

Article

Nest Change and Individual Fitness in a Scopoli's Shearwater Population: A Capture-Recapture Multistate Analysis

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Supplementary materials

Supplementary Material S1 - Goodness of fit

The software U-CARE, version 2.3.4 (Choquet et al. 2009a), is specific to assess the fit of the Cormack-Jolly-Seber (CJS) models even in multistate form. In this section, we present the results of the global test and the specific tests (test of memory, test of transience, composite test and test of trap dependence) applied to our female and male datasets.

The GOF global test indicated a good fit of the model to the data of both sexes (females: $\chi^2 = 17.473$, d.f. = 34, p = 0.99; males: $\chi^2 = 15.060$, d.f. = 45, p = 1). All the specific tests has resulted non-significative. The M.LTEC test, for males, could not be run.

Table S1.1. - Females.

GLOBAL MULTISTATE TEST, group =1

Test 3G (sta, pval, df)
15.329 0.994 32.000

Test M (sta, pval, df)
2.144 0.342 2.000

Goodness-of fit Test for the JMV Model (sta, pval, df)
17.473 0.991 34.000

TEST WBWA (test of memory: Where Before vs Where After) , group =1

H0(i,l) : there is no difference in the expected state of next reencounter among the individuals previously encountered in the different states.

TEST WBWA (sta, pval, df, phiP, phiF, phi(corrected) : Afroz et al. Biometrics 2019)
0.000 1.000 3.000 1.426 1.648 1.604

TEST 3G.SR (test of transience), group =1

H0(i,l) : there is no difference in the probability of being later reencountered between "new" and "old" individuals encountered at occasion i in state l.

TEST 3G.SR (sta, pval, df , phiP, phiF, phi(corrected) : Afroz et al. Biometrics 2019)
4.772 0.906 10.000 0.831 0.851 0.839

TEST 3G.Sm (composite test), group =1

there is no difference in the expected time of first reencounter between the individuals encountered at occasion in state l that have been encountered earlier and will be next reencountered in state j based on their state of most recent encounter.

TEST 3G.Sm (sta, pval, df, phiP, phiF, phi(corrected) : Afroz et al. Biometrics 2019)
 10.557 0.938 19.000 1.926 1.709 1.737

TEST M.ITEC (test of immediate trap-dependance), group =1

H0 : there is no difference in the probabilities of being reencountered in the different states between the animals encountered and not encountered at the previous occasion then in the same state, conditional on presence at both occasions

TEST M.ITEC (chi2, p(chi2), g2, p(g2), df)
 2.098 0.148 2.419 0.120 1.000

 TEST M.LTEC, group =1

H0(i) : there is no difference in the expected time and state of next reencounter between the individuals in the same state at occasion i that were not encountered at occasion i+1 whether encountered or not encountered at occasion i conditional on presence at both occasions i and i+2.

TEST M.LTEC (chi2, p(chi2), g2, p(g2), df)
 0.046 0.830 0.047 0.829 1.000

Table S1.2. - Males.

GLOBAL MULTISTATE TEST, group =1

Test 3G (sta, pval, df)
 12.177 1.000 44.000

Test M (sta, pval, df)
 2.883 0.090 1.000

Goodness-of fit Test for the JMV Model (sta, pval, df)
15.060 1.000 45.000

TEST WBWA (test of memory: Where Before vs Where After) , group =1

H0(i,l) : there is no difference in the expected state of next reencounter among the individuals previously encountered in the different states.

TEST WBWA (sta, pval, df, phiP, phiF, phi(corrected) : Afroz et al. Biometrics 2019)
 0.000 1.000 6.000 0.519 0.744 0.585

TEST 3G.SR (test of transience), group =1

H0(i,l) : there is no difference in the probability of being later reencountered between “new” and “old” individuals encountered at occasion i in state l.

TEST 3G.SR (sta, pval, df , phiP, phiF, phi(corrected) : Afroz et al. Biometrics 2019)
 7.845 0.644 10.000 1.262 1.194 1.221

TEST 3G.Sm (composite test), group =1

there is no difference in the expected time of first reencounter between the individuals encountered at occasion i in state l that have been encountered earlier and will be next reencountered in state j based on their state of most recent encounter.

TEST 3G.Sm (sta, pval, df, phiP, phiF, phi(corrected) : Afroz et al. Biometrics 2019)

4.331	1.000	28.000	0.990	0.995	0.993

TEST M.ITEC (test of immediate trap-dependance), group =1

H0 : there is no difference in the probabilities of being reencountered in the different states between the animals encountered and not encountered at the previous occasion then in the same state, conditional on presence at both occasions

TEST M.ITEC (chi2, p(chi2), g2, p(g2), df)
2.883 0.090 3.659 0.056 1.000

TEST M.LTEC group =1

H0(i) : there is no difference in the expected time and state of next reencounter between the individuals in the same state at occasion i that were not encountered at occasion i+1 whether encountered or not encountered at occasion i conditional on presence at both occasions i and i+2.

TEST M.LTEC (chi2, p(chi2), g2, p(g2), df)
0.000 NaN 0.000 NaN 0.000

Supplementary Material S2. Stochastic model for cumulative Nest change probability estimation (R-script code)

Estimation of the demographic variables' confidence intervals. We performed an analysis to examine each variable's mean bootstrap distribution. Each mean value that is extracted for the bootstrap loop is taken from a beta distribution of the values around the mean and is between the two limits of the CI for the variable.

```
library(damppack) #for beta distribution alpha and beta parameters estimation
```

Table S2.1. - Females.

```
ASexpf<- matrix(nrow=1000,ncol=25) # Percentage of females who changed nest over the years vs. those who didn't change.
```

```
NNf <- matrix(nrow=1000,ncol=25) #Number of females in a new nest per year
OOf <- matrix(nrow=1000,ncol=25) #Number of females in an old nest per year
for(i in 1:1000){ meanASfw <- 0.897 #Winner-Females' Apparent survival
minASfw <- 0.834; maxASfw <- 0.939
distASfw <- vector()
muASfw <- (minASfw + 4*meanASfw + maxASfw)/6
dev.stASfw <- (maxASfw-minASfw)/6
alphaASfw <- beta_params(muASfw, dev.stASfw)[1]
betaASfw <- beta_params(muASfw, dev.stASfw)[2]
ASfw <- rbeta(1,alphaASfw$alpha,betaASfw$beta)

meanASfl <- 0.725 #loser-Females' Apparent survival
minASfl <- 0.531; maxASfl <- 0.860
distASfl <- vector()
muASfl <- (minASfl + 4*meanASfl + maxASfl)/6
dev.stASfl <- (maxASfl-minASfl)/6
alphaASfl <- beta_params(muASfl, dev.stASfl)[1]
betaASfl <- beta_params(muASfl, dev.stASfl)[2]
ASfl <- rbeta(1,alphaASfl$alpha,betaASfl$beta)

meanNCfw <- 0.000 # Winner-Females' Nest change probability
minNCfw <- 0.000; maxNCfw <- 0.037
distNCfw <- vector()
muNCfw <- (minNCfw + 4*meanNCfw + maxNCfw)/6
dev.stNCfw <- (maxNCfw-minNCfw)/6
alphaNCfw <- beta_params(muNCfw, dev.stNCfw)[1]
betaNCfw <- beta_params(muNCfw, dev.stNCfw)[2]
NCfw <- rbeta(1,alphaNCfw$alpha,betaNCfw$beta)

meanNCfl <- 0.376 # Loser-Females' Nest change probability
minNCfl <- 0.207; maxNCfl <- 0.581
distNCfl <- vector()
muNCfl <- (minNCfl + 4*meanNCfl + maxNCfl)/6
dev.stNCfl <- (maxNCfl-minNCfl)/6
alphaNCfl <- beta_params(muNCfl, dev.stNCfl)[1]
betaNCfl <- beta_params(muNCfl, dev.stNCfl)[2]
NCfl <- rbeta(1,alphaNCfl$alpha,betaNCfl$beta)

meanBCfw <- 0.889 # Winner-Females' Breeding success change probability
minBCfw <- 0.825; maxBCfw <- 0.932
distBCfw <- vector()
muBCfw <- (minBCfw + 4*meanBCfw + maxBCfw)/6
dev.stBCfw <- (maxBCfw-minBCfw)/6
alphaBCfw <- beta_params(muBCfw, dev.stBCfw)[1]
betaBCfw <- beta_params(muBCfw, dev.stBCfw)[2]
BCfw <- rbeta(1,alphaBCfw$alpha,betaBCfw$beta)

meanBCfl <- 0.666 # Loser-Females' Breeding success change probability
minBCfl <- 0.400; maxBCfl <- 0.857
distBCfl <- vector()
muBCfl <- (minBCfl + 4*meanBCfl + maxBCfl)/6
dev.stBCfl <- (maxBCfl-minBCfl)/6
alphaBCfl <- beta_params(muBCfl, dev.stBCfl)[1]
betaBCfl <- beta_params(muBCfl, dev.stBCfl)[2]
BCfl <- rbeta(1,alphaBCfl$alpha,betaBCfl$beta)
```

```

meanBSf1y <- 0.765 #First year breeding-Females' Breeding success probability
minBSf1y <- 0.694; maxBSf1y <- 0.834
distBSf1y <- vector()
muBSf1y <- (minBSf1y + 4*meanBSf1y + maxBSf1y)/6
dev.stBSf1y <- (maxBSf1y-minBSf1y)/6
alphaBSf1y <- beta_params(muBSf1y, dev.stBSf1y)[1]
betaBSf1y <- beta_params(muBSf1y, dev.stBSf1y)[2]
BSf1y <- rbeta(1,alphaBSf1y$alpha,betaBSf1y$beta)

OL1f <- 100*(1-BSf1y); OW1f <- 100*BSf1y
OL2f <- 0; NL2f <- 0; OW2f <- 0; NW2f <- 0; O2f <- 0; N2f <- 0
for(j in 2:25){OL2f[j] <- OL1f*(1-NCfl)+OW1f*(1-NCfw)*(1-BCfw)
  OW2f[j] <- OL1f*(1-NCfl)*BCfl+OW1f*(1-NCfw)*BCfw
  NL2f[j] <- OL1f*NCfl*(1-BCfl)+OW1f*NCfw*(1-BCfw)
  NW2f[j] <- OL1f*NCfl*BCfl+OW1f*NCfw*BCfw
  OL2f[j] <- ASfl*OL2f[j-1]*(1-NCfl)*(1-BCfl)+ASfw*OW2f[j-1]*(1-NCfw)*(1-BCfw)
  OW2f[j] <- ASfl*OL2f[j-1]*(1-NCfl)*BCfl+ASfw*OW2f[j-1]*(1-NCfw)*BCfw
  NL2f[j] <- ASfl*OL2f[j-1]*NCfl*(1-BCfl)+ASfw*OW2f[j-1]*NCfw*(1-BCfw)
    +ASfl*NL2f[j-1]*(1-BCfl)+ASfw*NW2f[j-1]*(1-BCfw)
  NW2f[j] <- ASfl*OL2f[j-1]*NCfl*BCfl+ASfw*OW2f[j-1]*NCfw*BCfw+ASfl*NL2f[j-1]*BCfl
    +ASfw*NW2f[j-1]*BCfw
  OL2f[j];OW2f[j];NL2f[j];NW2f[j]
  O2f[j] <- OL2f[j]+OW2f[j]
  N2f[j] <- NL2f[j]+NW2f[j]
  N2f[j]; O2f[j]
}

O2f[1]<-OL2f[1]+OW2f[1]
N2f[1]<-NL2f[1]+NW2f[1]
ASexpf[i,] <- N2f/(N2f+O2f) #Percentage of individuals who changed nest vs. total sampled population
NNf[i,] <- N2f
OOf[i,] <- O2f
}

NN1f <- data.frame(0,NNf)
OO1f <- data.frame(100,OOf)
ASexpfdf <- t(ASexpf)
meanASexpf <- rowMeans(ASexpfdf) #mean cumulative nest change probability
increasef <- vector()
for(i in 1:26){
  increasef[0] <- 0
  increasef[i] <- meanASexpf[i]-meanASexpf[i-1]
  increasef
}
mean(increasef[3:8]) #mean increase of cumulative nest change probability from third year
RLE <- 1/-log(0.867) #RLE of females
RLEfmean <- qnorm(0.5, mean(ASexpfdf[8,]), sd(ASexpfdf[8,])) #Cumulative NC probability at RLE
RLEfmin <- qnorm(0.025, mean(ASexpfdf[8,]), sd(ASexpfdf[8,]))
RLEfmax <- qnorm(0.975, mean(ASexpfdf[8,]), sd(ASexpfdf[8,]))
paste("Cumulative nest change probability at RLE", round(RLEfmean,3),",",round(RLEfmin,3),"-",
  round(RLEfmax,3),"")
femValues <- data.frame(round(meanASexpf,3))
colnames(femValues)<- c("Female NC prob")
rownames(femValues) <- c(seq(1,26,1));femValues

```

Table S2.2. - Males.

```

ASexpm <- matrix(nrow=1000,ncol=25) # Percentage of males who changed nest over the years vs. those who
didn't change.
NNm <- matrix(nrow=1000,ncol=25) #Number of males in a new nest per year
OOr <- matrix(nrow=1000,ncol=25) #Number of males in an old nest per year

for(i in 1:1000){ meanASm <- 0.895 #Males' Apparent survival
  minASm <- 0.851
  maxASm <- 0.927
  distASm <- vector()
  muASm <- (minASm + 4*meanASm + maxASm)/6

```

```

dev.stASm <- (maxASm-minASm)/6
alphaASm <- beta_params(muASm, dev.stASm)[1]
betaASm <- beta_params(muASm, dev.stASm)[2]
ASm <- rbeta(1,alphaASm$alpha,betaASm$beta)

meanNCml1 <- 0.086 #First year breeding-loser-males' Nest change probability
minNCml1 <- 0.013
maxNCml1 <- 0.400
distNCml1 <- vector()
muNCml1 <- (minNCml1 + 4*meanNCml1 + maxNCml1)/6
dev.stNCml1 <- (maxNCml1-minNCml1)/6
alphaNCml1 <- beta_params(muNCml1, dev.stNCml1)[1]
betaNCml1 <- beta_params(muNCml1, dev.stNCml1)[2]
NCml1 <- rbeta(1,alphaNCml1$alpha,betaNCml1$beta)

meanNCml2 <- 0.483 #Second year breeding-loser-males' Nest change probability
minNCml2 <- 0.192
maxNCml2 <- 0.787
distNCml2 <- vector()
muNCml2 <- (minNCml2 + 4*meanNCml2 + maxNCml2)/6
dev.stNCml2 <- (maxNCml2-minNCml2)/6
alphaNCml2 <- beta_params(muNCml2, dev.stNCml2)[1]
betaNCml2 <- beta_params(muNCml2, dev.stNCml2)[2]
NCml2 <- rbeta(1,alphaNCml2$alpha,betaNCml2$beta)

meanNCml3 <- 0.000 #Third+ year breeding-loser-males' Nest change probability
minNCml3 <- 0.000
maxNCml3 <- 0.034
distNCml3 <- vector()
muNCml3 <- (minNCml3 + 4*meanNCml3 + maxNCml3)/6
dev.stNCml3 <- (maxNCml3-minNCml3)/6
alphaNCml3 <- beta_params(muNCml3, dev.stNCml3)[1]
betaNCml3 <- beta_params(muNCml3, dev.stNCml3)[2]
NCml3 <- rbeta(1,alphaNCml3$alpha,betaNCml3$beta)

meanNCmw1 <- 0.014 #First year breeding-winner-males' Nest change probability
minNCmw1 <- 0.003
maxNCmw1 <- 0.138
distNCmw1 <- vector()
muNCmw1 <- (minNCmw1 + 4*meanNCmw1 + maxNCmw1)/6
dev.stNCmw1 <- (maxNCmw1-minNCmw1)/6
alphaNCmw1 <- beta_params(muNCmw1, dev.stNCmw1)[1]
betaNCmw1 <- beta_params(muNCmw1, dev.stNCmw1)[2]
NCmw1 <- rbeta(1,alphaNCmw1$alpha,betaNCmw1$beta)

meanNCmw2 <- 0.121 #Second year breeding-winner-males' Nest change probability
minNCmw2 <- 0.043
maxNCmw2 <- 0.297
distNCmw2 <- vector()
muNCmw2 <- (minNCmw2 + 4*meanNCmw2 + maxNCmw2)/6
dev.stNCmw2 <- (maxNCmw2-minNCmw2)/6
alphaNCmw2 <- beta_params(muNCmw2, dev.stNCmw2)[1]
betaNCmw2 <- beta_params(muNCmw2, dev.stNCmw2)[2]
NCmw2 <- rbeta(1,alphaNCmw2$alpha,betaNCmw2$beta)

meanNCmw3 <- 0.000 #Third+ year breeding-winner-males' Nest change probability
minNCmw3 <- 0.000
maxNCmw3 <- 0.034
distNCmw3 <- vector()
muNCmw3 <- (minNCmw3 + 4*meanNCmw3 + maxNCmw3)/6
dev.stNCmw3 <- (maxNCmw3-minNCmw3)/6
alphaNCmw3 <- beta_params(muNCmw3, dev.stNCmw3)[1]
betaNCmw3 <- beta_params(muNCmw3, dev.stNCmw3)[2]
NCmw3 <- rbeta(1,alphaNCmw3$alpha,betaNCmw3$beta)

meanBCmOw <- 0.789 #OLD-winner-Males' Breeding success change probability
minBCmOw <- 0.693

```

```

maxBCmOw <- 0.861
distBCmOw <- vector()
muBCmOw <- (minBCmOw + 4*meanBCmOw + maxBCmOw)/6
dev.stBCmOw <- (maxBCmOw-minBCmOw)/6
alphaBCmOw <- beta_params(muBCmOw, dev.stBCmOw)[1]
betaBCmOw <- beta_params(muBCmOw, dev.stBCmOw)[2]
BCmOw <- rbeta(1,alphaBCmOw$alpha,betaBCmOw$beta)

meanBCmNw <- 0.835 #NEW-winner-Males' Breeding success change probability
minBCmNw <- 0.623
maxBCmNw <- 0.940
distBCmNw <- vector()
muBCmNw <- (minBCmNw + 4*meanBCmNw + maxBCmNw)/6
dev.stBCmNw <- (maxBCmNw-minBCmNw)/6
alphaBCmNw <- beta_params(muBCmNw, dev.stBCmNw)[1]
betaBCmNw <- beta_params(muBCmNw, dev.stBCmNw)[2]
BCmNw <- rbeta(1,alphaBCmNw$alpha,betaBCmNw$beta)

meanBCmOl <- 0.610 #OLD-loser-Males' Breeding success change probability
minBCmOl <- 0.412
maxBCmOl <- 0.775
distBCmOl <- vector()
muBCmOl <- (minBCmOl + 4*meanBCmOl + maxBCmOl)/6
dev.stBCmOl <- (maxBCmOl-minBCmOl)/6
alphaBCmOl <- beta_params(muBCmOl, dev.stBCmOl)[1]
betaBCmOl <- beta_params(muBCmOl, dev.stBCmOl)[2]
BCmOl <- rbeta(1,alphaBCmOl$alpha,betaBCmOl$beta)

meanBCmNI <- 1.000 #NEW-loser-Males' Breeding success change probability
minBCmNI <- 0.997
maxBCmNI <- 1.000
distBCmNI <- vector()
muBCmNI <- (minBCmNI + 4*meanBCmNI + maxBCmNI)/6
dev.stBCmNI <- (maxBCmNI-minBCmNI)/6
alphaBCmNI <- beta_params(muBCmNI, dev.stBCmNI)[1]
betaBCmNI <- beta_params(muBCmNI, dev.stBCmNI)[2]
BCmNI <- rbeta(1,alphaBCmNI$alpha,betaBCmNI$beta)

meanBSm1y <- 0.673 #First year breeding-Males' Breeding success probability
minBSm1y <- 0.580
maxBSm1y <- 0.754
distBSm1y <- vector()
muBSm1y <- (minBSm1y + 4*meanBSm1y + maxBSm1y)/6
dev.stBSm1y <- (maxBSm1y-minBSm1y)/6
alphaBSm1y <- beta_params(muBSm1y, dev.stBSm1y)[1]
betaBSm1y <- beta_params(muBSm1y, dev.stBSm1y)[2]
BSm1y <- rbeta(1,alphaBSm1y$alpha,betaBSm1y$beta)

OL1m <- 100*(1-BSm1y); OW1m <- 100*BSm1y
OL2m <- 0; NL2m <- 0; OW2m <- 0; NW2m <- 0; O2m <- 0; N2m <- 0
for(j in 3:25){OL2m[1] <- OL1m*(1-NCml1)*(1-BCmOl)+OW1m*(1-NCmw1)*(1-BCmOw)
  OW2m[1] <- OL1m*(1-NCml1)*BCmOl+OW1m*(1-NCmw1)*BCmOw
  NL2m[1] <- OL1m*NCml1*(1-BCmNI)+OW1m*NCmw1*(1-BCmNw)
  NW2m[1] <- OL1m*NCml1*BCmNi+OW1m*NCmw1*BCmNw
  OL2m[2] <- ASm*OL2m[1]*(1-NCml2)*(1-BCmOl)+ASm*OW2m[1]*(1-NCmw2)*(1-BCmOw)
  OW2m[2] <- ASm*OL2m[1]*(1-NCml2)*BCmOl+ASm*OW2m[1]*(1-NCmw2)*BCmOw
  NL2m[2] <- ASm*OL2m[1]*NCml2*(1-BCmNI)+ASm*OW2m[1]*NCmw2*(1-BCmNw)
    +ASm*NL2m[1]*(1-BCmNI)+ASm*NW2m[1]*(1-BCmNw)
  NW2m[2] <- ASm*OL2m[1]*NCml2*BCmNi+ASm*OW2m[1]*NCmw2*BCmNw+ASm*NL2m[1]*BCmNI
    +ASm*NW2m[1]*BCmNw
  OL2m[j] <- ASm*OL2m[j-1]*(1-NCml3)*(1-BCmOl)+ASm*OW2m[j-1]*(1-NCmw3)*(1-BCmOw)
  OW2m[j] <- ASm*OL2m[j-1]*(1-NCml3)*BCmOl+ASm*OW2m[j-1]*(1-NCmw3)*BCmOw
  NL2m[j] <- ASm*OL2m[j-1]*NCml3*(1-BCmNI)+ASm*OW2m[j-1]*NCmw3*(1-BCmNw)
    +ASm*NL2m[j-1]*(1-BCmNI)+ASm*NW2m[j-1]*(1-BCmNw)
  NW2m[j] <- ASm*OL2m[j-1]*NCml3*BCmNi+ASm*OW2m[j-1]*NCmw3*BCmNw
    +ASm*NL2m[j-1]*BCmNi+ASm*NW2m[j-1]*BCmNw
  OL2m[j];OW2m[j];NL2m[j];NW2m[j]}

```

```

O2m[j] <- OL2m[j]+OW2m[j]
N2m[j] <- NL2m[j]+NW2m[j]
N2m[2] <- NL2m[2]+NW2m[2]
O2m[2] <- OL2m[2]+OW2m[2]
}

O2m[1]<-OL2m[1]+OW2m[1]
N2m[1]<-NL2m[1]+NW2m[1]
ASexpm[i,] <- N2m/(N2m+O2m) #Percentage of individuals who changed nest vs. total sampled population
NNm[i,] <- N2m
OOm[i,] <- O2m
}

NN1m <- data.frame(0,NNm)
OO1m <- data.frame(100,OOm)
ASexpm1 <- data.frame(0,ASexpm)

ASexpmdf <- t(ASexpm1)
meanASexpm <- rowMeans(ASexpmdf) #mean cumulative nest change probability
increasem <- vector()
for(i in 1:26) {
  increasem[0] <- 0
  increasem[i] <- meanASexpm[i]-meanASexpm[i-1]
  increasem
}
mean(increasem[4:10]) #mean increase of cumulative nest change probability from third year
RLEm 1-/log(0.895) #RLE of males
RLEmmean <- qnorm(0.5, mean(ASexpmdf[10,]), sd(ASexpmdf[10,])) #Cumulative NC probability at RLE
RLEmmmin <- qnorm(0.025, mean(ASexpmdf[10,]), sd(ASexpmdf[10,]))
RLEmax <- qnorm(0.975, mean(ASexpmdf[10,]), sd(ASexpmdf[10,]))
twoymmean <- qnorm(0.5, mean(ASexpmdf[3,]), sd(ASexpmdf[3,])) #Cumulative NC probability at 2 years
twoymmin <- qnorm(0.025, mean(ASexpmdf[3,]), sd(ASexpmdf[3,]))
twoymax <- qnorm(0.975, mean(ASexpmdf[3,]), sd(ASexpmdf[3,]))
paste("Cumulative nest change probability at RLE (males)", round(RLEmmean,3),",",round(RLEmmmin,3),"-
",round(RLEmax,3),"")
paste("Cumulative nest change probability at two years (males)",round(twoymmean,3),",", round(twoym-
min,3),"-",round(twoymax,3),"")
}

malValues <- data.frame(round(meanASexpm,3))
colnames(malValues)<- c("Male NC prob")
rownames(malValues) <- c(seq(1,26,1));malValues

```

Table S2.3. – Yearly nest change probability for females and males Scopoli's shearwater estimated with stochastic simulation. Year [1] is an individual's first reproduction ever.

year	males	females
[1]	0.0637	0.0946
[2]	0.2175	0.0452
[3]	0.0042	0.0386
[4]	0.0042	0.0364
[5]	0.0041	0.0347
[6]	0.0041	0.0331
[7]	0.004	0.0315
[8]	0.004	0.0301
[9]	0.004	0.0287
[10]	0.0039	0.0274
[11]	0.0039	0.0261
[12]	0.0039	0.0249
[13]	0.0038	0.0238
[14]	0.0038	0.0227

Supplementary Material S3. Models

Table S3.1. - female model definition (model F1).

# of step for initial state	1
Phrase for step 1 pattern matrix (IS)	to p * - -
# of step for transition:	3
Phrase for step 1 pattern matrix (AS)	f(1 3, 2 4) $\left[\begin{array}{ccccc} y & - & - & - & * \\ - & y & - & - & * \\ - & - & y & - & * \\ - & - & - & y & * \\ - & - & - & - & * \end{array} \right]$
Phrase for step 2 pattern matrix (NC)	f $\left[\begin{array}{ccccc} * & - & y & - & - \\ - & * & - & y & - \\ - & - & * & - & - \\ - & - & - & * & - \\ - & - & - & - & * \end{array} \right]$
Phrase for step 3 pattern matrix (BSC)	f(1 3, 2 4) $\left[\begin{array}{ccccc} * & y & - & - & - \\ * & y & - & - & - \\ - & - & * & y & - \\ - & - & * & y & - \\ - & - & - & - & * \end{array} \right]$
# of step for encounter :	1
Phrase for step 1 pattern matrix (R)	firste+nexte.t $\left[\begin{array}{ccccc} * & b & - & - & - \\ * & - & b & - & - \\ * & - & - & b & - \\ * & - & - & - & b \\ * & - & - & - & - \end{array} \right]$

IVFV (Initial Values and Fixed Values of parameters in Capture-recapture models)

- All initial values have been set to “random”.
- Probability of first capture has been fixed to 1.00.
- Transition parameter beta#4 - NC 2, 4 (From, To) is fixed to 0.00 (because it is a value at the boundary of 0.00). This parameter is the chance that an individual in state OLD_t-winner_t transits to state NEW_{t+1}-winner_t.

Table S3.2. - male model definition (model M1).

# of step for initial state	1
Phrase for step 1 pattern matrix (IS)	to p * - -
# of step for transition:	3
Phrase for step 1 pattern matrix (AS)	i $\left[\begin{array}{ccccc} y & - & - & - & * \\ - & y & - & - & * \\ - & - & y & - & * \end{array} \right]$

	-	-	-	y	*
	-	-	-	-	*
<hr/>					
Phrase for step 2	f+a				
pattern matrix (NC)	*	-	y	-	-
	-	*	-	y	-
	-	-	*	-	-
	-	-	-	*	-
	-	-	-	-	*
<hr/>					
Phrase for step 3	f				
pattern matrix (BSC)	*	y	-	-	-
	*	y	-	-	-
	-	-	*	y	-
	-	-	*	y	-
	-	-	-	-	*
<hr/>					
# of step for encounter :	1				
<hr/>					
Phrase for step 1	firste+nexte.t				
pattern matrix (R)	*	b	-	-	-
	*	-	b	-	-
	*	-	-	b	-
	*	-	-	-	b
	*	-	-	-	-

IVFV (Initial Values and Fixed Values of parameters in Capture-recapture models)

- All initial values have been set to “random”.
- Probability of first capture has been fixed to 1.00.
- Transition parameters beta#5 - NC 1, 3, 3, 2 and 2, 4, 3, 2 (From, To, Age, Step) is fixed to 0.00 (because it is a value at the boundary of 0.00). These parameters are the chance that an individual in state OLD_t-loser_t transits to state NEW_{t+1}-loser_{t+1} or that an individual in state OLD_t-winner_t transits to state NEW_{t+1}-winner_{t+1}.
- Transition parameter beta#8 - NC 3, 4, 3 (From, To, Step) is fixed to 1.00 (because it is a value at the boundary of 1.00). This parameter is the chance, that an individual in state NEW_{t+1}-loser_{t+1} transits to state NEW_{t+1}-winner_{t+1}.

Table S3.3. - Model selection of capture-recapture analysis for females and males. Notation: ϕ , AS; ψ , NC, β , BS; Q , R; np , n. of parameters; Dev , deviance; $QAICc$, Akaike Information Criterion corrected for small sample size; $\Delta AICc$, AICc difference between the model with the lowest AICc and the current one; w_{AICc} , weight of relative likelihood of models; w_{ϕ} , w_{ψ} , w_{β} , w_Q , weight of relative likelihood of parameters; f , difference between states; $f13$, f referred to BS of previous year; $f12$, f referred to NC; i , constant, no difference between states; t , time, temporal variation; $a2$, two age classes (one year after the first capture or older); $a3$, three age classes (one or two years after the first capture or older); $a12$, two age classes (one and two years after the first capture or older); +, additive effect of variables.

Model structure						Model ranking				Parameter's ranking			
Females	ϕ	ψ	β	Q	np	Dev	QAICc	$\Delta AICc$	w_{AICc}	w_{ϕ}	w_{ψ}	w_{β}	w_Q
F1	f13	f	f13	t	14	740.45	770.22	0.00	0.17	0.25	0.96	0.46	1.00
F2	a12	f	f13	t	14	740.75	770.51	0.30	0.15	0.22			
F3	a2	f	f13	t	14	741.03	770.79	0.57	0.13	0.19			
F4	i	f	f13	t	13	743.96	771.49	1.27	0.09	0.14			
F5	f13	f	i	t	13	744.10	771.62	1.40	0.08			0.23	
F6	f13	f	a3	t	15	740.62	772.65	2.43	0.05	0.08			
F7	f	f	f13	t	16	738.48	772.78	2.56	0.05	0.07			
F8	f13	f	f12	t	14	743.81	773.58	3.36	0.03			0.09	
F9	f12	f	f13	t	14	743.85	773.61	3.39	0.03	0.05			
F10	f13	f	a12	t	14	744.02	773.79	3.57	0.03			0.08	
F11	f13	f	a2	t	14	744.10	773.86	3.64	0.03			0.07	
F12	f13	f	f	t	16	740.42	774.72	4.51	0.02			0.05	
F13	f13	f	a3	t	15	743.96	775.98	5.77	0.01			0.03	
F14	f13	f+a3	f13	t	16	742.69	777.00	6.78	0.03		0.03		
F15	f+a3	f	f13	t	19	736.45	777.71	7.49	0.00	0.01			
F16	f13	f	f+a3	t	18	740.33	779.25	9.03	0.00			0.01	
F17	f13	i	f13	t	14	752.01	781.77	11.56	0.00		0.00		
F18	f13	a12	f13	t	15	751.71	783.74	13.52	0.00		0.00		
F19	f13	a2	f13	t	15	751.77	783.79	13.57	0.00		0.00		
F20	f13	a3	f13	t	16	751.71	786.02	15.80	0.00		0.00		
GM	f+a3	f+a3	f+a3	t	24	737.81	791.07	20.85	0.00				
F21	f13	f	f13	f13	8	824.68	841.27	71.05	0.00			0.00	
F22	f13	f	f13	a12	8	826.94	843.53	73.31	0.00			0.00	
F23	f13	f	f13	a3	9	825.76	844.50	74.28	0.00			0.00	
F24	f13	f	f13	a2	7	829.91	844.37	74.15	0.00			0.00	
F25	f13	f	f13	f12	8	828.12	844.71	74.50	0.00			0.00	
F26	f13	f	f13	f	10	824.24	845.15	74.93	0.00			0.00	
F27	f13	f	f13	i	7	831.03	845.49	75.27	0.00			0.00	
Males	ϕ	ψ	β	Q	np	Dev	QAICc	$\Delta AICc$	w_{AICc}	w_{ϕ}	w_{ψ}	w_{β}	w_Q
M1	i	f+a3	f	t	16	829.00	863.23	0.00	0.20	0.35	0.67	0.37	1.00
M2	i	f+a3	i	t	14	834.64	864.35	1.12	0.11			0.21	
M3	f13	f+a3	f	t	17	828.13	864.65	1.43	0.10	0.17			
M4	f12	f+a3	f	t	17	828.36	864.88	1.65	0.09	0.15			
M5	a12	f+a3	f	t	17	828.77	865.29	2.06	0.07	0.12			
M6	a2	f+a3	f	t	17	828.98	865.50	2.28	0.06	0.11			
M7	i	f+a3	f+a12	t	17	828.99	865.51	2.29	0.06			0.12	
M8	i	f+a3	f	t	15	834.02	865.98	2.75	0.05	0.17			
M9	i	f+a3	a2	t	15	834.08	866.04	2.82	0.05			0.09	
M10	i	f+a3	a12	t	15	834.52	866.48	3.25	0.04			0.07	
M11	i	f+a3	f13	t	16	832.50	866.73	3.50	0.03			0.06	
M12	i	f+a3	f12	t	16	832.69	866.92	3.69	0.03			0.06	
M13	i	a3	f	t	16	832.83	867.06	3.84	0.03	0.10			
M14	a3	f+a3	f	t	18	828.37	867.20	3.97	0.03	0.05			
M15	f	f+a3	f	t	19	826.67	867.82	4.60	0.02	0.03			
M16	i	a12	f	t	15	837.65	869.61	6.39	0.01	0.03			
M17	f+a12	f+a3	f	t	20	826.60	870.10	6.87	0.01	0.01			
M18	i	f+a3	a3	t	17	834.03	870.54	7.32	0.01			0.01	
M19	i	i	f	t	14	841.49	871.19	7.97	0.00		0.01		
M20	i	f13	f	t	15	839.24	871.20	7.97	0.00		0.01		
M21	i	f+a3	f+a3	t	20	828.90	872.40	9.18	0.00			0.00	
M22	f+a3	f+a3	f	t	21	826.60	872.46	9.24	0.00	0.00			
M23	i	f13 + a2	f	t	16	838.81	873.04	9.81	0.00		0.00		
M24	i	a2	f	t	15	841.27	873.23	10.00	0.00		0.00		
GM	f+a3	f+a3	f+a3	t	24	826.50	879.59	16.36	0.00				
M25	i	f+a3	f	i	9	918.23	936.95	73.72	0.00			0.00	
M26	i	f+a3	f	f13	10	917.77	938.65	75.42	0.00			0.00	
M27	i	f+a3	f	f12	10	918.04	938.92	75.69	0.00			0.00	
M28	i	f+a3	f	a3	12	916.02	941.28	78.05	0.00			0.00	
M29	i	f+a3	f	f	12	916.79	942.05	78.82	0.00			0.00	

Supplementary Material S4. Simulation of nest and mate change in a single cohort of breeders

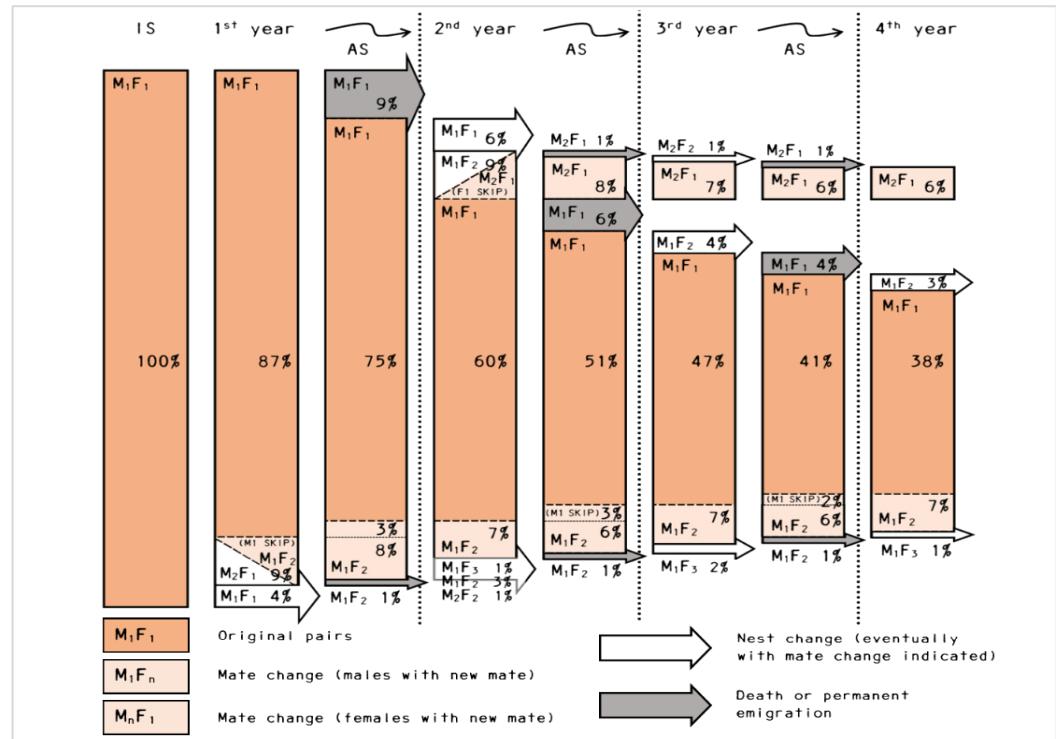


Figure S1. Simulation of the fate of 100 pairs from the same cohort that breed in their first nest. Percentages indicate the number of nest vs the original number of pairs. Nests may decrease due to nest change (showed in white), mate change (in light orange), death or permanent emigration (in grey). All the variations that lead to a change of nest or the complete turnover of the original breeders are shown with arrows and removed from the diagram. Notations: IS, initial state; AS, Apparent Survival rate. Where SKIP is indicated, the breeder has lost his partner and could also skip the reproductive season.