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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Supplemental Methods

Light-level geolocation

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

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 km^2) and non-breeding seasons (250,000 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 $^{-yr}$) followed by the stationary non-breeding landscapes (mean = -28.45, range

64   = -38.98 - -2.57 thousand ha $^{-yr}$), stopover regions post Atlantic crossing (mean = -49.79, range =

65   -79.41 - -15.13 thousand ha $^{-yr}$) and finally the breeding grounds (mean = -14.01, range = -21.57

66   - -7.29 thousand ha $^{-yr}$).

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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

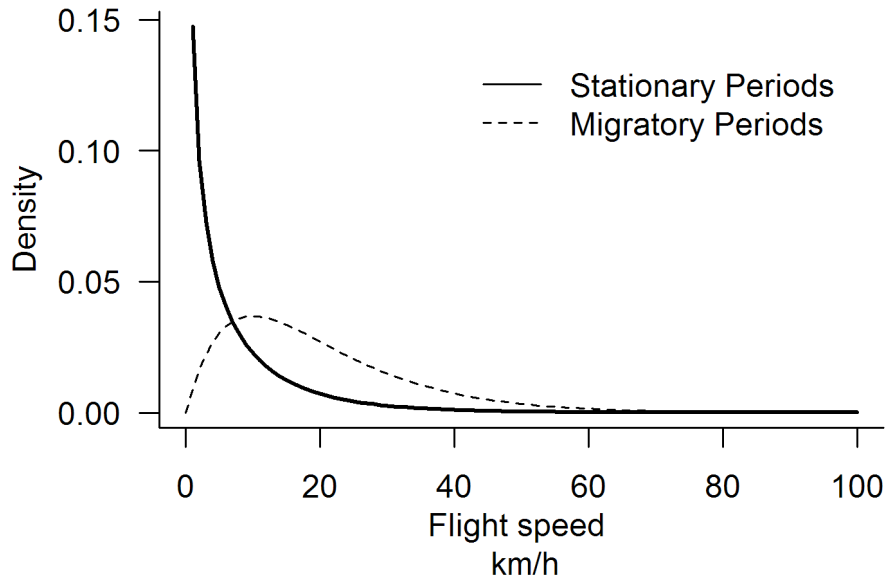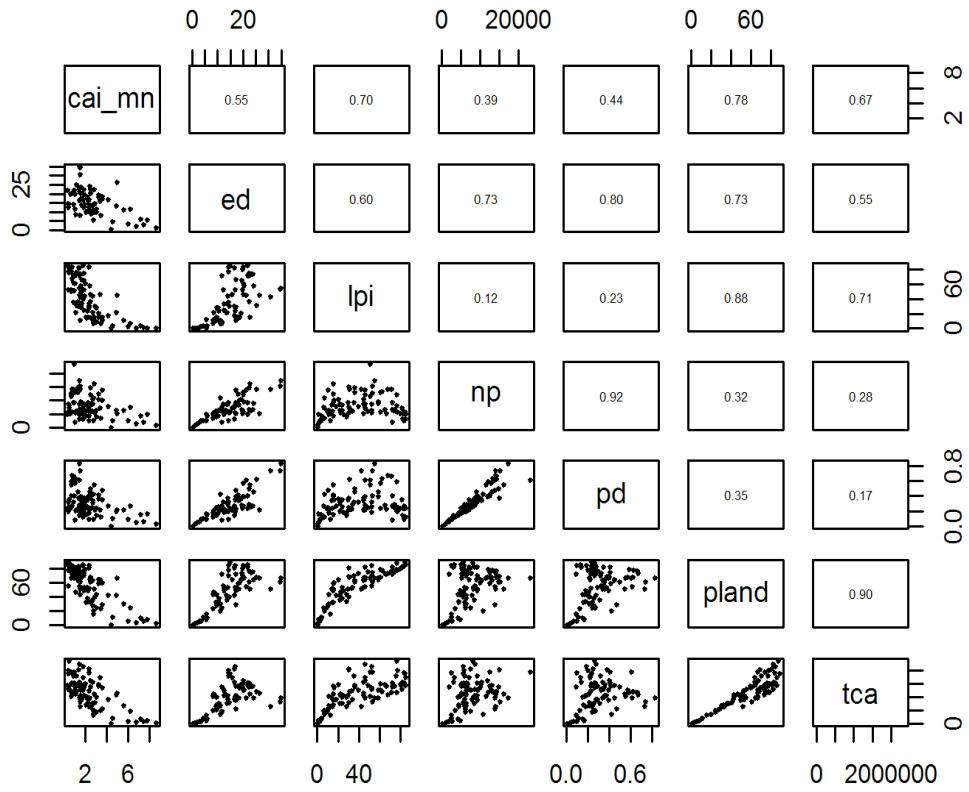98   regions used by Connecticut warblers during spring and fall migration are similar.
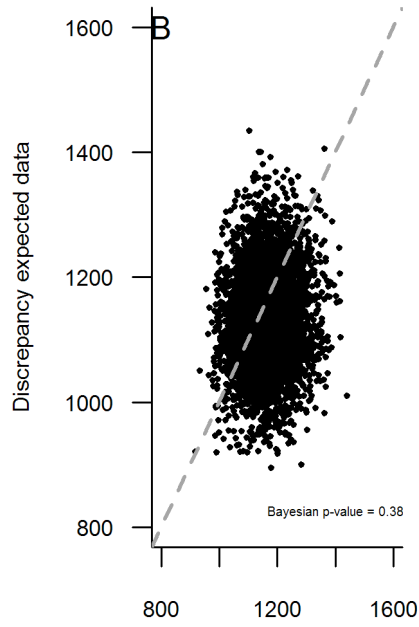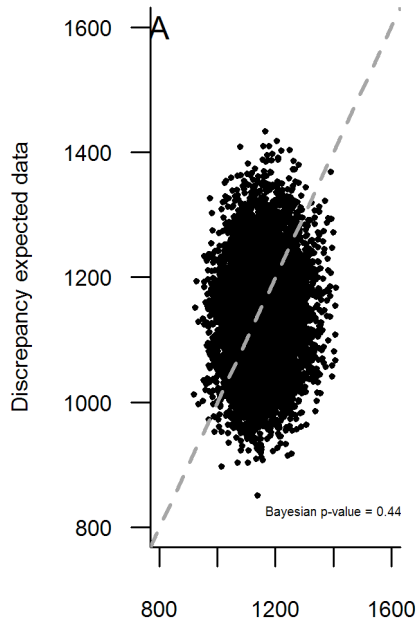
99

100   **Fig. S1**

101

102

103   **Fig. S2**

104

105

106   **Fig. S3**

107

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109   **Fig. S4**
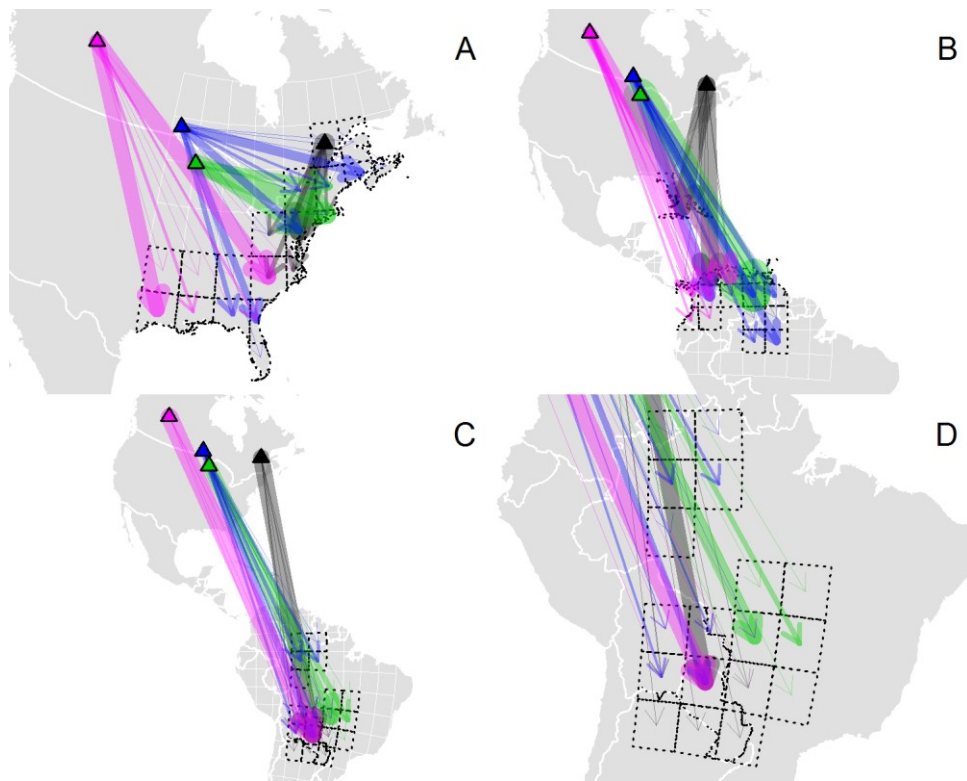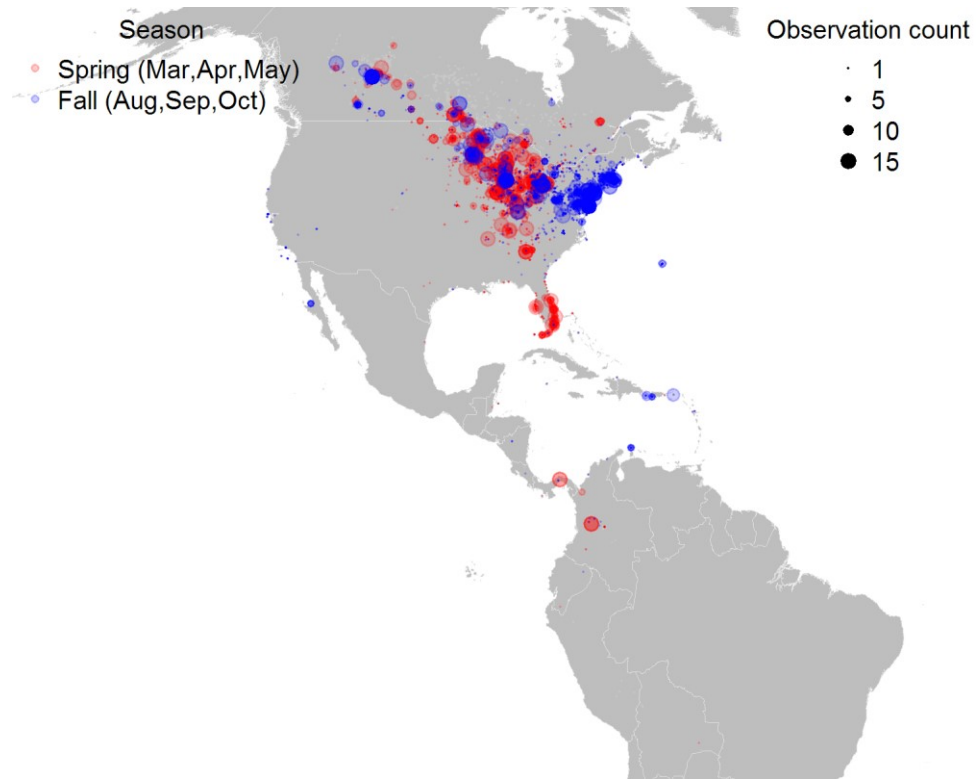

110   Discrepancy observed data

111

112   **Fig. S5**

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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)
```

```
372    ## tau.npWinter ~ dgamma(0.001,0.001)
373    ## tau.lpiPost ~ dgamma(0.001,0.001)
374    ## tau.lpiPre ~ dgamma(0.001,0.001)
375    ## tau.lpiWinter ~ dgamma(0.001,0.001)
376    ## tau.tcaPost ~ dgamma(0.001,0.001)
377    ## tau.tcaPre ~ dgamma(0.001,0.001)
378    ## tau.tcaWinter ~ dgamma(0.001,0.001)
379    ##
380    ## # error for each observer
381    ## for(o in 1:nobservers){
382    ## obs[o] ~ dnorm(Hyper_obs,tau.w)
383    ## }
384    ## # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # #
385    ## #                          Likelihood statement                              #
386    ## # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # #
387    ## for(i in 1:nroutes){
388    ## for(t in 1:18){
389    ## for(p in 1:npopulations){
390    ##  eps[p,i,t] ~ dnorm(Hyper_eps,tau.eps) # random error
391    ##  }
392    ##
393    ## w[i,t] <- obs[observer[i,t]] # random effect observer
394    ##
395    ##
396    ## # Capture History Array - poisson of expected abundance
397    ## CH.array[i,t] ~ dpois(lambda[i,t])
398    ##
399    ## # expected abundance using log link
400    ## log(lambda[i,t]) <- alpha[population[i]] +
401    ##                     beta.trend[population[i]] * year[t] +
402    ##               # FOREST LOSS METRICS #
403    ##               beta.cumbreed[population[i]] * cumbreedLoss[i,t] +
404    ##               beta.cumwinter[population[i]] * cumwinter[population[i],t] +
405    ##               beta.cumpre[population[i]] * cumpre[population[i],t]+
406    ##               beta.cumpost[population[i]] * cumpost[population[i],t]+
407    ##
408    ##               # Cumulative loss throughout the annual cycle #
409    ##               beta.cumloss[population[i]] * (cumbreedLoss[i,t] +
410    ##                                      cumwinter[population[i],t]+
411    ##                                      cumpre[population[i],t]+
412    ##                                      cumpost[population[i],t]) +
413    ##                # FRAGMENTATION METRICS #
414    ##                # total core area #
415    ##                   beta.breed.tca[population[i]] * breedTCA[i,t] +
416    ##                   beta.winter.tca[population[i]] * winterTCA[population[i],t] +
```

```
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    ## }
```