Report: Acoustic spatial capture-recapture models for the CalCurCEAS sonobuoy data set

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8 July 2017

1 Introduction

The purpose of this report is to describe my attempts at fitting maximum-likelihood acoustic spatial capture-recapture (SCR) models to the CalCurCEAS sonobuoy data set.

Acoustic SCR methods estimate call density from detections of animal vocalisations across an array of detectors (e.g., Dawson & Efford, 2009; Kidney et al., 2016; Measey et al., 2017). One particular advantage of this approach is that the location at which each call is emitted is never assumed to be known; instead, the models treat locations as latent variables, which are integrated over in the computation of the likelihood for models fitted by maximum likelihood, or sampled over within an MCMC algorithm for models fitted in a Bayesian framework. Nevertheless, the data must hold some information about these locations, and the more informative the data are about the locations, the more precise the density estimate will be.

Standard SCR obtains this information from the locations at which detections are made: a vocalisation is likely to have been emitted close to the detectors that detected it, and further from those that did not. SCR surveys typically collect enough spatial information for precise parameter estimates by deploying many detectors (10+) across the survey area. One particular advantage of acoustic SCR is that additional information is often collected that is informative about the locations; examples include estimated bearings, distances, signal strengths, and times of arrival (Borchers et al., 2015; Stevenson et al., 2015). With

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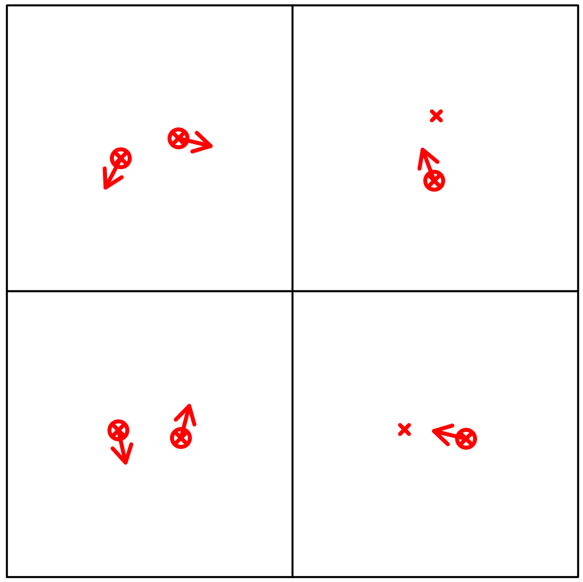

Figure 1: Four problematic call detections: The first column shows detections with conflicting bearing estimates. The second column shows detections with bearing estimates that are unlikely to be plausible, as they are pointing directly at a sonobuoy that did not detect the call. These four examples include a blue whale A call, a blue whale B call, and two fin whale calls.

use of such data, precise density estimates can be obtained even if only a small number of detectors are deployed; for example, Stevenson et al. (2015) and Measey et al. (2017) used six microphones to detect frog clicks, and Kidney et al. (2016) used just three human observers to detect gibbons calls.

To summarise, attempts at fitting maximum-likelihood acoustic SCR models to the CalCurCEAS sonobuoy data set were ultimately unsuccessful. Models fitted to data from each station (pairs of sonobuoys deployed simultaneously) resulted in nonconvergence of the optimisation algorithm in some cases, and parameter estimates that are not biologically plausible in others. In my opinion, this is likely to be caused by a lack of spatial information about call locations, due to a combination of three factors: (1) mismatched calls, (2) inaccurate bearing estimates, and (3) a suboptimal survey design.

2 Problematic detection data

The issues mentioned directly above are evident in a large number of detections within the CalCurCEAS data set. In particular, there are two types of irregulaties that are prevalent at almost all stations, and for all three call types (blue whale A, blue whale B, and fin whale calls). Both classes are shown in Figure 1: (1) some calls were detected at both sonobuoys, but were accompanied by conflicting bearing estimates, and (2) some calls were detected by only one sonobuoy, but the bearing estimate pointed in the direction of the other sonobuoy.

One mechanism that may explain class (1) is that the bearing estimates are very imprecise. The SCR model estimates the accuracy of estimated bearings; when there are detections similar to the left-hand column of Figure 1, the model must estimate that bearing estimates are incredibly variable. Almost all spatial information that the bearings do hold is lost, as the model determines that they are unreliable. With only two detectors, detection locations by themselves only provide a trifling amount of spatial information, and so resulting call density estimates are incredibly imprecise and of little practical use.

Another mechanism that may explain class (1) is that some calls are being incorrectly matched; that is, the sonobuoys are detecting two *different* calls with different locations, but they are falsely being matched as two detections of the *same* call with the same location. In this case, the data being given to the SCR model are incorrect. If false matching occurs with a nonnegligible proportion of the detections, then it would be unwise to treat the resulting call density estimate with credibility.

The issue with class (2) is that one would expect *both* sonobuoys to detect the call if the bearing estimate is accurate. From inspecting the data, it appears that bearings associated with calls detected at a single sonobuoy disproportionately point in the direction of the other sonobuoy. After discussion with Shannon Rankin, we suspect that this is caused by survey protocol: following the deployment of the sonobuoys, the boat moved backwards and forwards between them during the survey. It is likely that many bearing estimates are pointing towards the sound of the boat, rather than the source location of the whale vocalisation. Again, inaccuracies in bearing estimates severely impact the amount of spatial information available to estimate call density.

3 Survey design

SCR models are able to estimate how far an acoustic array can 'hear', allowing the estimation of call density. To get a good indication of the area over which a detector array can detect calls, it is necessary to have them in a suitable configuration. With only two detectors, one must simply consider the spacing between them. If they are optimally spaced, some calls will be detected by both, but many will only be detected by one. If they are too close, then both detectors will almost always detect each detected call, and information about the detetion range is lost.

The spacing between the detectors for the CalCurCEAS data set often appeared to suffer from this problem. In my opinion, precision of call density estimates is likely increase with a larger spacing between buoys—although I acknowledge that this is difficult due to time constraints and the range of the radio receivers that collect data from the sonobuoys.

4 Concluding remarks

Overall, I remain optimistic about the applicability of SCR methods to acoustic data of cetaceans. With improvement in call matching and bearing estimation methods, along with improved survey protocol and sonobuoy spacing, I believe that the resulting data will contain enough information to obtain useful estimates of call density.

References

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