Student Poster

Improving the Calculation of Fix-Rate Bias in Automated Telemetry Systems

Miriam Hodge[1], Jennifer Brown[1] and Marco Reale[1]

[1] Mathematics and Statistics Department, University of Canterbury, Private Bag 4800, Christchurch, New Zealand

Abstract: GPS and other radio tracking equipment are becoming more widely used by researchers for modelling animal habitat. In a typical monitoring program an animal will be fitted with a tracking collar. This tracking collar will fix the animal's location at a set time interval. These fixes of the animal's location can then be cross referenced on a digital map (GIS) containing habitat information and the animal's preferred habitat can be modelled.
Care must be used in modelling the habitat because radio tracking collars have different transmission probabilities in different habitats. The habitat observations are biased towards habitats that allow good transmission. One way to minimise this bias is to weight observations by a measure of transmission quality.
Researchers have attempted to estimate the detection weighting by placing stationary collars in the study area and recording the fix-rate. The results of these studies are unsatisfactory because stationary collars do not account for animal movement and behaviour. Johnson (1998) used a surrogate for stationary collars by analysing 6 hour time periods where the animal was relatively stationary. We will develop this method further by incorporating the non-stationary sites in the detection rate calculation.

Keywords: fix-rate; bias; telemetry collar.

1 Source of Fix-Rate Bias

The use of radio collars to collect information on habitat can be biased when habitat influences detection.(Lewis 2007, D'Eon 2002) The number of fixes for an animal at a location, f, is the number of times a fix is attempted from that location. These fixes are either successful, f_s, or unsuccessful, f_u.

$$f = f_s + f_u$$

Unsuccessful fixes can occur for many reasons. Links have been made between fix-rate and many habitat qualities to include slope(Lewis, 2007), tree density (Rumble Lindzey 1999), and terrain conditions (D'Eon 2002). Fix-rate, r, at a location is the number of successful radio fixes of an animal in that location divided by the total number of attempted radio fixes.

$$r = \frac{f_s}{f_s + f_u}$$

The detection weighting, w, at a given location is the inverse of the detection rate. Applying the detection weighting corrects for fix-rate bias.

$$w \cdot f_s = \frac{f_s + f_u}{f_s} \cdot f_s$$

$$w \cdot f_s = f$$

One technique to estimate fix-rate bias is to place collars in different locations within the study area and recording the fix-rate. Because each collar is stationary at a location the fix-rate at that location is the number of successful fixes divided by the number of fix attempts. Placing collars in each habitat type in a large study area very expensive and time consuming. Additionally, fix-rates from stationary collar studies do not accurately predict fix-rates in collars worn by animals. This disparity has been linked to animal movement and behaviour (Edenius 1997, Moen 1996).
Johnson (1998) used a surrogate for stationary collars by identifying time periods when the animal was relatively stationary and measuring the fix-rate in these periods. To find stationary periods they broke the day into four time periods(TP) each lasting 6 hours. Because the actual location of the animal is unknown, Johnson used the arithmetic mean of the successful fixes during a time period as the location. The animal was judged stationary if it had at least four fixes in the time period and one or less fixes were more than 200 metres from the mean location of the observed animal fixes. He recorded the detection weighting at each stationary site as the total number of fix attempts divided by the number of successful fixes in the time period. Because there are not stationary time periods in every location, Johnson goes on to calculate the detection weighting for all locations in the forest by employing five linear models of the form, $\mathbf{Y} = \mathbf{X}\,\beta + \epsilon$, where $\mathbf{Y}$ is the vector of observation rates, $\mathbf{X}$ is a design matrix of environmental variables, β is the design matrix and ϵ is the error term. Johnson's most successful model, the kriging model on a 180 m pixel grids omitted the environmental covariates.
Instead of using a linear model, we will estimate the weighting function at every site by assuming that at each location we are doing repeated samples and that over the length of the study the probability of radio transmission at a given location is constant and that the amount of time the animal spends in each location during a time period is constant. We then apply MacKenzie's (2002) detection rate technique to define the probability of detecting each fix and estimate the weighting function with Markov Chain Monte-Carlo techniques.

2 Calculation of Fix-Rate Bias

MacKenzie (2002) developed a technique for incorporating detection probabilities for animals into large-scale site occupancy surveys. We adjust this technique by detecting locations instead of animals to incorporate fix-rate bias in radio telemetry studies. MacKenzie builds his model on two assumptions. The first assumption is that the area of inference is too large to be surveyed. The second is that detectability is not perfect. MacKenzie's assumptions are met by radio telemetry studies. The area in use by all animals is too large to be surveyed and the fix-rate in not one-hundred percent.

We define presence at a location as a six hour time period, TP, during which an animal has one successful fix at that location. An animal can be present at multiple locations during the same time period if the animal has successful fixes at multiple locations during a time period. We construct our detection probabilities by looking at fix records one time period at a time. In a given time period $p_{(p,1)}$ is the probability of being at location 1, $1-p_{(p,1)}$ is the probability of not being at location 1, $p_{(d,1)}$ is the probability of being detected at location 1, and $1 - p_{(d,1)}$ is the probability of not being detected at location 1. For example, the probability of the following detection history at location 1

$$f_1, f_1, f_u, f_u, f_u, f_2, f_1$$

where f_1 is a fix at location 1, f_2 is a fix at location 2, and f_u is an unsuccessful fix. Is as follows:

$$(p_{(p,1)}p_{(d,1)})^3((1 - p_{(p,1)})p_{(d,2)})(p_{(p,1)}(1 - p_{(d,1)}) + (1 - p_{(p,1)})(1 - p_{(d,?)}))^3$$

assuming that all location visited by the animal in the time period have the same detection probability, this simplifies to

$$(p_{(p,1)}p_d)^3((1 - p_{(p,1)})p_d)(1 - p_d)^3$$

3 Results for Sample Data Set

The sample data set is the Starkey Experimental Forest and Range in Oregon, USA. The same data set from used by Johnson (1998). The 10,102-ha reserve is surrounded by a game-proof fence and includes diverse topography. Elk (Cervus elaphus), mule deer (Odocoileus hemionus), and cattle were fitted with radio collars and tracked by an Automated Telemetry System (ATS). For more detailed information on the ATS, the tracking data, and habitat information see the U.S. Forest Service web site, http://www.fs.fed.us/pnw/starkey/.

The survey area is broken into a grid with each pixel being 30 m to a side. In the MCMC model a location is defined as a single pixel in this grid. Each location, L, has a distinct probability of the animal being at the site, $p_{(p,L)}$. The probability of detection p_d is assumed constant over the study area. The model parameters are estimated with Markov Chain Monte Carlo

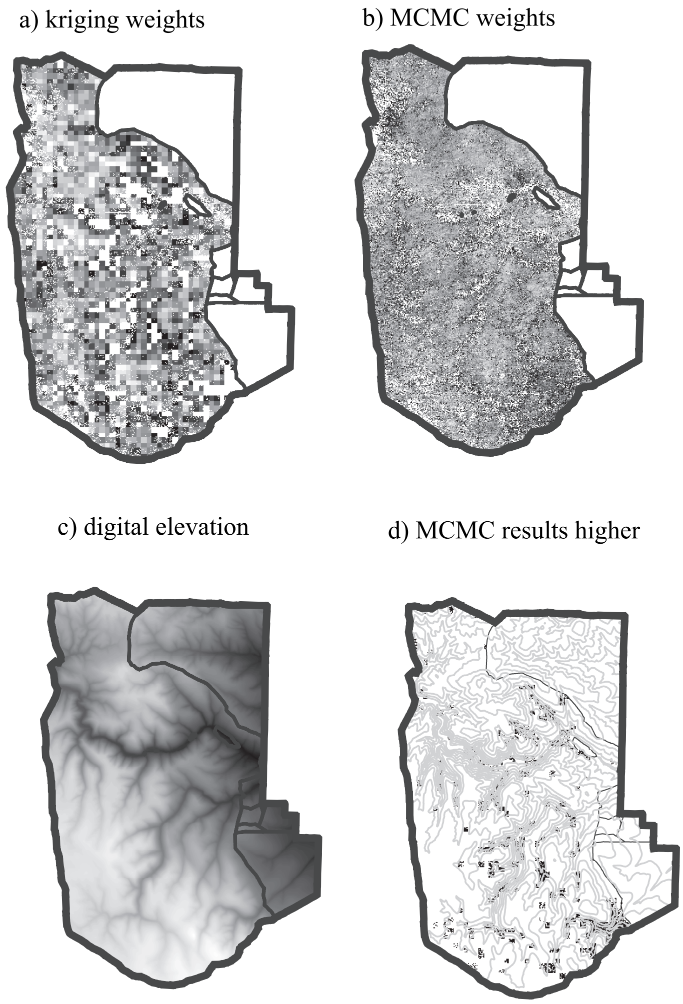

FIGURE 1. Models applied to Starkey data. Digital map boundaries, elevation contours, digital elevation model, and Johnson's weightings were obtained from U.S. forest service web site. The grey scale in map a and b is scaled from low to high fix-rate with dark to light shades.

using Winbugs software. (Lunn 2000) The $p_{(p,L)}$ values are given a vague priors.
The MCMC model has greater variation and higher average weighting than

Johnson's kriging model (1998). Figure Maps a), b) and c) show that both kriging model and the the MCMC model follow the digital elevation model of the study area. Figure Maps d) shows the elevation contours in grey and the locations where the MCMC model gives a higher weighting than the kriging model in black. The MCMC model is showing more missing fixes in areas with low elevation adjacent to steep slopes.

4 Future Work

A metric which can quantify the differences between models would facilitate the comparison of models developed with different theoretical frameworks. A possible source for such a metric are the deformation metrics being developed in anatomical fields to compare highly irregular body parts such as portions of the brain.
In addition to comparison metrics, we are looking to incorporate habitat and animal covariates into our model of detection probability, p_d. We will introduce a hierarchical model of p_d. This will allow for different behaviours by different animals in the same location.
We are also looking at incorporating adjacency information into the model of presence, p_p, using Geobugs component of the Winbugs software.(Lunn 2000) The MCMC probability of an animal being present at a location is calculated independently of all of the other location values. Incorporating adjacency information will allow us to recover the geographic relationship between locations that Johnson (1998) leverages through kriging.

5 Conclusion

Johnson (1998) considered one source of variation due to radio transmission and carefully constructed his stationary time periods to eliminate all other sources of variation. We introduce a second source of variation, namely detectability, that allows us to look at time periods that Johnson (1998) discarded from his model fitting process. We are able to fit our model based on all time periods where the automated telemetry system is working, not just those where the animal was stationary.

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