

Supplementary Material

Section S1. Mean hourly transmissions per year

The proportion of unique Argos transmissions received per year, per hour, after filtering of duplicated locations. In 2017, transmissions were received in a 6-hour window from 12:00 to 18:00, and in 2018 and 2019, transmissions were received over a 24-hour window. The majority of unique transmissions occurred during daylight hours (06:00 – 21:59 = 90.3%).

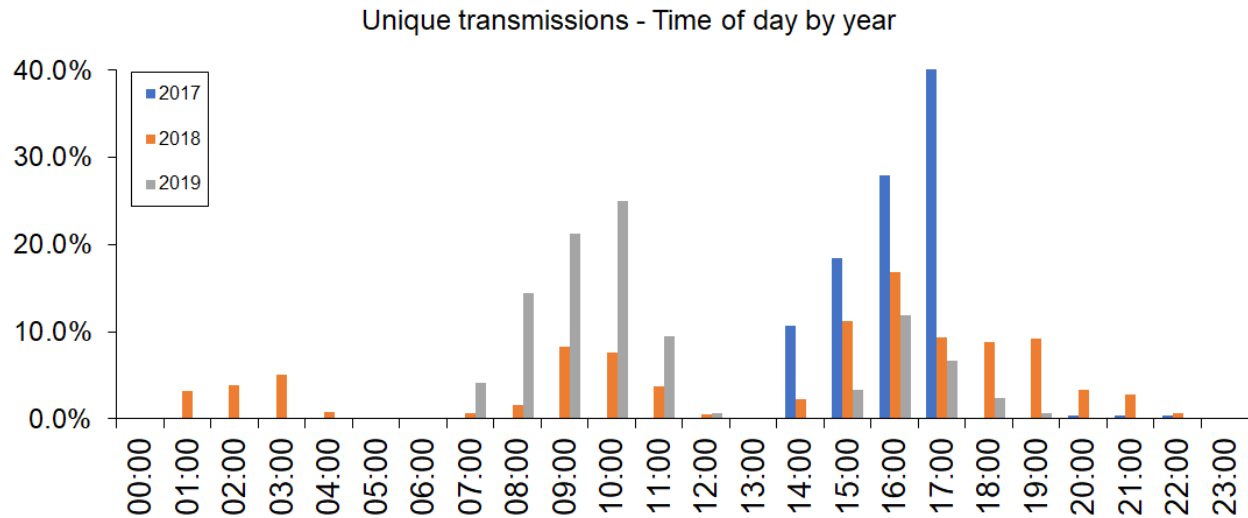


Fig. S1: The proportion of unique Argos transmissions per year by hour.

Section S2. Applying a date threshold to solar-powered devices

As some of the solar units deployed were reliant on more than eight hours of daylight to transmit location data effectively (M. Flagg, Desert Star Systems, pers. comm.), we removed all location data obtained after 30 April (< 10 hours daylight in Dunedin and Christchurch) from residence and secondary dispersal analyses. Figure S2 indicates the reduction in the number of transmissions for the three remaining solar units between April and August 2019.

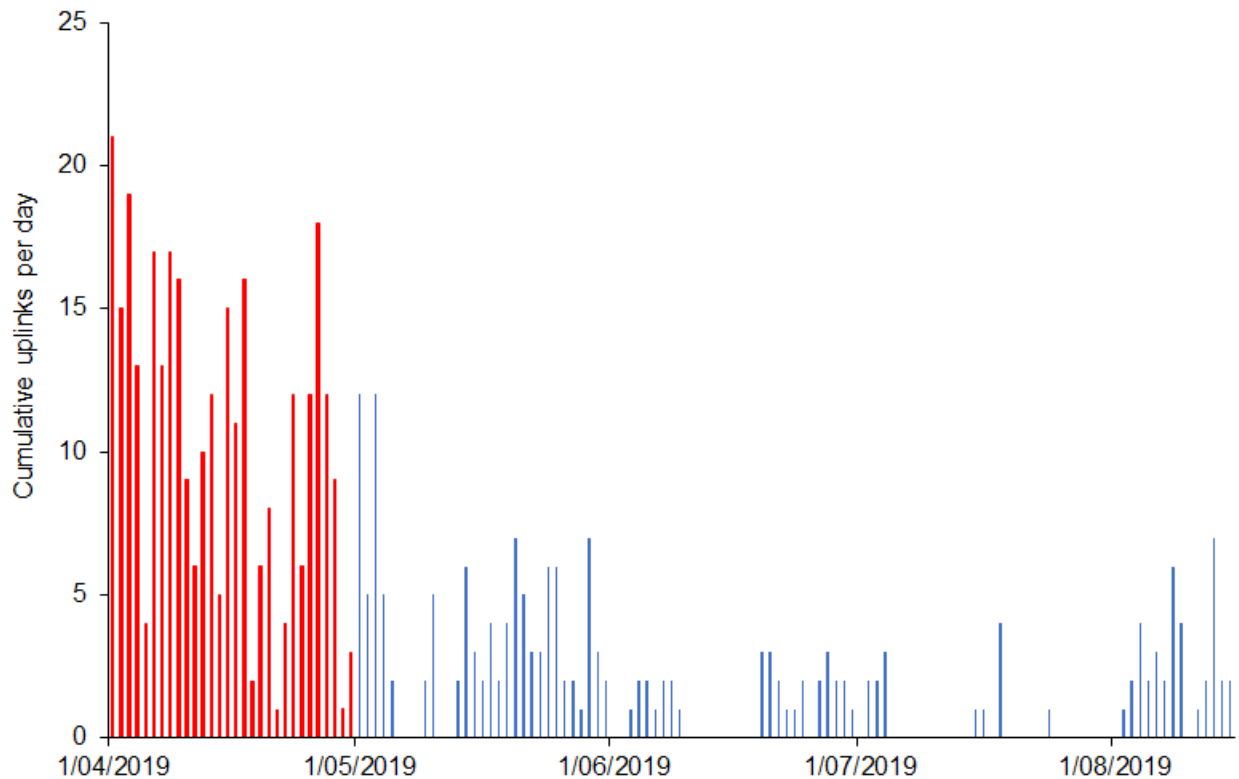


Fig. S2: Cumulative daily uplinks for three Seatag-tt 25 units transmitting to Argos from 1 April 2019 to 15 August 2019.

Section S3. Mean uplinks per unit per day

Following SDA filtering and manual curation of on-land locations, we assessed the mean number of uplinks per unit type per day (\pm SE), to ensure that the different types of transmitters had comparable rates of transmissions.

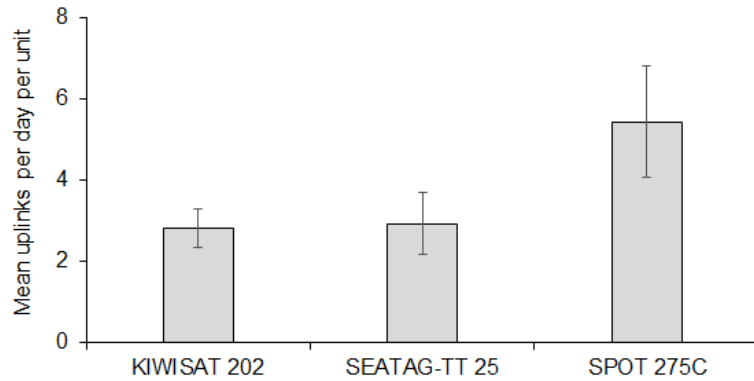


Fig. S3: The mean number of uplinks per day per unit type (\pm SE), across all three years, from the start of transmissions, until 30 April.

Section S4. Behavioural change point analysis code

The following R code is based on a comprehensive tutorial presented by Picardi (2018).

```
# Load packages
> library(adehabitatLT)
> library(lubridate)
> library(raster)
> library(sp)

# Load filtered data, one bird at a time
> Data <- read.csv("PTT49743_TEST_BCPA.csv")
> str(Data)
> Data$NZST <- as.POSIXct(strptime(as.character(Data$NZST), "%Y-%m-%d %H:%M:%S", tz =
"UTC"))
> DATA <- data.frame(latitude = Data$Latitude, longitude = Data$Longitude, id =
Data$Platform_ID, acquisition_time = Data$NZST, x = Data$x, y = Data$y)
> saveRDS(DATA, file = "PTT49743_TEST_BCPA.rds")
> Data <- readRDS("PTT49743_TEST_BCPA.rds")

# The acquisition time has automatically saved as a POSIXct object in .rds format
> str(Data)
> class(Data$acquisition_time)

# convert the locations into a SpatialPointsDataFrame and give them a projection
> Data <- Data[!is.na(Data$x),]
> Data <- Data[!is.na(Data$y),]

# convert 'Data' into a spatial points data frame
> coordinates(Data) <- c("x", "y")
> class(Data)

# Add the projection for New Zealand Transverse Mercator to the SPDF (i.e. work in
metres)
> proj4string(Data) <- CRS("+init=epsg:2193")

# Create a movement trajectory using the ltraj function in adehabitatLT – this has an irregular
time lag between each of the observations
> class(Data$id)
> summary(Data$id)
```

```
> Irregular <- as.ltraj(coordinates(Data),date=Data$acquisition_time,id=Data$Id, typeI=TRUE)
# Expect to get an error message - "non-unique dates for a given burst"
> summary(duplicated(Data$acquisition_time))
# There might still be duplicate values that need to be removed, deal with this and then
# come back to here, then check different chunks of information for the Irregular
# trajectory:
> summary(Irregular)
> Irregular
> class(Irregular)
> is.regular(Irregular)
# "Regularise" the trajectory (note that it gives NZDT as the time zone automatically):
> refda <- min(Data$acquisition_time)
# Set the lag time. I have set this to be 1 hour, since using 24 hours removes lots of
# observations, because I have a window of observations each day that are closely spaced in
# time.
> Regular_NA <- setNA(Irregular, refda, 1, units = "hour")
> head(Regular_NA)
# Round the timestamps to be one hour apart, based on the first timestamp:
> Regular_1 <- sett0(Regular_NA, refda, 1, units = "hour")
> is.regular(Regular_1)
# Using Lavielle's method with net squared displacement (NSD), undertake behavioural change
# point analysis by segmenting the trajectory into logical pieces:
> df_49743 <- ld(Regular_1[1])
> df_49743 <- df_49743 [!is.na(df_49743$x),]
> df_49743 <- df_49743 [!is.na(df_49743$y),]
> df_49743$fpt_r50 <- fpt_49743 [[1]]$r50
> traj_49743<- dl(df_49743)
> traj_49743<- setNA(traj_49743, refda, 1, units="hour")
> traj_49743<- sett0(traj_49743, refda, 1, units="hour")
> is.regular(traj_49743)
# this code plots the trajectory in a time series, where "R2n" = NSD
> plotltr(traj_49743, which = "R2n")
```

```
> laviellemethod_49743<- lavielle(traj_49743, Lmin=10, Kmax=10, type="mean", which="R2n")
# Display the scree plot, selecting the value where the plot tapers off to use for segmentation
> chooseseg(laviellemethod_49743)
# In this case, K = 4 is the suggested optimal number of segments
Then specify this K value in the next bit of code:
> segmented_49743<- findpath(laviellemethod_49743, 4)
# Have a look at where each of the segments fall on the trajectory to see if they make sense:
> plot(segmented_49743)
# And also like this:
> par(mfrow=c(1,4))
> plot(seg_49743 [1],ylim=c(4600000,5100000),xlim=c(1100000,1800000))
> plot(seg_49743 [2],ylim=c(4600000,5100000),xlim=c(1100000,1800000))
> plot(seg_49743 [3],ylim=c(4950000,5100000),xlim=c(1100000,1800000))
> plot(seg_49743 [4],ylim=c(4800000,5100000),xlim=c(1100000,1800000))
```

Section S5. Behavioural change point analysis examples

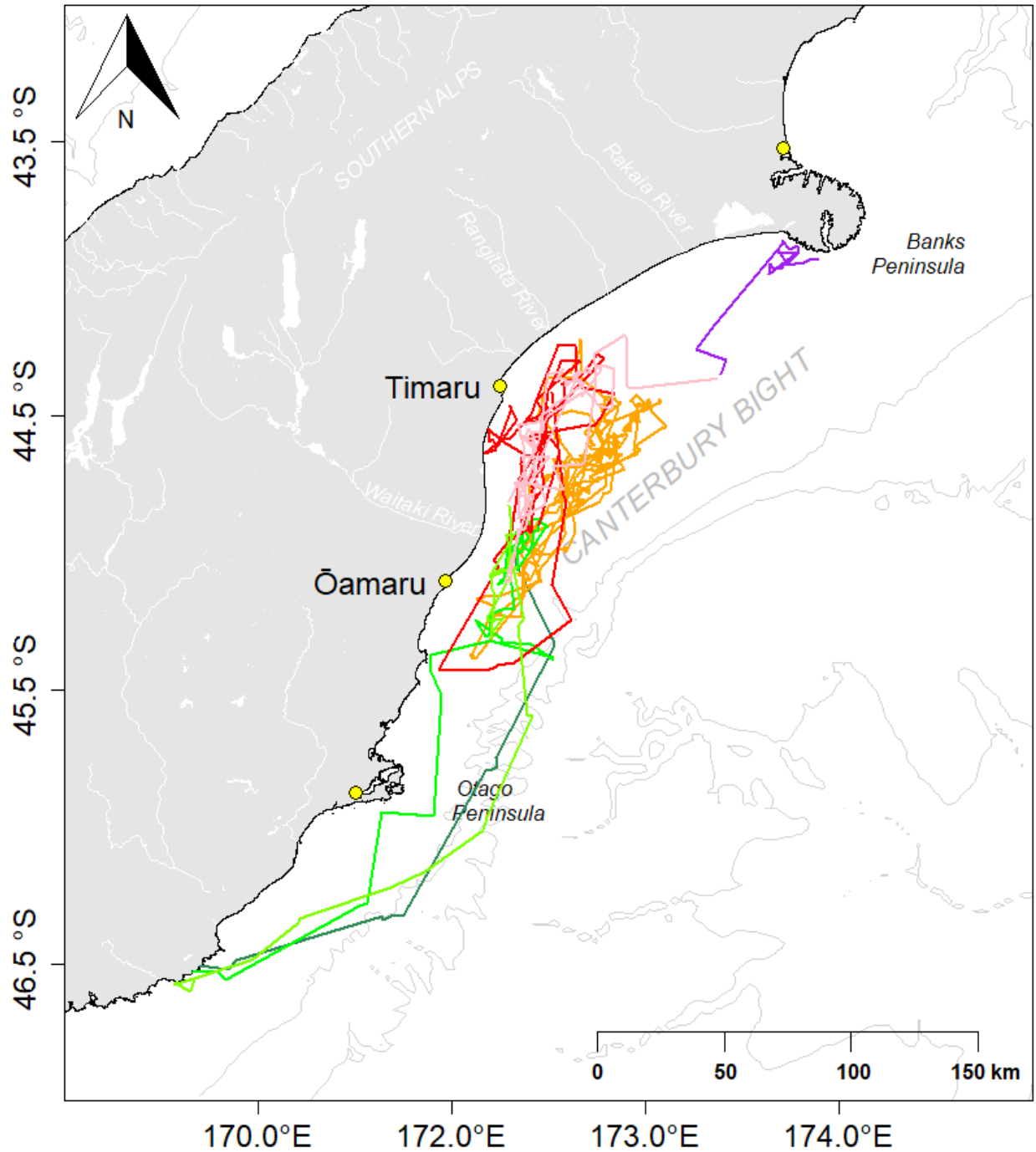


Fig. S4. Post-fledging dispersal tracks showing initial dispersal (green) and residence (red, orange, pink), and secondary dispersal (purple), calculated for PTT 49746, 49751, and 152464 using behavioural change point analysis.

Section S6. Core foraging hotspots by year

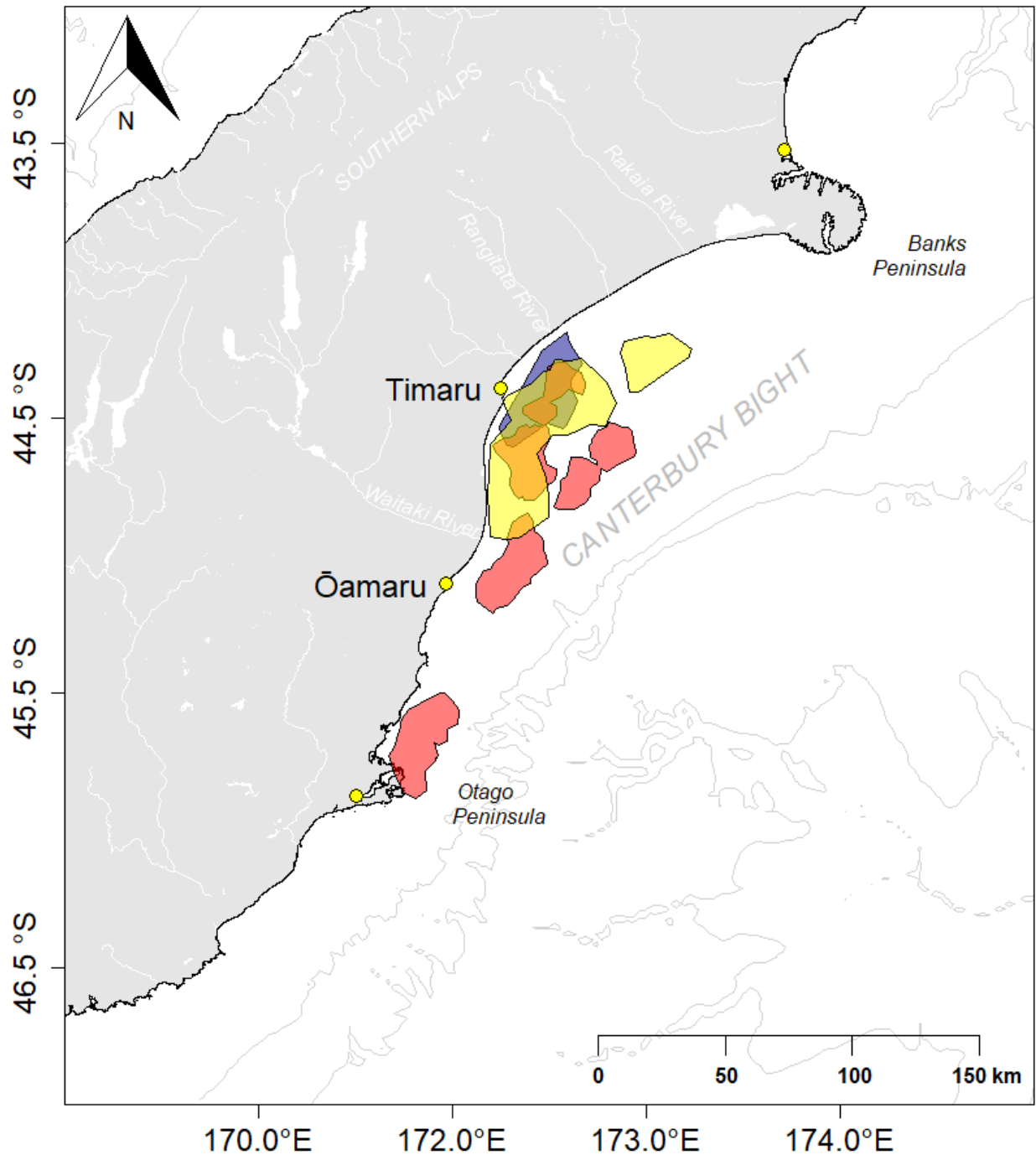


Fig. S5: Core foraging hotspots (50% k-LoCoH isopleths, where $k = 25$ was the value for the 'minimum spurious hole covering', following Getz & Wilmers 2004, Getz et al. 2007) in 2017 (purple, $n = 3$ birds), 2018 (pink, $n = 18$ birds), and 2019 (yellow, $n = 7$ birds). Isobaths (grey) are at 500m intervals.

LITERATURE CITED

- Getz WM, Wilmers CC (2004) A local nearest-neighbor convex-hull construction of home ranges and utilization distributions. *Ecography* 27: 489–505
- Getz WM, Fortmann-Roe S, Cross PC, Lyons AJ, Ryan SJ, Wilmers CC (2007) LoCoH: nonparametric kernel methods for constructing home ranges and utilization distributions. *PLOS ONE* 2:e207
- Picardi S (2018) Wildlife tracking data in R. www.rgators.com/2018/01/31/wildlife-tracking-data-in-r/ (accessed 1 Sep 2019)