Antarctic minke whale density in relation to sea ice: helicopter surveys in the Weddell Sea

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INTRODUCTION

The Antarctic minke whale (*Balaenoptera bonaerensis*) is a denizen of the pack ice (Tynan and Russell 2008). Quantifying the relationship between minke whale density and sea ice conditions is logistically challenging, however, in part because few ships are capable of surveying for whales in pack ice (Branch 2006). Even when such ships are available, it is difficult to design and conduct a systematic line transect survey in heavily ice-covered waters. And even if these design-associated difficulties could be overcome, there are outstanding practical issues associated with surveys of cetaceans in the ice in terms of estimating g(0) and evaluating whether whales are responding to the noise of ships breaking through the ice: responsive movement could introduce substantial bias in any resulting abundance estimate (Kock et al. 2010). It is known that existing abundance estimates of Antarctic minke whales are negatively biased because "some minke whales remain within the pack ice out of the reach of the survey vessel" (Branch 2006), but it is unknown what fraction of the population is found in the ice. As a result of these logistical constraints and data gaps, "*The Commission is unable to provide reliable estimates at the present time*[1]*.*"

A number of complementary techniques will be required to estimate minke whale density inside and outside the pack ice. In 2006, helicopter surveys were initiated from the ice-breaking ship RV Polarstern (Scheidat et al. 2007, Kock et al. 2010). The combination of ice-breaking ship and dedicated minke whale surveys from the helicopter offers tremendous flexibility. This paper describes minke whale density as a function of spatial and environmental (ice-related) covariates and outlines plans for future analyses.

METHODS

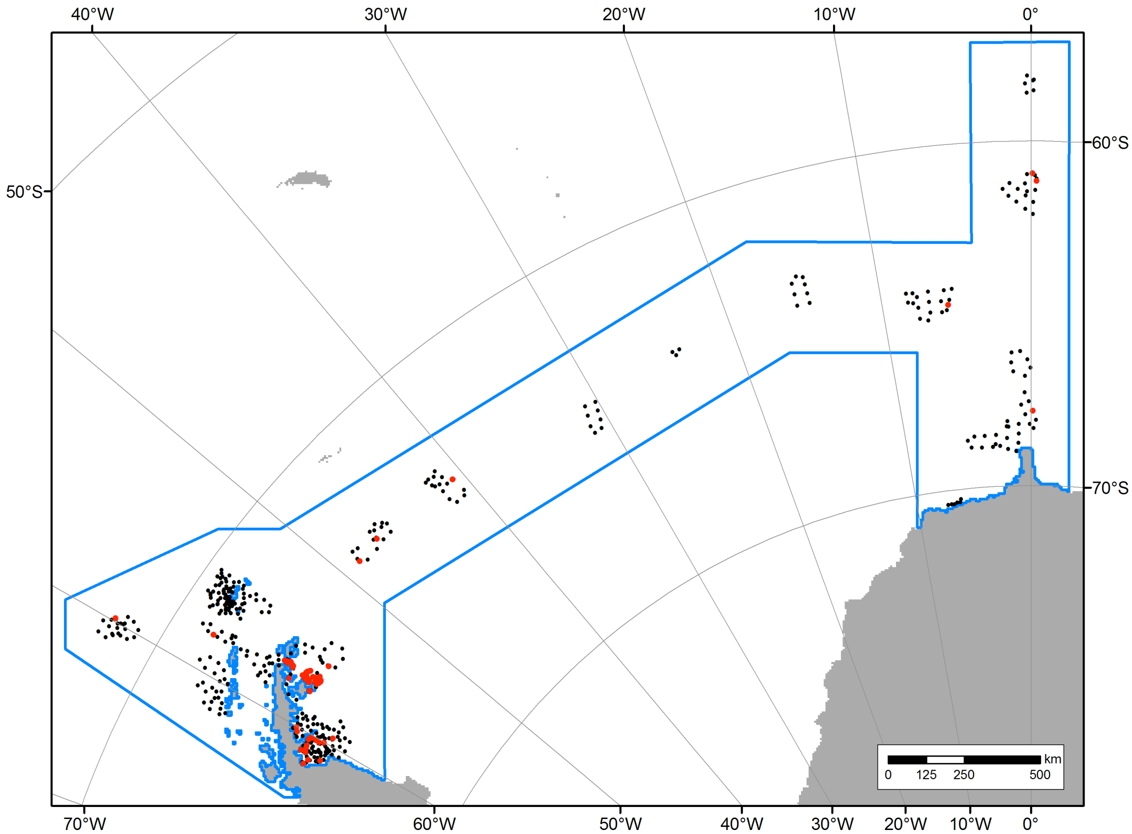
Helicopter surveys

[1] http://www.iwcoffice.org/conservation/estimate.htm

Helicopter surveys were conducted during two Antarctic cruises from the R/V Polarstern in November to January 2006/07 and in December/January 2008/09. Further information including itineraries, cruise tracks etc. is detailed in Gutt (2008) and Boebel (2009). Survey design and field protocol issues are described in Kock et al. (2010).

Effort and sightings

In 2006/7 helicopter survey flights covered 13124 km in 34 days of observation. In 2008/9 a total of 13417 km were covered with survey flights during 23 survey flights. Figure 1 gives an overview of the effort (black dots) and the minke whale sightings (red dots) aggregated in 10nm sections. More detail on survey effort can be found in Kock et al. (2010).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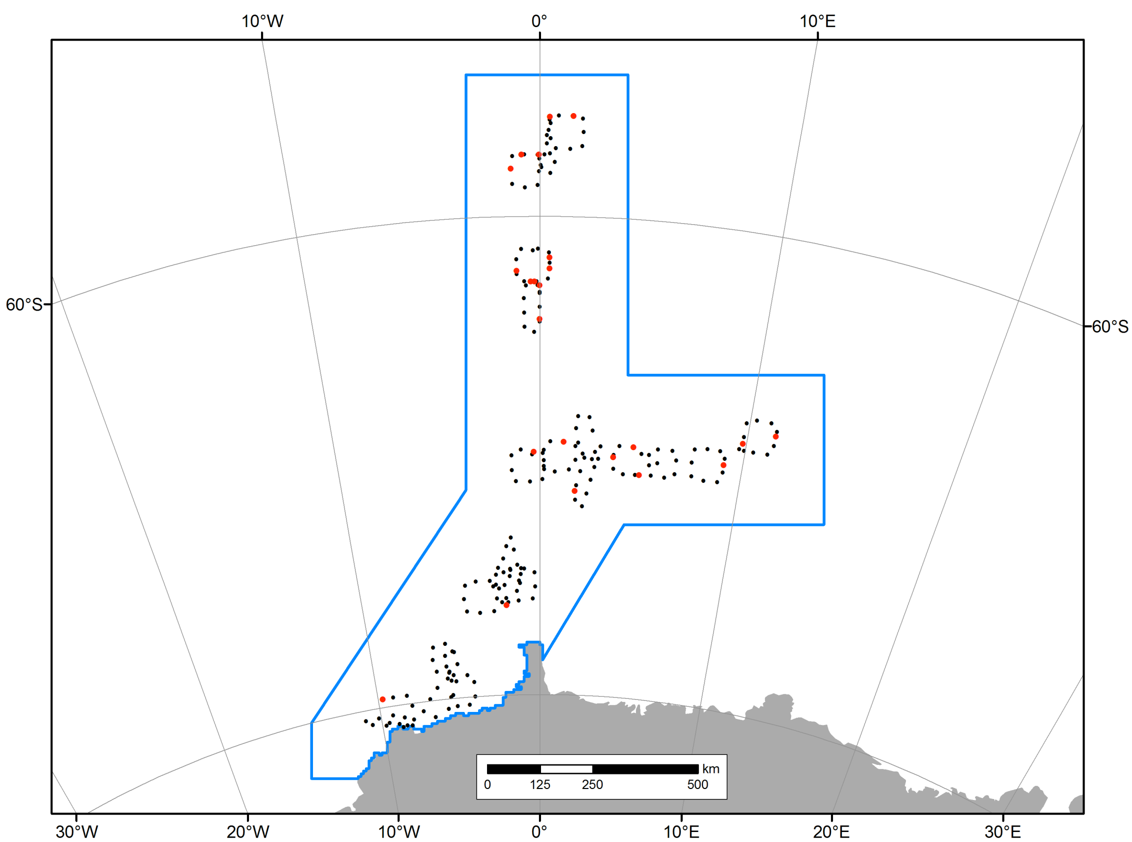
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Figure 1. Effort and sightings from both years of helicopter surveys: 2006-07 (top) and 2008-09 (bottom). Black dots are aggregated segment midpoints (i.e., dots placed, on average, every 17.2 nm along the helicopter trackline) used for density surface modelling. Red dots are sightings of Antarctic minke whales. The blue boxes delineate the boundaries of the study areas in the respective years, and defined the prediction grids across which minke whale density was modelled. These maps, and all subsequent maps, are projected in Polar Stereographic projection with 70 °S as the latitude of true scale.

Two ice concentration measures were considered: (1) "ice_conc" is ice concentration observed along the trackline as judged by observers; and (2) "UBIceConc" is ice concentration interpolated from satellite remote sensing (daily estimates derived from the Advanced Microwave Scanning Radiometer for EOS (ASMR-E) at 6.25 km resolution by the University of Bremen with the Spreen et al. (2008) algorithm, interpolated at survey segment midpoints and whale sighting points using *ArcGIS 9.3.1* (ESRI 2009) and *Marine Geospatial Ecology Tools* (Roberts et al. in press) software). These two measures are obviously related, but we found that the correlation[2] was relatively poor (R^2~0.76). Even this correlation was driven in large part by good agreement between the two measurements in open water (0% ice cover) or completely ice-covered areas (100% ice cover). When cells in open water were eliminated from the correlation, R^2 was 0.66. We used the observer-derived data for the CART, because this is the operational measure: that is, the one that actually determined whether a ship could penetrate into the region. But the GAM requires that the value of all covariates be available for every cell in the prediction grid. Therefore, the second, remotely sensed measure of ice concentration ("UBIceConc") was used in the GAM.

Analysis 1: CART (sightings only)

Following the recommendation of Friedlaender et al. (2006), we conducted exploratory analyses using an iterative process that employed both classification and regression trees (CARTs, Breiman et al. 1984) to explore relationships between ice conditions and distribution patterns of minke whales. We used tree-based regression models as an exploratory technique to uncover structure within the data and to identify variables that contributed significantly to variation in cetacean distributions. Tree-based hierarchical models, such as CART, are based on binary, recursive partitioning methods that aim to resolve relationships to response variables by recursively partitioning data into increasingly homogeneous subgroups (Breiman et al. 1984). CART models can handle a broad range of response types, are invariant to monotonic transformations of the explanatory variables, are easy to construct and interpret, can interpret missing values in both response and explanatory variables, and are able to capture interaction effects among predictor variables (De'ath and Fabricius 2000). CART models are also an attractive analytical tool because, unlike linear models, they do not assume an *a priori* relationship between the response variable and predictor variables; rather, the data are divided into several groups where each has a different predicted value of the response variable (Guisan & Zimmerman 2000, Redfern et al. 2006). Although CART has been used in marine ecological studies primarily for developing predictive models, as with most nonparametric statistical tools, it is more suitable as an exploratory data analysis tool, since it results in a discontinuous prediction surface that may not be scientifically defensible. When the underlying relationship between the response and the predictor is close to linear,

[2] See Appendix 1 for plots comparing various along-transect and satellite-derived measures of ice concentration.

CART can be extremely inefficient. As a result, it is often used as a variable selection method. Qian & Anderson (1999) illustrated the use of CART for identifying predictor variables that contribute significantly to variation in response variables. They described such use of CART as 'ANOVA in reverse'.

Analysis 2: GAM/DSM (effort and sightings)

We followed the recommendation of Ashe et al. (2010) and supplemented the CART analysis with an analysis using generalised additive models (GAMs) for parameter estimation and for generating predictions. We used the 'count' method of Hedley et al. (1999). Transects were split into segments. Initially, we used a mean segment length of 3.38 km (1.82 nm), but the large number of zeroes and poor model fit required us to increase it to 31.8 km (17.2 nm).

Candidate covariates were latitude, longitude and two ice-related covariates: satellite-derived ice concentration; and distance from the 'ice edge', defined as the smooth line defining the 15% ice concentration margin (Ainley et al. 2007). The extent of the ice edge was calculated for each daily satellite image with *ArcGIS Spatial Analyst* functions (ESRI 2009) by selecting the largest polygon of contiguous pixels with ≥ 15% ice concentration (i.e. the polygon encompassing the land-fast ice), extracting the outermost edge, and smoothing it using the *Spatial Analyst* "Boundary Clean" operator with the default parameters.

Animal density was modelled using the density surface modelling (DSM) engine in *Distance 6.0 Release 2* (Thomas *et al.* 2010) using the 'count' method first developed by Hedley et al. (1999), which involves: (1) fitting a detection function; (2) estimating whale abundance in each segment as a function of spatial covariates; and (3) using the descriptive model to predict whale density throughout the study region. Candidate forms for the detection function were the hazard-rate and half-normal models. Model selection was guided by AIC, GCV score, term-wise confidence interval coverage and approximate term-wise p–values using the recommendations of Wood (2001) for choosing to drop or retain terms, or replace smooths with linear terms.

Track line detection probability was assumed to be certain (i.e. $g(0)$ was assumed to be 1). The log of school size, $\ln(s)$, was regressed on the estimated detection probability at the perpendicular distance for each school. The predicted value of $\ln(s)$ at zero distance (where detection probability was assumed to be 1) was then back-transformed to provide the required estimate.

The saturated model ['Model 1'] was of the general form:

$$N \sim te(longitude, latitude) + s(UBIceConc) + s(UBIceDist) + offset$$

This saturated model was used unless a term was not significant at $p<0.05$, or if GCV score increased when the term was dropped. If the estimated degrees of freedom associated with a smooth was 1, the smooth was replaced with a linear term, or dropped if $P>0.05$ for the linear term.

There is a strong correlation between latitude and ice concentration, so a second approach ['Model 2'] considered a model of the general form:

$$N \sim te(UBIceConc, longitude) + s(UBIceDist) + offset$$

Two gridded datasets were created, one for each survey year (2006-07 and 2008-09), containing a value in every grid cell for each explanatory variable in the model. The extents of the grids (Figure 1) were defined by discarding survey legs north of 55 °S, buffering the remaining survey legs by 100 km, manually drawing a simple polygon that enclosed all of the buffers, and erasing areas classified as land by the satellite sea ice dataset. (The original land mask for this dataset classified the collapsed Larsen B ice shelf as land; we manually reclassified these cells as water by overlaying several MODIS thermal infrared images (NSIDC 2009) from 2006-09 that clearly showed the true extent of land.) The grids used the geographic projection (polar stereographic, true scale at 70 °S). Average cell size of the prediction grid was $400km^2$. Values for the explanatory variables (latitude, longitude, UBIceConc and UBIceDist) were calculated using the value at the midpoint of each grid square. The prediction grid data were passed to the selected model for each species in *Distance*, which called the predict.gam function in mgcv. The output of the model was an estimate of the predicted number of whale schools in each grid cell, based on each cell's latitude, longitude, ice cover, distance to ice edge, and area. Animal abundance was calculated by multiplying the predicted density in each cell by expected school size from the size-bias regression in the detection function modelling step and by the area of each cell, and taking the sum of all values in the grid.

RESULTS

Analysis 1: CART

The CART was used to generate summary statistics for all cetacean sightings collected in relation to two ice-related, environmental response variables: distance to ice edge, and % ice cover (Figure 2). We included 177 cetacean sightings. The first fundamental split in the tree occurred at a distance of ~142km from the ice edge (Figure 2). The vast majority of cetaceans found farther than this distance were humpback and fin whales. Of the remaining 100 sightings made within this distance to the ice edge, 94 were minke whales. Of these 94 sightings, 87 were made in ice cover >5%, all of which were minke whales. Thus, the vast majority of minke whale sightings (87 of 94) were made within the pack ice. Receiver operator characteristic (ROC) curves were fitted to the sightings data as a means to measure the likelihood of false positives in the CART (sensitivity versus specificity). A value of 1.0 would indicate no chance of false positives, and for minke whales we calculated an ROC value of 0.96, an indication of the validity of our sightings and analytical analysis.

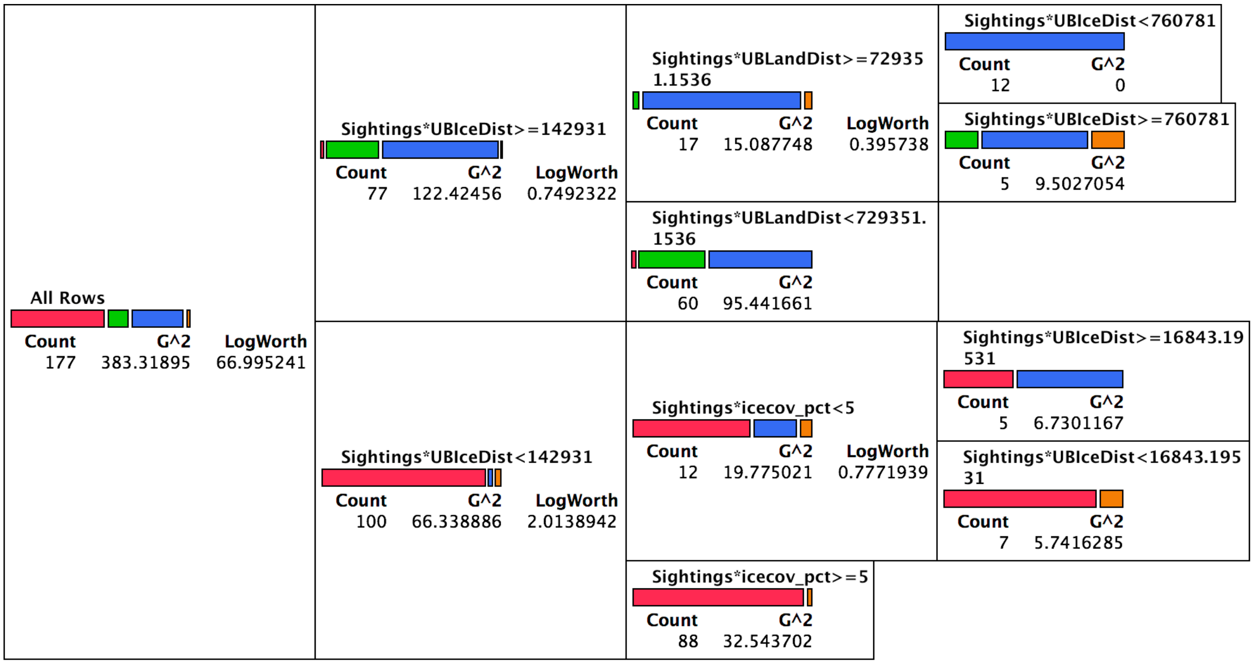


Figure 2. CART results. Minke sightings (red); fin (green), humpback (blue) and killer whale (orange) as functions of percent ice cover (observed along the trackline, i.e. "icecov_pct") and distance to ice edge ("UBIceDist", which is distance to the ice edge in meters). The length of the bar corresponds to number of sightings of that species. Note that the first split (the one that explains the most variability) suggests that sightings made >143km from the ice edge are likely to be humpback or fin whales; while those <143km are likely to be minke whales. The second split, within minkes, suggests that most minkes were found in waters with >5% ice concentration.

Analysis 2: GAM

Model 1 included a truly 2D spatial smooth (te(lon, lat)) and a fairly simple remaining relationship between minke density and ice concentration (Figure 3). The term for distance to ice edge (UBIceDist) was not significant.

Family: quasipoisson
Link function: log

Formula:
N ~ te(lon, lat) + s(ubiceconc) + offset(off.set)

Parametric coefficients:

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -171.24      62.95   -2.72  0.00666 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
              edf Ref.df      F  p-value
te(lon,lat)  15.25  15.25  9.534  < 2e-16 ***
s(ubiceconc)  3.90   3.90 20.520 8.58e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.263   Deviance explained = 52.4%
GCV score = 1.5473  Scale est. = 1.4797    n = 829

Method: GCV   Optimizer: outer newton
full convergence after 8 iterations.
Gradient range [-9.578165e-09,2.013986e-07]
(score 1.547292 & scale 1.479746).
Hessian positive definite, eigenvalue range [0.001029214,0.002290779].
```

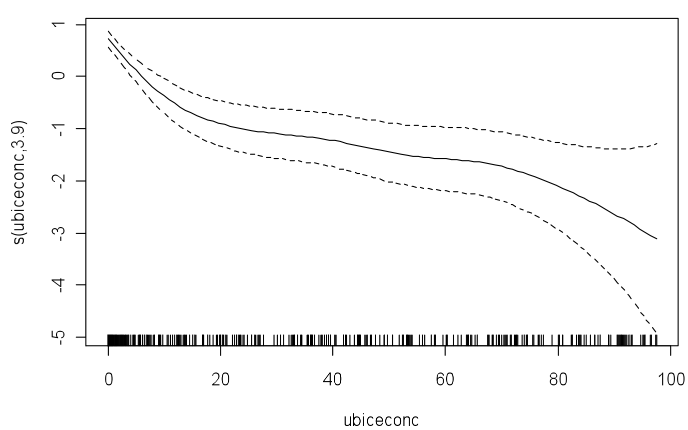


Figure 3. Partial effect of ice concentration (i.e., satellite-derived value, "UBIceConc") on the x-axis, and minke whale abundance on the y-axis. Values above 0 on the y-axis imply a higher than average probability of detecting a minke whale in that segment, while negative values imply low probability of detecting a minke whale in that segment. A rugplot along the x-axis shows observations (distribution of effort). Dashed lines indicate 95% confidence intervals: in cases where the intervals span 0, the effect is not significant.

Model 2 replaced the 2D location smooth (lon, lat) with a tensor-product smooth of ice and longitude (te(UBIceConc, lon)). In this instance, distance to ice edge was retained in the model.

```
Family: quasipoisson
Link function: log

Formula:
N ~ te(ubiceconc, lon) + s(ubicedist) + offset(off.set)

Parametric coefficients:
```

```
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    -5626       2109  -2.667   0.0078 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
                  edf Ref.df     F  p-value
te(ubiceconc,lon) 15.63  15.63 8.104  < 2e-16 ***
s(ubicedist)       6.45   6.45 8.512 1.77e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.197   Deviance explained = 46.9%
GCV score = 1.7422  Scale est. = 1.6551    n = 829

Method: GCV   Optimizer: outer newton
iteration limit reached after 200 iterations.
Gradient range [-0.0005767284,0.01555837]
(score 1.742224 & scale 1.655136).
Hessian positive definite, eigenvalue range [0.001752719,10.77258].
```

Both models require additional work, and our intent in presenting these preliminary results is to solicit guidance on how the analyses should proceed. We show the residuals in Figure 4. For illustrative purposes, we report preliminary, tentative estimates of abundance produced from Model 1 in Table 1.

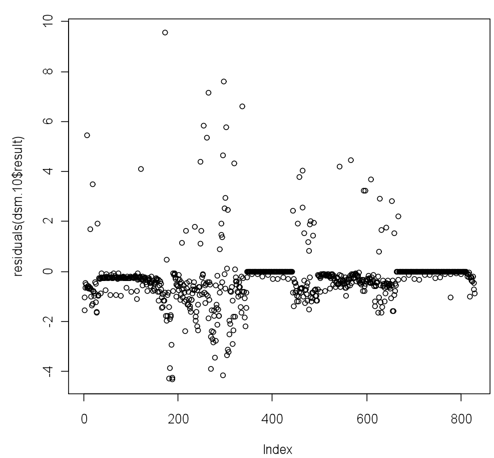
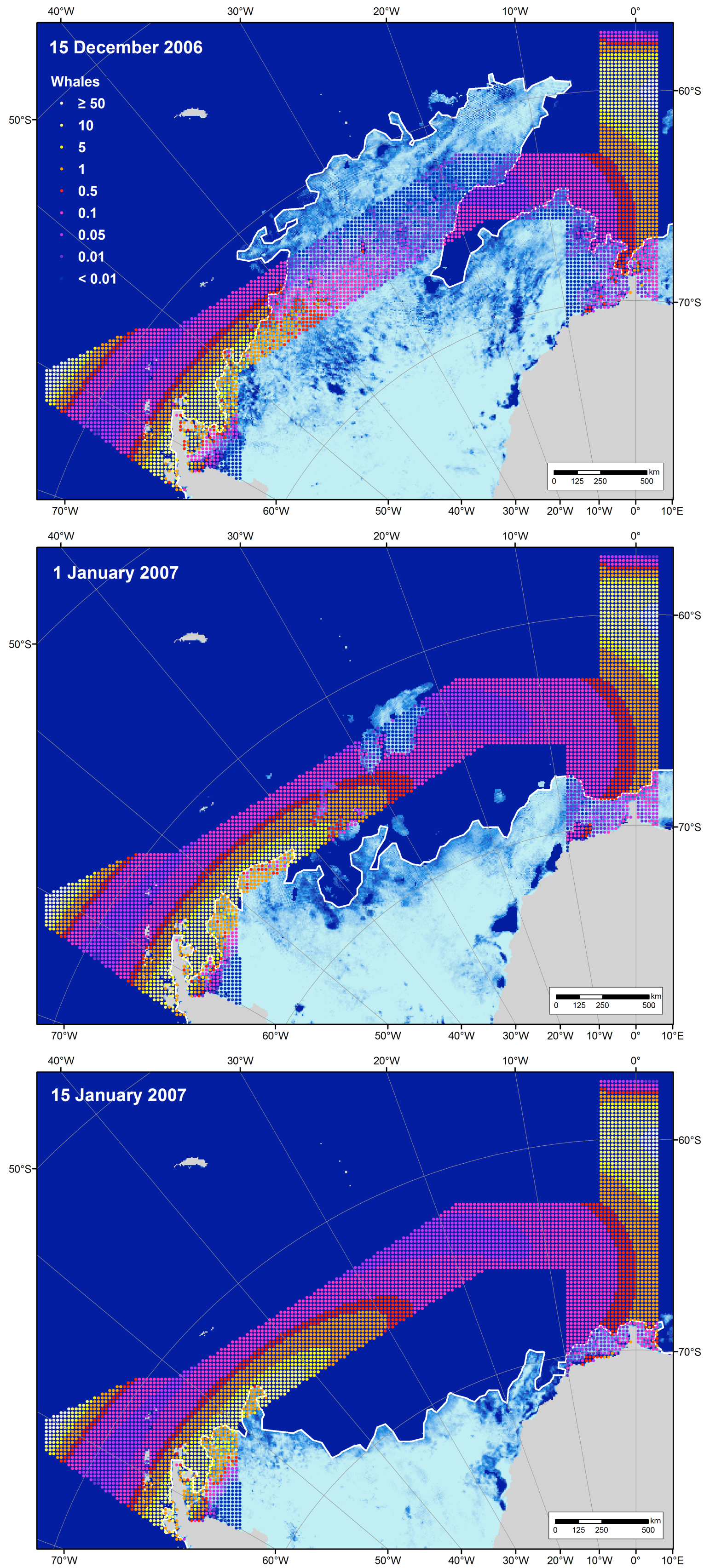


Figure 4. Residuals from the fitted model (Model 1).

Survey	N
Year 1, beginning	24,017
Year 1, middle	25,821
Year 1, end	26,196
Year 2, beginning	6,396
Year 2, middle	18,585
Year 2, end	18,736

Table 1. Abundance of minkes predicted from Model 1. Note that the size of the prediction grid (study area) was much smaller in year 2 than in year 1 (see figure 1).

Based on this tentative model, predicted density surfaces (three-panel [early, mid and late season] plots for each of the two years) are shown below for minke whales, overlain on ice conditions. The first pair of multi-panel plots are predictions for Year 1 and Year 2 from Model 1. The second pair of multi-panel plots are predictions for Year 1 and Year 2 from Model 2. Please note that the scales are the same within year, but differ between years. The scale bar (shown) is on a constant log interval, in order to emphasise the contrast within the study area. The heavy white line shows the computed "ice edge".


15 December 2006
Whales
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10
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0.05
0.01
< 0.01
40°W
30°W
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10°W
0°
50°S
60°S
70°S
70°W
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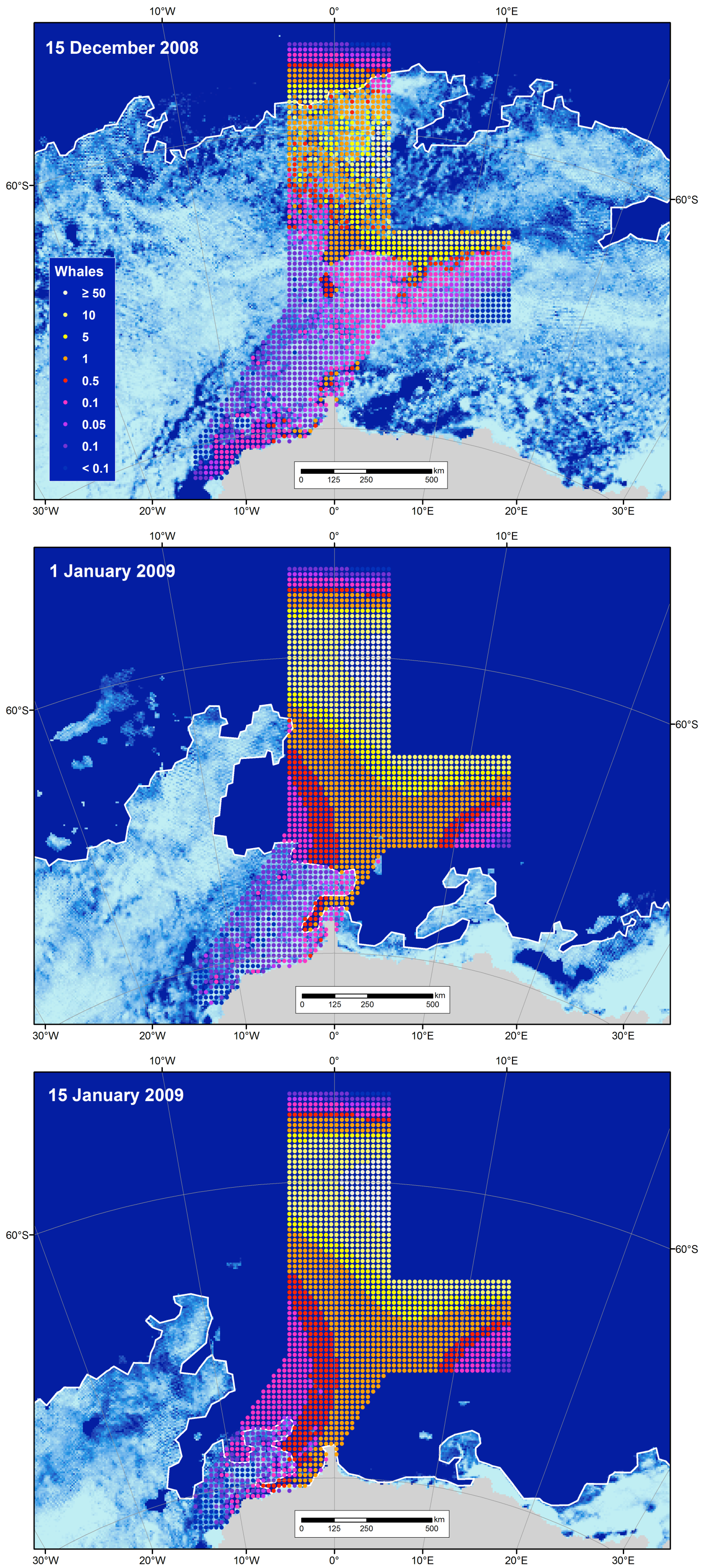
km
0 125 250 500
1 January 2007
15 January 2007


15 December 2008
Whales
≥ 50
10
5
1
0.5
0.1
0.05
0.1
< 0.1
1 January 2009
15 January 2009
10°W
0°
10°E
60°S
30°W
20°W
10°E
20°E
30°E
km
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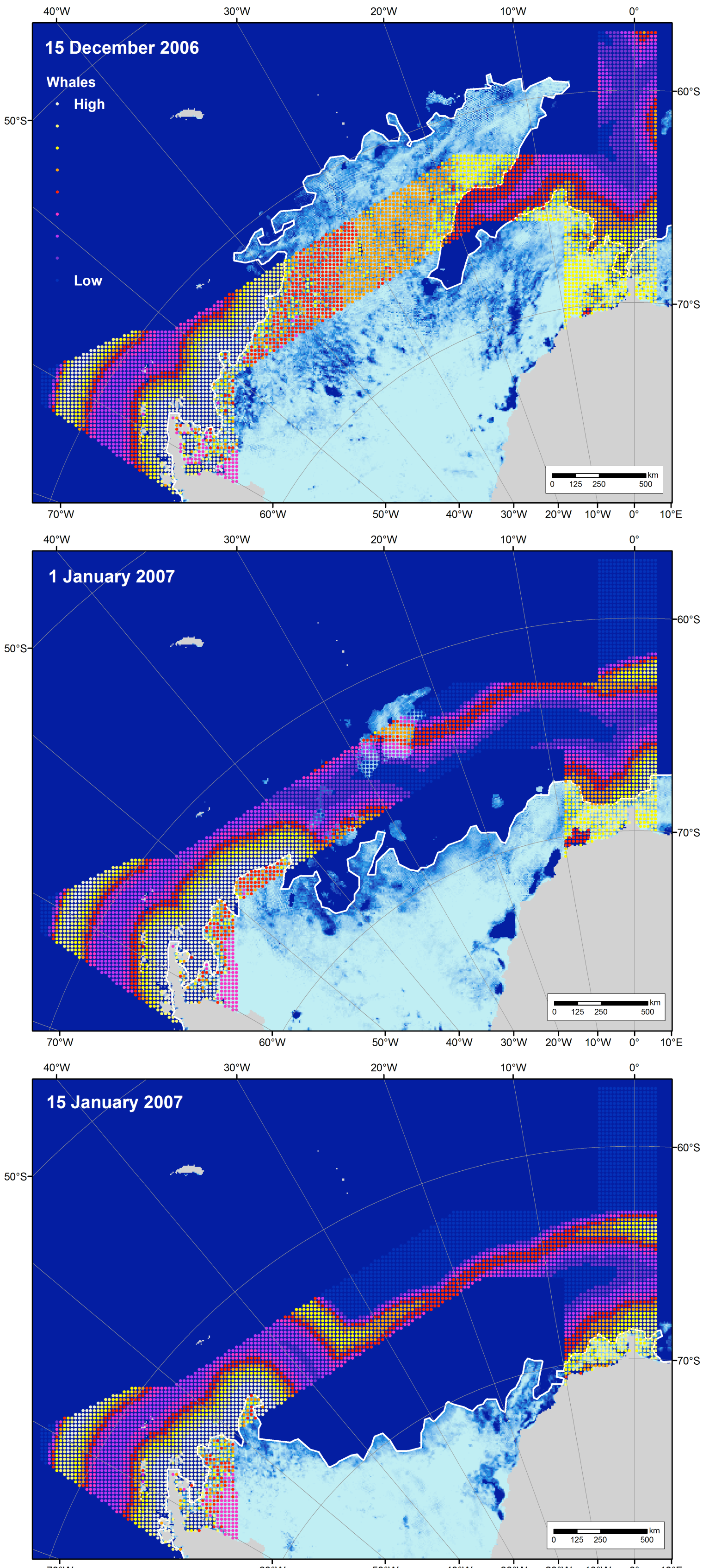
125
250
500

Predicted density surface from Model 2


15 December 2006
Whales
High
Low
1 January 2007
15 January 2007
40°W
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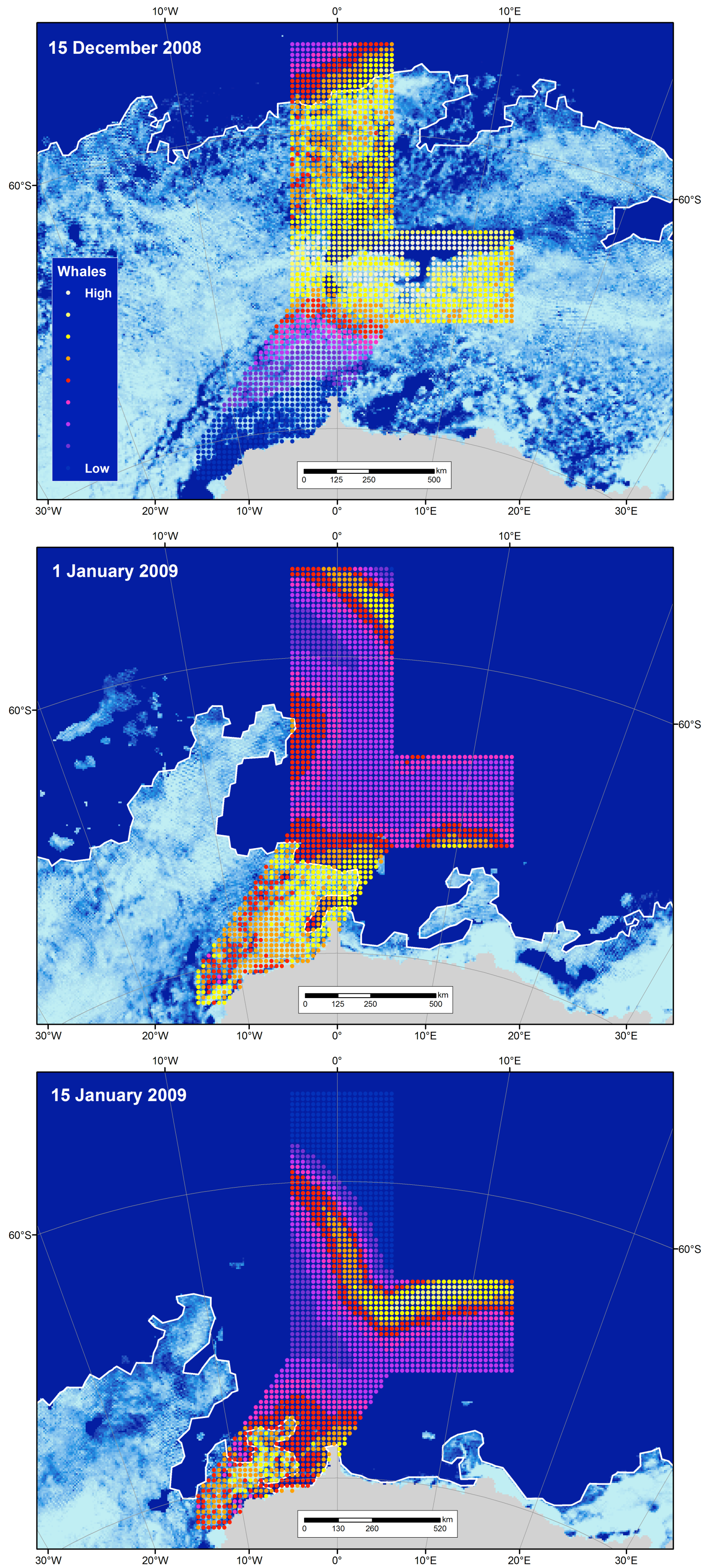
15 December 2008
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DISCUSSION

It is premature to draw definitive conclusions from the density surface modeling (see below for suggestions), but the CART shows clearly that the number of sightings of minke whales was high in waters with >5% ice cover.

The GAM analysis is still very much at the exploratory stage. Both models showed strong support for the existence of a relationship between sea ice and minke whale density; both models showed that minke whale density was highest in waters with moderate ice concentration. But additional analyses are required to estimate the bounds of that moderate ice concentration and therefore habitat preference. Neither model is yet suitable for parameter estimation. Both models exhibit problems in the residuals. The second model (ice,lon) shows that ice is more important as a predictor than it is if you offer a purely spatial term (lon,lat) first. But we are, in both cases, fitting fairly complex models to few data, and we do not claim to have results at this stage – rather, our point is simply to solicit feedback at this meeting to guide future analysis. In the first model (which uses lon,lat), predicted density does not appear to change much even when ice conditions change dramatically, because the lon,lat term had much stronger predictive power than the ice terms. The model is essentially claiming that minkes showed a preference for specific geographic regions, but that this strong preference was moderated somewhat by the ice conditions at the time. The second model te(UBIceConc, lon) + s(UBIceDist) shows a stronger effect of ice as a predictor, but the effect is not a straight-forward one.

Our primary intent for this paper is to show preliminary results to solicit feedback that can be used to guide future analyses. Hedley and Bravington have developed new methods (described in Williams et al. SC/62/SHXX) that we intend to apply to these data. Suggestions from Hedley include:

1. rescale latitude and longitude so that they represent the same distance in each direction (or used projected positions in meters) and use an isotropic smoother (specifically, package 'soap').

2. The 'soap' package requires specification of a survey boundary. We would like some guidance about whether the boundary we defined (Figure 1) is appropriate, or whether there are stock boundary or other management needs that would warrant consideration of another boundary.

3. Try different distributions (e.g., Tweedie).

4. Evaluate whether the ice variables and latitude are measuring the same thing. In other words, the lack of within-year variability in Figure 5 may indicate that our approach did not allow the model to track the true effect of changing ice conditions. A tensor product of ice, longitude may allow a better representation of the variables we suspect are driving minke whale distribution. (We tried this in our second model, but this will change when we use 'soap' and different family/distribution.)

5. Additional model diagnostics: (a) 'gam.check' within mgcv; (b) choice of k; (c) residual checking (plot(model,residuals=T) and residuals(model)).

In summary, even after accounting for effects of latitude and longitude, there is a strong relationship between ice concentration and minke whale abundance. The CART and GAM both showed that minke whales were most likely to be seen in waters with >5% ice concentration. There is a large difference (Appendix 1) between ice concentration as derived from satellite imagery and that observed in the field (along the trackline) – it is easier to use the former in a spatial model (because we have a value for every point in the grid), but it is essential to find out which metric is the one that is used operationally (for a go/no-go decision in SOWER surveys). For trend analysis, it is vital to know whether survey protocols changed over time: is the operational definition of “ice-covered” waters that are unavailable for survey those that are covered by >5 or 10% ice cover as observed along the trackline, or inferred from satellite imagery? In other words, has this go/no-go threshold changed over time?

Finally, it should be noted that these models provide a snapshot at the time when our study took place. Our efforts have focused on modelling the relationship(s) between sea ice and minke whale density as we observed it during our surveys. We cannot know whether this relationship has changed over time. We see no reason to assume that the proportion of minkes in the ice has changed from CP-II to CP-III, and until then, assume that this proportion is a constant.

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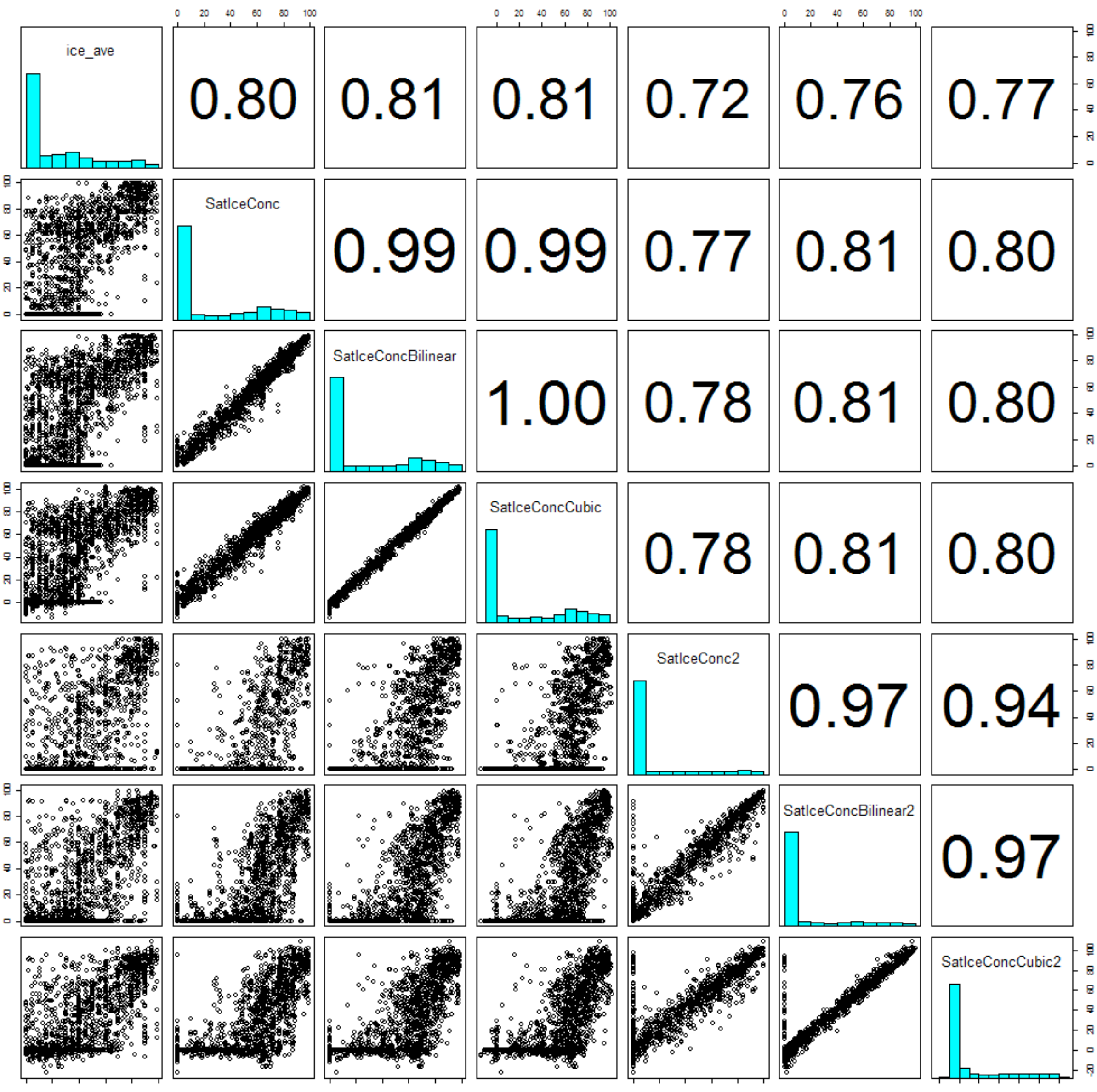
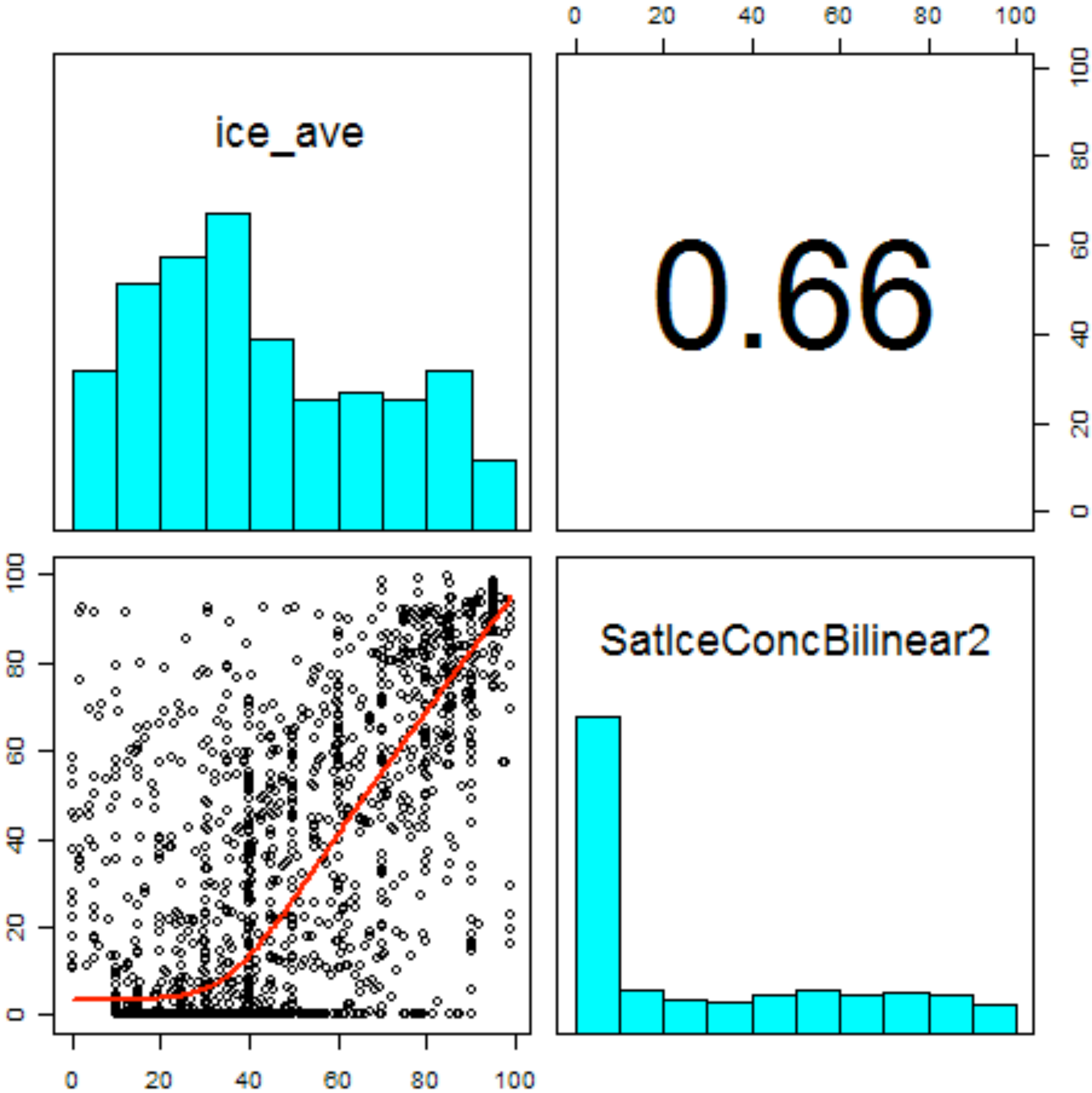
Appendix 1. Comparison of ice concentration measured along the trackline and remotely sensed (satellite imagery) data. The scatterplot matrix at the top uses all data, while the lower figure removes all open-water observations (i.e., zero ice concentration); red line is a lowess smooth.





ice_ave
0.66
SatIceConcBilinear2
0
20
40
60
80
100