

# Standardisation of IDCR/SOWER Sightability Variable

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## Abstract

The OK and SPLINTR minke whale analyses both use the IDCR/SOWER Sightability measure as a covariate to model the environmental effects on the probability of detection on the track line,  $g(0)$ . Sightability corresponds to a single ordinal measure that encompasses/summarises all of the various environmental visual effects, to give an indicator of how easy it is to observe a whale. It is important, in these models, that the Sightability measure is consistent across time and space. However, since Sightability is a subjective ordinal category, based on experience and judgment, this may not be the case. IDCR/SOWER also collected a number of other environmental variables: Visibility, Air Temperature, Surface Temperature, Wind Speed, Weather, and Sea State. In this paper we present a tree-based analysis that maps these various environmental covariates to Sightability, allowing the prediction of Sightability for given conditions. This model is built using recent data from a single vessel and then predictions made for all the data providing a standardised and consistent measure of Sightability, across time and different vessels.

## 1 Introduction

There are reasons to doubt the long-term consistency of the Sightability variable in the IDCR/SOWER dataset, as the observed values are based on personal experience and judgment. Over the long time period covered by IDCR/SOWER it is possible that this subjective decision process may have changed, or differ between vessels. To address this issue, we propose a standardisation of the IDCR/SOWER Sightability variable. The goal motivating this procedure is that all the standardised Sightability data will have a similar underlying mechanism/relationship to the other environmental measures, and the interpretation of Sightability will be consistent across all time periods and vessels.

## 2 Methods

We began by partitioning the data (CP2/3) into three time periods (1986-1992, 1993-1998 and 1999-2003), and taking the most recent time period 1999 - 2003, as our standard (training data). Using the training data, we modelled the relationship between Sightability and other recorded variables (Visibility, Air Temperature, Surface Temperature, Wind Speed, Weather, Sea State, and Vessel). We then predicted for all time periods from this model, using the SM2 Vessel as the baseline. This gives predictions for all observations using the corresponding observed environmental data but assuming that the Vessel used was

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SM2. Hence, we obtain a re-calibration of the Sightability variable for the earlier time periods, based on the most recent period of SM2.

To model the Sightability we are primarily interested in a predictive model; interpretation is of secondary importance. We used aggregated boosted trees (ABT; De'ath 2006), a variant of the popular boosted regression trees (BRT; see Hastie et al., 2001). The results of ABTs and BRTs are typically very similar, although the aggregated version tends to have slightly better predictive capability. Both ABTs and BRTs provide excellent predictive models by exploiting the predictive power of ensemble models (Hastie et al, 2001).

ATSTs are not designed to be used on multi-class data, such as the Sightability variable. To overcome this problem, we employed a well-known approach for multinomial data. The three Sightability response categories (2, 3, and 4&5) were modelled using two separate ABT models. The models specify  $\Pr(\text{Sightability} > 2)$ , and  $\Pr(\text{Sightability is 4\&5} \mid \text{Sightability} > 2)$ . The second model is obtained by sub-setting the data. Predictions of the multiple class outcomes are made by suitably combining the predicted probabilities from each individual model. This leads to the vector of class membership for each observation, which is hard-clustered to produce a prediction of the most likely class.

One issue that arose was that the Visibility variable itself went through a substantial change in the way it was recorded. In the time period up until 1994 Visibility was estimated by the officer in the wheelhouse, whereas after this time this was performed by the Captain. This change can be seen by a sustained drop in visibility in 1994; pre-1994 Visibility ranged from 0-6 Nm, after 1994 the range is 0-3 Nm (Figure 1). After comparing radial sighting distances to recorded visibility it appears that pre-1994 the visibility measure corresponds more towards the maximum possible distance at which sightings could occur, whereas from 1994 onwards the visibilities recorded are more conservative and relate more closely to the average or reasonable distance at which a sighting could occur. To correct for this change we altered the Visibility variable so that the distribution functions of the two periods were similar. This was done by stratifying on Weather and Sea state and quantile matching the early data to the latter data (Figure 2). The stratification was done to allow for the possibility that the overall pattern of weather conditions may have systematically been different between time periods (e.g. this would occur if the latitudinal distribution of survey effort differed in any of the time periods).

### 3 Results

The resulting models suggested that all the variables considered had, at least, a small affect on the value of Sightability. The Visibility variable was most important, while Vessel and Weather were least important.

There did appear to be a difference in the scoring of Sightability over the three time periods. In particular, it appears that the scoring in the earlier period tended to have higher values than those in the later period, and is subsequently adjusted (see Figure 3).

### 4 Discussion

Given the range of weather conditions experienced in Antarctic waters, any distance sampling analysis of Antarctic whales will generally require some suitable environmental covariate(s) to take in to account the effect on  $g(0)$ . The subjective nature of Sightability and the long time period of IDCR/SOWER suggests that some empirical examination of the environmental measures was warranted.

Examining the new standardised Sightability measure it was as expected consistent with the other enviromental variables. The actual definition, or value, of Sightability is arbitrary in that Sightability values themselves do not directly correspond to a specific physical quantity. Therefore, attempting

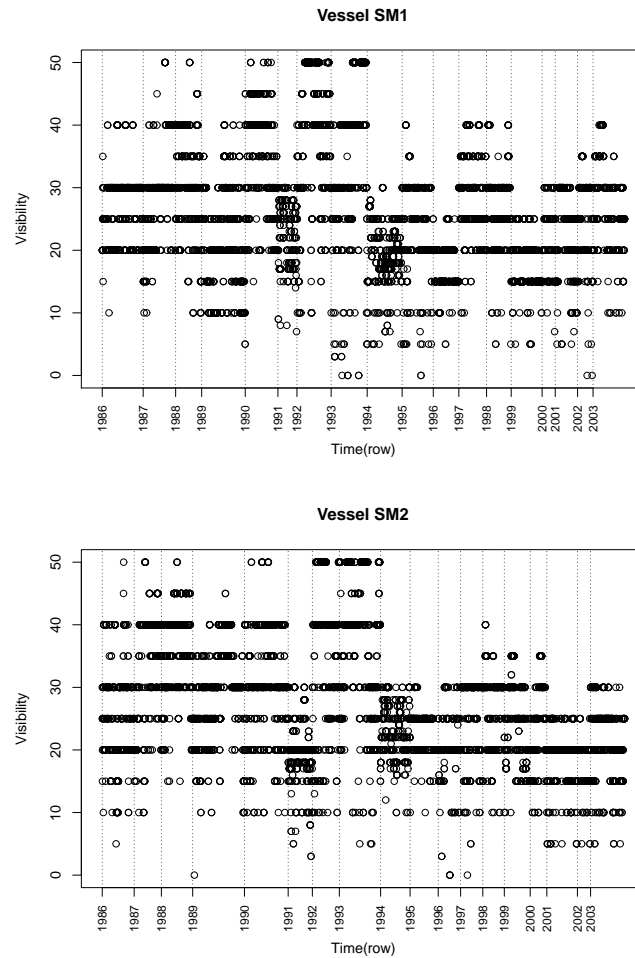


Figure 1: Plots of the Visibility measure versus time (row number of ordered data). Notice the large change in Visibility for both vessels at 1994

to validate, or interpret, the tree classification does not make sense. Instead the new standardised Sightability measure should be judged on its effect on the subsequent SPLINTR and OK models. The overall abundance estimate from these models may possibly not be greatly effected by the choice of Sightability metric; where it is hoped the effect will be seen in improved and more consistent model diagnostics.

## References

De'ath, G. 2007. Boosted Trees for Ecological Modelling and Prediction. *Ecology* 88:243-251.

Hastie, T.J., Tibshirani, R.J., and Friedman, J.H. 2001. *The Elements of Statistical Learning*. Springer-Verlag, New York, USA.

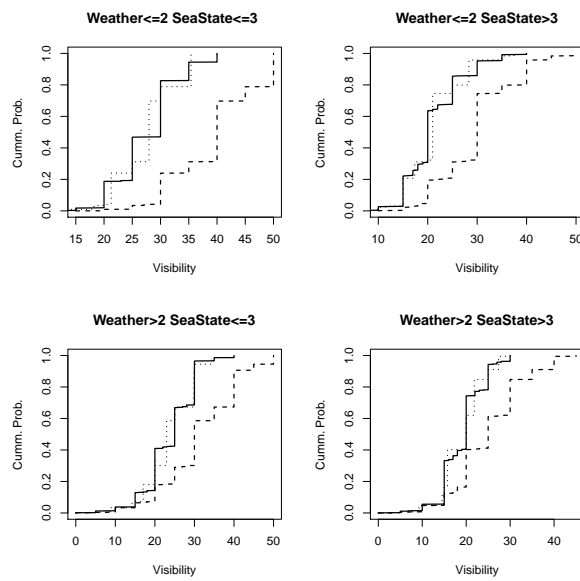


Figure 2: Results from the quantile matching for the Visibility variable, solid line = post 1994 era, dash line=pre 1994, dotted line= corrected pre 1994 data.

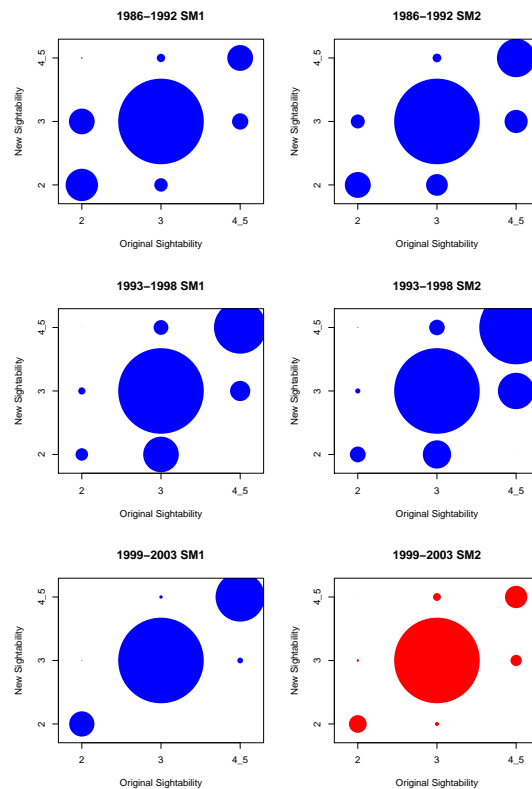


Figure 3: Plots comparing the new predicted Sightability with the original Sightability for the different time periods and vessels. These plots show that as expected for the training data (bottom right plot) Sightability was generally unchanged; for the earliest time period Sightability was changed slightly; whereas for the middle time period the original Sightability recorded was higher and the standardisation lowered the values overall.