma(0.001,0.001)
359 ## tau.w ~ dgamma(0.001,0.001)
360 ## tau.trend ~ dgamma(0.001,0.001)
361 ## tau.eps ~ dgamma(0.1,0.1)
362 ## tau.cumBreed ~ dgamma(0.001,0.001)
363 ## tau.cumPre ~ dgamma(0.001,0.001)
364 ## tau.cumPost ~ dgamma(0.001,0.001)
365 ## tau.cumWinter ~ dgamma(0.001,0.001)
366 ## tau.cumLoss ~ dgamma(0.001,0.001)
367 ## tau.breedLPI ~ dgamma(0.001,0.001)
368 ## tau.breedNP ~ dgamma(0.001,0.001)
369 ## tau.breedTCA ~ dgamma(0.001,0.001)
370 ## tau.npPost ~ dgamma(0.001,0.001)
371 ## tau.npPre ~ dgamma(0.001,0.001)
```



```

417 ##          beta.pre.tca[population[i]] * preTCA[population[i],t] +
418 ##          beta.post.tca[population[i]] * postTCA[population[i],t] +
419 ##
420 ##          # Largest Patch Index #
421 ##          beta.breed.lpi[population[i]] * breedLPI[i,t] +
422 ##          beta.winter.lpi[population[i]] * winterLPI[population[i],t] +
423 ##          beta.pre.lpi[population[i]] * preLPI[population[i],t] +
424 ##          beta.post.lpi[population[i]] * postLPI[population[i],t] +
425 ##
426 ##          # nearest patch #
427 ##          beta.breed.np[population[i]] * breedNP[i,t] +
428 ##          beta.winter.np[population[i]] * winterNP[population[i],t] +
429 ##          beta.pre.np[population[i]] * preNP[population[i],t] +
430 ##          beta.post.np[population[i]] * postNP[population[i],t] +
431 ##
432 ##          # Naive observer effects and random error #
433 ##          beta.naive * naive[i,t] + w[i,t] + eps[population[i],i,t]
434 ##
435 ## # Fit assessments: Chi-square test statistic & posterior predictive check #
436 ## #observed
437 ## chi2[i,t] <- pow((CH.array[i,t]-lambda[i,t]),2) / (sqrt(lambda[i,t])+0.0001)
438 ## # expected
439 ## new.est[i,t] ~ dpois(lambda[i,t])
440 ## chi2.new[i,t] <- pow((new.est[i,t]-lambda[i,t]),2) / (sqrt(lambda[i,t])+0.0001)
441 ## } # end t years
442 ## } # end i routes
443 ##
444 ## fit <- sum(chi2[,])
445 ## fit.new <- sum(chi2.new[,])
446 ##
447 ## for(t in 1:18){
448 ## meanAbun[1,t] <- mean(lambda[pop1,t])
449 ## meanAbun[2,t] <- mean(lambda[pop2,t])
450 ## meanAbun[3,t] <- mean(lambda[pop3,t])
451 ## meanAbun[4,t] <- mean(lambda[pop4,t])
452 ## meanAbun[5,t] <- mean(lambda[pop5,t])
453 ## meanAbun[6,t] <- mean(lambda[pop6,t])
454 ## meanAbun[7,t] <- mean(lambda[pop7,t])
455 ## meanAbun[8,t] <- mean(lambda[pop8,t])
456 ## }
457 ## for(p in 1:8){
458 ## rel.abun[p,1:18] <- meanAbun[p,1:18]/max(meanAbun[p,1])
459 ## rel.2000[p,1:18] <- meanAbun[p,1:18]/meanAbun[p,1]
460 ## }

```

461 ##  
462 ## }