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Center

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A Calibration Function for Correcting Mean Net Spread Values Obtained from Marport Spread Sensors Used in Conjunction with the Marport MK II Receiver

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INTRODUCTION

Acoustic net mensuration is used on chartered Alaska Fisheries Science Center (AFSC) bottom trawl (BT) survey vessels to monitor and record net spread during standard survey operations. Net spread measurements are a critical component for calculating area swept by the survey BT at each station (Alverson and Pereyra 1969). Area swept estimates are used to extrapolate catch sample weights and numbers to estimate survey abundance and biomass of commercially important bottom fishes and crabs to monitor their population trends (BSAI Groundfish Plan Team 2013). By the late 2000s, the existing inventory of the AFSC's acoustic net mensuration sensors and receivers, produced by either Scanmar or Netmind, Northstar Technical, Inc., were aging and becoming increasingly unreliable and costly to maintain and repair; hence, replacements had to be found. In 2009, the AFSC committed to replacing its inventory with sensors and receivers produced by a new and different manufacturer, Marport Deep Sea Technologies, Inc.. By 2013, the AFSC had purchased a sufficient quantity of Marport MK II acoustic receivers and net mensuration sensors to completely outfit its primary bottom trawl surveys. Previous dock tests using Scanmar and Netmind systems showed that either system produced accurate measurements of distance with a resolution of +/- 0.1 m (R. Lauth unpublished data). To ensure that measurements from the new Marport system were comparable to the old AFSC net mensuration systems, further dock tests were conducted by the AFSC in 2012 to compare net spread measurements produced by the Scanmar and Marport systems. Results indicated that Marport spread sensors, when used in conjunction with the MK II acoustic receiver, produced imprecise and inaccurate spread measurements. Ensuing discussions with Marport representatives and engineers prompted Marport to conduct a more controlled test tank experiment in Lorient, France. The experiment was done using three fixed distances (11.90 m, 26.20 m, and 48.93 m) and a combination of the Marport spread sensors with three different acoustic receivers: the Marport MK II, the Marport M4 prototype, and the Scanmar Scanbass. Bottom depth and water salinity within the test tank were static and the master Marport spread sensor was preprogrammed with a 2-m offset and a default speed of sound in water of 1,482 m s^{-1}. Results from the tank test showed that the Marport spread sensors, when used in conjunction with the Marport M4 prototype and Scanmar Scanbass acoustic receivers, produced accurate results with good precision; however, results with the same spread sensors used in conjunction with the MK II acoustic receiver (the receiver used in AFSC BT surveys) were biased with poor precision (Table 1). Using the MK II receiver, the bias of the mean spread distance was + 0.81 m at the shortest fixed distance of 11.92 m. The bias of the mean spread distance was reduced slightly at fixed distances of 26.20 m (+ 0.64 m) and 48.90 m (- 0.15 m), but poor precision remained unchanged.

In anticipation of the switch to Marport in 2013, a field experiment was conducted during the 2012 EBS shelf BT survey (Lauth and Nichol 2013) to determine how the Marport net spread measurements using the MK II receiver varied as a function of Netmind net spread. Data collected from the experiment were used to derive a calibration function for adjusting the mean Marport net spread measurements in subsequent survey years whenever Marport net spread sensors were used in combination with the MK II acoustic receiver.

METHODS AND ANALYSIS

Comparison net spread data were collected on the survey charter vessels *Alaska Knight* and *Aldebaran* during the 2012 AFSC EBS shelf BT survey using both the Netmind and Marport acoustic net mensuration systems. The Netmind system, which has been used on EBS shelf BT surveys since 2002 (Acuna et al. 2003), provided the benchmark for mean spread measurements. Net spread was measured as the distance between two sensors attached immediately forward of the connection of the upper breastline to the dandyline. The Marport and Netmind spread sensors were deployed on the same net at the same time with the master Marport spread sensor located forward of the starboard wing and the master Netmind spread sensor in the same location forward of the port wing. Slave sensors were attached to dandylines forward of the first set of sensors opposite of their respective master. A Marport MK II acoustic receiver was used for processing raw spread data from the Marport spread sensors, and a Netmind receiver was used for processing raw spread data from the Netmind sensors. The targeted standard tow duration was 30 minutes with a speed over ground of 3.0 knots.

A 2-m offset was preprogrammed into the Marport master spread sensor aboard the *Aldebaran* but not into the Marport sensor aboard the *Alaska Knight*; hence, the mean Marport net spread values for tows from the *Alaska Knight* were adjusted downward by 2-m to make them comparable to those from the *Aldebaran*. Master spread sensors from both vessels were preprogrammed with the speed of sound set at 1,500 m s^{-1}. Start and end times for each tow were selected using bottom contact sensor data to determine the time when the footrope first touched the seafloor and the time it departed the seafloor.

Net spread data near the start and end times of tows were often sparse or missing, and this data scarcity varied by vessel, depth of tow, and the type of net mensuration system being used. To minimize bias caused by these potentially non-random begin- and end-of-tow effects, only data from 3 minutes after start time to 3 minutes before end time were used in the analysis. Because asymmetrically distributed outliers and an unequal density of net spread values are typical in raw net spread data and introduce bias when calculating an arithmetic mean (Kotwicki et al. 2011), the following steps were taken to calculate net spread means and standard deviations. First, the R program was used to iteratively apply sequential outlier rejection (SOR; Kotwicki et al. 2011) and smoothing procedures to the raw Netmind and Marport net spread data (Appendix 1). To avoid the large influence of sparse data points on the smoothing algorithm, sparse data were removed first. “Sparse” was defined as less than 4 data points in any 1-minute interval during a tow. The SOR procedure was initiated by fitting a cubic spline smoother (Hastie and Tibshirani 1990) to the net spread data and removing a single data point that was identified as having largest absolute value of the residual from smoothing procedure. This procedure was iteratively repeated until the stopping rule for the SOR was reached based on simulations performed by Kotwicki et al. (2011). Second, the mean net spread and standard deviation were calculated from the fitted smoothed line of the remaining data points. This procedure resulted in reduced bias in the estimation of mean net spread compared to the usual method of using a simple arithmetic mean of observed net spread values within a fixed range of values from 8 to 22 m. Finally, a simple linear regression of mean Netmind net spread as a function of mean Marport net spread was done for each vessel. If between-vessel differences in the regression slopes and intercepts were not significant, datasets were pooled and the regression analysis repeated with combined data.

RESULTS AND DISCUSSION

Paired Netmind and Marport spread data were obtained from 136 tows aboard the *Aldebaran* and 122 tows aboard the *Alaska Knight*. Mean net spread and standard deviation were calculated for all 258 tows using the SOR procedure (Appendix 2, Fig. 1). Good linear regression fits were obtained using mean Netmind net spread as the dependent variable and mean Marport net spread as the independent variable for both the *Aldebaran* ($R^2 = 0.97$, $P = 1.8 \times 10^{-103}$) and the *Alaska Knight* ($R^2 = 0.97$, $P = 7.42 \times 10^{-95}$). The relationship for both vessels indicated a decreasing offset in the mean Netmind spread as the Marport spread increased. There were no significant differences between the slopes (P = 0.58) and intercepts (P = 0.99) of the two linear regressions, so data from both vessels were pooled and the regression analysis was repeated. Good fits were also obtained with combined data ($R^2 = 0.97$, $P = 6.9 \times 10^{-191}$) producing the following equation:

$$\text{Mean Netmind spread} = 0.9357 \times \text{Mean Marport spread} + 0.4005.$$

There was general agreement between the results from this field experiment and the test tank results from Lorient, France, done by Marport using the MK II acoustic receiver (Fig. 2). Both indicated decreasing bias with increasing separation between the master and slave spread sensors. The good agreement between the test tank results using known fixed distances and the experimental results using Netmind spread measurements as a proxy for “true” distances corroborates that the measurements from the Netmind net mensuration system provided a good benchmark for unbiased estimates of net spread (Fig. 2). The difference in slope (~0.08) was not significant because of the relative low sample size from the test tank experiment (n = 3) compared to the field experiement (n = 258); however, two factors could have resulted in such a difference. First, the speed of sound through water varies with changes in water temperature, salinity, and pressure (Kotwicki et al. 2011) and changes in these physical variables can affect how acoustic net spread measurements are processed. The field experiment was conducted under *in situ* conditions capturing a wide range of bottom depths, temperatures, and salinities, but the default speed of sound for processing acoustic signals from sensors used the field experiment was fixed at 1,500 m s^{-1}. The speed of sound for processing acoustic signals from the test tank experiment was set at 1,482 m/s, and the depth, temperature, and salinity in the test tank was relatively constant. A second explanation could be that estimates of mean net spread from the field experiment using a SOR procedure and cubic spline smoother resulted in lower bias estimates than the simple arithmetic means from the test tank experiment.

The combination of Marport spread sensors and the Marport MK II acoustic receiver was used to collect net spread data during the 2013 EBS shelf BT survey. In the analysis of all tows from the 2013 survey, the SOR and cubic spline smoother procedures (Kotwicki et al. 2011) were used to estimate mean Marport net spread and the calibration function from this experiment was used to adjust mean net spreads. The reason for doing this was to eliminate bias relative to mean net spreads estimated from previous survey years which were derived using only the observations from the Netmind gear mensuration system. The intention is to continue using the procedure above for adjusting Marport spread data in the future when using in combination with the MK II acoustic receiver. The adjustment may no longer be necessary once the Marport M4 is in production and being used in AFSC BT surveys. Nevertheless, this study underscores the importance of evaluating new or updated spread sensors and acoustic receivers prior to their introduction into AFSC BT surveys to avoid or minimize the introduction of bias into area swept calculations.

CITATIONS

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Table 1. Summary of results from a test tank experiment done in Lorient, France, using Marport spread sensors with three different acoustic receivers at three fixed distances.

	Measured distance by receiver (m)								
	MK II			M4 prototype			Scanmar Scanbass		
Fixed distance	Average	Precision	Error	Average	Precision	Error	Average	Precision	Error
11.90 m	12.71	Poor	0.81	11.93	Good	0.03	11.92	Good	0.02
26.20 m	26.84	Poor	0.64	26.25	Good	0.05	26.27	Good	0.07
48.93 m	48.78	Poor	-0.15	48.77	Good	-0.16	48.95	Good	0.02

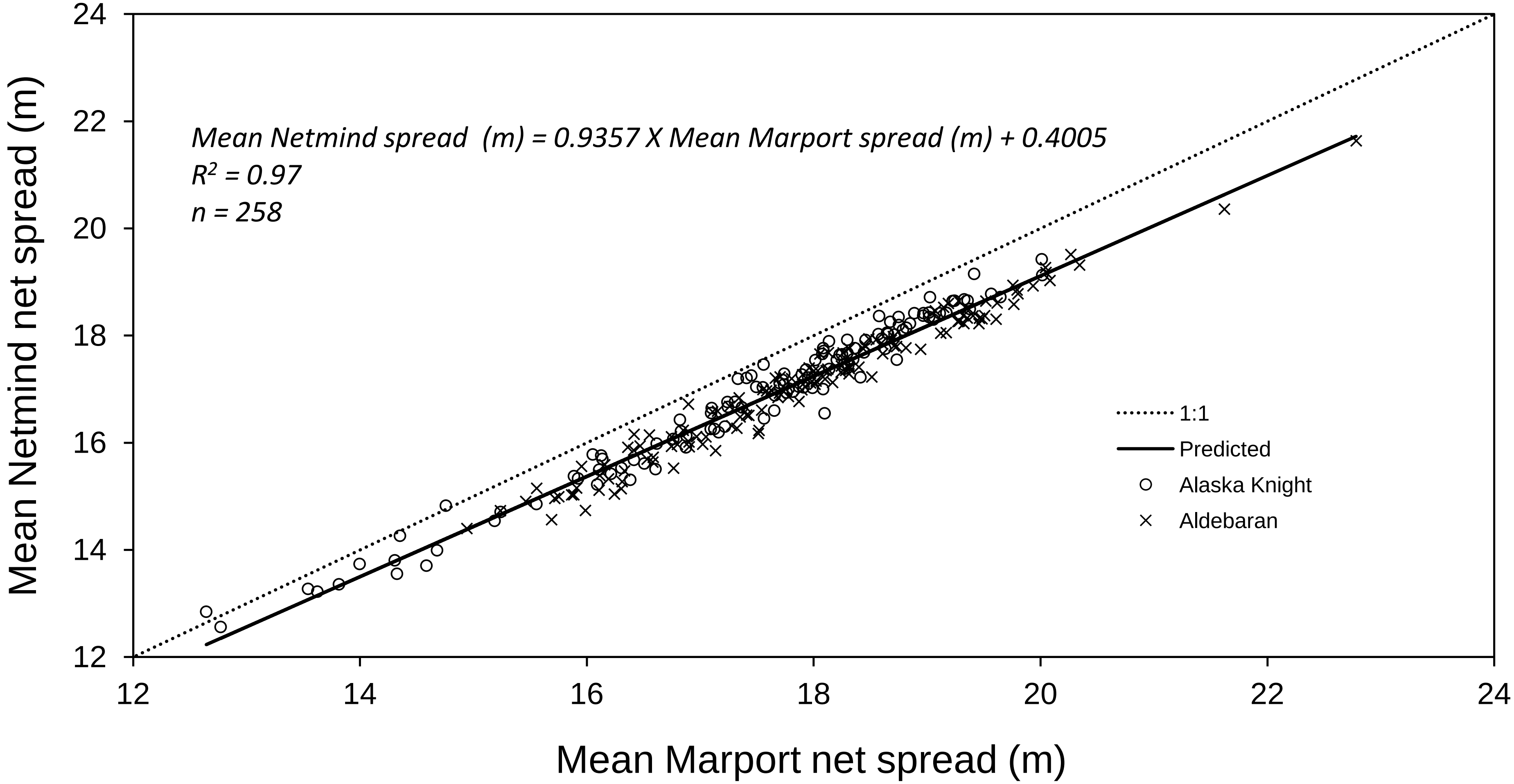

Figure 1. The relationship and simple linear regression of the mean Netmind net spread as a function of mean Marport net spread from field experiment conducted in summer 2012.

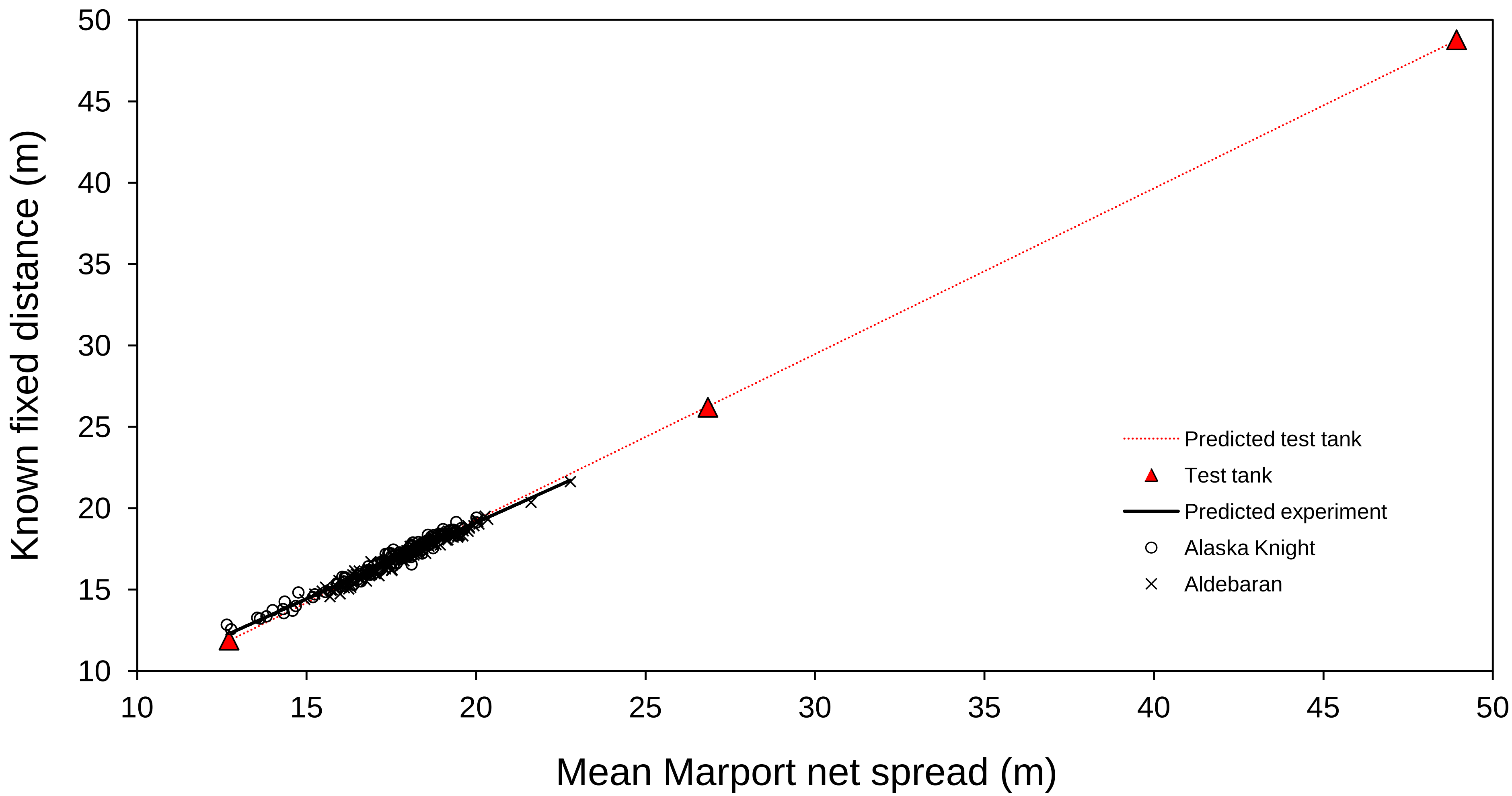

Figure 2. Test tank results from March 2012 using three known fixed distances overlaid with results from the 2012 field experiment. Tank tests were conducted by Marport Deepsea Technologies, Inc. using Marport spread sensors and a Marport Mark II acoustic receiver.

Appendix 1. SOR instructions and R code (version 2.1.5.2) used to obtain mean net spreads for Marport and Netmind.

SOR instructions

1. Copy and paste SOR_table folder into your working directory
2. Put events and spread file in the SOR_table directory
3. Open and run script "do_sor_table.R".
   It is important that you run this script line by line using (Ctr R). I can make it more user friendly later, but for now just run it one line at a time.
4. Scripts will produce csv files for each haul and one large csv file for all hauls that you have in the directory. At one point large file may become to large for R and R may crash. I do not know what this limit is, but if R crashes try to reduce number of hauls in both event and spread files.

R file do_sor_table.R

```
source('sor_table.R')
events=read.events()
haul.data=read.hauls()
sor(haul.data,events,flag=12)
output_sor_table()
dev.off()
sor.means = estimate.means(events)
write.csv(sor.means, 'sor_means.csv')
```

R file sor_table.R

```
require(tcltk)

read.events=function(){
events.file=tclvalue(tkgetOpenFile())
events=read.csv(events.file)
return(events)
}

read.hauls=function(){
haul.data.file=tclvalue(tkgetOpenFile())
haul.data=read.csv(haul.data.file)
return(haul.data)
}

sor = function(haul.data,events,flag=12){
events$DTIME = as.POSIXct(strptime(events$DTIME, "%m/%d/%Y
%H:%M:%OS"))
haul.list=unique(haul.data$HAUL)
for(i in haul.list){
 sgt=haul.data[haul.data$HAUL==i,]
```

```
 #sgt$DATE_TIME=sub('/12','/2012',sgt$DATE_TIME)
 sgt$DATE_TIME = as.POSIXct(strptime(sgt$DATE_TIME, "%m/%d/%Y
%H:%M:%OS"))
 sgt=sgt[sgt$CABINET_SENSOR_FLAG==flag,]
 haul=sgt$HAUL[1]
 if(length(which(events$HAUL==haul))==2){
 on.bottom=events[events$HAUL==haul & events$EVENT==3,]$DTIME
 off.bottom=events[events$HAUL==haul & events$EVENT==7,]$DTIME
 yy=sgt$MEASUREMENT_VALUE[sgt$MEASUREMENT_VALUE<30 &
sgt$DATUM_CODE==0]
 xx=cbind(sgt$RECORD_ID,sgt$DATE_TIME)[sgt$MEASUREMENT_VALUE<30 &
sgt$DATUM_CODE==0,]
 point.density = as.data.frame(cbind(
  aa1=c(1000,1000,1000,xx[,2][4:(length(xx[,2]))]-
xx[,2][1:(length(xx[,2])-3)]),
  aa2=c(1000,1000,xx[,2][3:(length(xx[,2]))]-xx[,2][1:(length(xx[,2])-
2)]),
  aa3=c(1000,xx[,2][2:(length(xx[,2]))]-xx[,2][1:(length(xx[,2])-1)]),
  aa4=c(xx[,2][1:(length(xx[,2])-1)]-xx[,2][2:length(xx[,2])],-1000),
  aa5=c(xx[,2][1:(length(xx[,2])-2)]-xx[,2][3:length(xx[,2])],-1000,-
1000),
  aa6=c(xx[,2][1:(length(xx[,2])-3)]-xx[,2][4:length(xx[,2])],-1000,-
1000,-1000)
 ))
 idx.rej=(point.density$aa2<60 | point.density$aa5>-60 |
          point.density$aa3-point.density$aa4<60)
 xx2=xx[idx.rej,]
 yy2=yy[idx.rej]
 if(length(yy2)>10){
 par(mfrow=c(3,1),mar=c(2, 4, 1, 2))
 plot(xx[,2],yy,ylim=c(0,40),main=paste('Haul',haul,'all data'),
     xlim=c(on.bottom-360,off.bottom+360))
 md1=smooth.spline(yy~xx[,2],spar=.8)
 smooth=predict(md1)
 lines(smooth,col='red')}
 xx1=xx[xx[,2]>on.bottom & xx[,2]<off.bottom,]
 yy1=yy[xx[,2]>on.bottom & xx[,2]<off.bottom]
 if(length(yy1)>10){
 plot(xx1[,2],yy1,ylim=c(0,40),
     xlim=c(on.bottom-360,off.bottom+360))
 abline(v=on.bottom,col=2)
 abline(v=off.bottom,col=2)
 mtext("click here", side = 3, line=0)
 md2=smooth.spline(yy1~xx1[,2],spar=.8)
 smooth2=predict(md2)
 lines(smooth2,col='red')}
 xx3=xx2[xx2[,2]>on.bottom & xx2[,2]<off.bottom,]
 yy3=yy2[xx2[,2]>on.bottom & xx2[,2]<off.bottom]
 if(length(yy3)>10){
 plot(xx3[,2],yy3,ylim=c(0,40),
     xlim=c(on.bottom-360,off.bottom+360))
 abline(v=on.bottom,col=2)
```

```
abline(v=off.bottom,col=2)
mtext("sparse data removed", side = 3, line=0)
md3=smooth.spline(yy3~xx3[,2],spar=.8)
smooth3=predict(md3)
lines(smooth3,col='red')
a = locator(n=1)

resids=yy3-smooth3$y
max.dist = max(abs(resids))
if(sd(resids)<5) {
 stop.dist=-0.3034*sd(resids)^2 + 2.9428*sd(resids)-0.1112
 } else {stop.dist=7}
idx=which(abs(resids)==max.dist)
yy4=yy3
xx4=xx3
for(j in 1:length(yy3)){
 yy4=yy4[-idx]
 xx4=xx4[-idx,]
 #plot(xx4,yy4,ylim=c(0,40))
 md4=smooth.spline(yy4~xx4[,2],spar=.8)
 smooth=predict(md4)
 #lines(smooth,col='red')
 resids=yy4-smooth$y
 max.dist = max(abs(resids))
 if(max.dist>stop.dist){
  idx=which(abs(resids)==max.dist)
  #a = locator(n=1)
  } else {
  print("stopping distance reached")
  #plot(xx4,yy4,ylim=c(0,40))
  md4=smooth.spline(yy4~xx4[,2],spar=.8)
  smooth=predict(md4)
  #lines(smooth,col='red')
  #mtext("data after SOR", side = 3)
  #mtext("click here to acknowledge plot review", side = 1, line=4)
  #a = locator(n=1)
  break
  }
}
plot(xx4[,2],yy4,ylim=c(0,40),xlim=c(on.bottom-360,off.bottom+360),
    ,main=paste('Haul',haul,'data after SOR'))
lines(smooth,col='red')
abline(v=on.bottom,col=2)
abline(v=off.bottom,col=2)

accept = readline("Do you accept SOR solution? (y or n)")
if(accept=="y"){
 DATUM_CODE_N=data.frame(DATUM_CODE_N=rep.int(0,length(xx4[,2])))
 XX=data.frame(xx4)
 colnames(XX)[1]="RECORD_ID"
 newdata=cbind(XX,DATUM_CODE_N)
 newdata1 = merge(sgt,newdata,all=T)
```

```
  newdata1=newdata1[,-11]
  newdata1$DATE_TIME=format(newdata1$DATE_TIME, "%m/%d/%Y %H:%M:%S")
  newdata1$DATUM_CODE_N[is.na(newdata1$DATUM_CODE_N)]=10

newdata1$DATUM_CODE_N[newdata1$DATUM_CODE!=0]=newdata1$DATUM_CODE[newd
ata1$DATUM_CODE!=0]
  newdata1$DATUM_CODE=newdata1$DATUM_CODE_N
  newdata1=newdata1[,-11]
  write.csv(newdata1,paste("sor_h",haul,".csv",sep=""), quote =
F,row.names = F)
  } else {
  DATUM_CODE_N=data.frame(DATUM_CODE_N= rep.int(10,length(sgt[,1])))
  newdata1=cbind(sgt,DATUM_CODE_N)
  newdata1$DATE_TIME=format(newdata1$DATE_TIME, "%m/%d/%Y %H:%M:%S")

newdata1$DATUM_CODE_N[newdata1$DATUM_CODE!=0]=newdata1$DATUM_CODE[newd
ata1$DATUM_CODE!=0]
  newdata1$DATUM_CODE=newdata1$DATUM_CODE_N
  newdata1=newdata1[,-11]
  write.csv(newdata1,paste("sor_h",haul,".csv",sep=""), quote =
F,row.names = F)
  print("Spread data rejected")}
 } else {
  plot(0,0,pch="",main=paste('Haul',haul))
  text(0,0,"data not sufficient")
  a=locator(n=1)
 }
} else {
plot(0,0,pch="",main=paste('Haul',haul))
text(0,0,"no on bottom times for this haul")
a=locator(n=1)
}
}

}

#sor(haul.data,events)

output_sor_table=function(){
file.type = 'sor_h'
file.list=list.files(pattern=file.type)
sor.data=NA
for(i in 1:length(file.list)){
 sor.data1=read.csv(file.list[i])
 sor.data=rbind(sor.data,sor.data1)
}
sor.data=sor.data[-1,]
write.csv(sor.data,"sor_output.csv")
}
```

```
estimate.means = function(events){

events$DTIME = as.POSIXct(strptime(events$DTIME, "%m/%d/%Y
%H:%M:%OS"))
haul.data = read.csv('sor_output.csv')
haul.list=unique(haul.data$HAUL)

Haul=NA
mean.spread=NA
N=NA
resid.sd=NA

for(i in 1:length(haul.list)){
 sgr=haul.data[haul.data$HAUL==haul.list[i],]
 sgr$DATE_TIME = as.POSIXct(strptime(sgr$DATE_TIME, "%m/%d/%Y
%H:%M:%OS"))
 haul=sgr$HAUL[1]
 Haul[i]=haul
 if(length(which(events$HAUL==haul))==2){
  on.bottom=events[events$HAUL==haul & events$EVENT==3,]$DTIME
  off.bottom=events[events$HAUL==haul & events$EVENT==7,]$DTIME
  xx=sgr$DATE_TIME[sgr$DATUM_CODE==0]
  yy=sgr$MEASUREMENT_VALUE[sgr$DATUM_CODE==0]
  xx1=xx[xx>on.bottom & xx<off.bottom]
  yy1=yy[xx>on.bottom & xx<off.bottom]
  if(length(yy1)>10){
   plot(xx1,yy1,ylim=c(0,40),main=haul,
     xlim=c(on.bottom-360,off.bottom+360))
   abline(v=on.bottom,col=2)
   abline(v=off.bottom,col=2)
   md2=smooth.spline(yy1~xx1,spar=.8)
   smooth2=predict(md2)
   lines(smooth2,col='red')#
   min.xx1=min(xx1)
   max.xx1=max(xx1)

preds=predict(md2,x=as.numeric(seq(min.xx1,max.xx1,length.out=500)))
   difs.xx=smooth2$x[2:length(smooth2$x)]-
smooth2$x[1:(length(smooth2$x)-1)]
   difs.preds=preds$x[2]-preds$x[1]
   gaps=which(difs.xx>20)
   for(gg in gaps){
    xx1.from=smooth2$x[gg]
    xx1.to=smooth2$x[gg+1]
    idx.preds=which(preds$x>xx1.from & preds$x<xx1.to)
    yyp1=preds$y[min(idx.preds)-1]
    yyp2=preds$y[max(idx.preds)+1]
    xxp1=preds$x[min(idx.preds)-1]
    xxp2=preds$x[max(idx.preds)+1]
    incr.gap=(yyp2-yyp1)/(length(idx.preds)+1)
    predsb=yyp1+c(1:length(idx.preds))*incr.gap
    preds$y[idx.preds]=predsb
```

```
    }
   lines(preds,col=3)
   mean.spread[i]=mean(preds$y)
   N[i]=length(yy1)
   resid.sd[i]=sd(residuals(md2))
   mtext(paste('Mean =',round(mean.spread[i],2),'SD
=',round(resid.sd[i],2)),
            side = 3, line=0)
   a=locator(n=1)
   } else {
    plot(0,0,pch="",main=paste('Haul',haul))
    text(0,0,"data not sufficient")
    a=locator(n=1)
   }
   } else {
   plot(0,main="no on or off bottom times")
   mean.spread=mean(preds$y)
   a=locator(n=1)
  }
}
summary.spreads =
as.data.frame(cbind(Haul=Haul,N=N,Mean=mean.spread,SD=resid.sd))
return(summary.spreads)
}

#estimate.means(events)
```

R file means_sor

```
estimate.means = function(events){

events$DTIME = as.POSIXct(strptime(events$DTIME, "%m/%d/%Y
%H:%M:%OS"))
haul.data = read.csv('sor_output.csv')
haul.list=unique(haul.data$HAUL)

Haul=NA
mean.spread=NA
N=NA
resid.sd=NA

for(i in 1:length(haul.list)){
 sgr=haul.data[haul.data$HAUL==haul.list[i],]
 sgr$DATE_TIME = as.POSIXct(strptime(sgr$DATE_TIME, "%m/%d/%Y
%H:%M:%OS"))
 haul=sgr$HAUL[1]
 Haul[i]=haul
 if(length(which(events$HAUL==haul))==2){
  on.bottom=events[events$HAUL==haul & events$EVENT==3,]$DTIME
  off.bottom=events[events$HAUL==haul & events$EVENT==7,]$DTIME
  xx=sgr$DATE_TIME[sgr$DATUM_CODE==0]
  yy=sgr$MEASUREMENT_VALUE[sgr$DATUM_CODE==0]
```

```
  xx1=xx[xx>on.bottom & xx<off.bottom]
  yy1=yy[xx>on.bottom & xx<off.bottom]
  if(length(yy1)>10){
   plot(xx1,yy1,ylim=c(0,40),main=haul,
     xlim=c(on.bottom-360,off.bottom+360))
   abline(v=on.bottom,col=2)
   abline(v=off.bottom,col=2)
   md2=smooth.spline(yy1~xx1,spar=.8)
   smooth2=predict(md2)
   lines(smooth2,col='red')

preds=predict(md2,x=as.numeric(seq(on.bottom,off.bottom,length.out=100
)))
   mean.spread[i]=mean(preds$y)
   N[i]=length(yy1)
   resid.sd[i]=sd(residuals(md2))
   mtext(paste('Mean =',round(mean.spread[i],2),'SD
=',round(resid.sd[i],2)),
            side = 3, line=0)
   a=locator(n=1)
   } else {
    plot(0,0,pch="",main=paste('Haul',haul))
    text(0,0,"data not sufficient")
    a=locator(n=1)
   }
   } else {
   plot(0,main="no on or off bottom times")
   mean.spread=mean(preds$y)
   a=locator(n=1)
  }
}
summary.spreads =
as.data.frame(cbind(Haul=Haul,N=N,Mean=mean.spread,SD=resid.sd))
return(summary.spreads)
}

#estimate.means(events)
```

Appendix 2. Mean, standard deviation, and ping count for Marport and Netmind net spreads by vessel and haul resulting from the sequential outlier rejection procedure.

Vessel	Haul	Mean Marport net spread	Number of pings	Standard deviation Marport net spread	Mean Netmind net spread	Number of pings	Standard deviation Netmind net spread
Alaska Knight	1	14.585	389	0.730	13.707	227	0.979
Alaska Knight	4	16.874	342	0.937	15.914	198	1.270
Alaska Knight	7	13.814	442	0.490	13.359	146	0.930
Alaska Knight	8	15.186	410	0.793	14.543	209	1.045
Alaska Knight	9	14.679	434	0.731	13.993	162	1.042
Alaska Knight	17	16.212	346	0.457	15.421	141	0.531
Alaska Knight	18	16.382	384	0.534	15.309	137	0.359
Alaska Knight	19	17.124	386	0.609	16.258	140	0.767
Alaska Knight	20	16.830	383	0.588	16.216	131	0.718
Alaska Knight	21	18.096	178	0.837	16.550	133	0.650
Alaska Knight	23	14.326	375	0.454	13.555	75	1.025
Alaska Knight	26	17.868	392	0.464	17.048	120	0.708
Alaska Knight	27	17.562	91	0.553	16.454	144	0.764
Alaska Knight	28	17.652	386	0.806	16.601	79	0.784
Alaska Knight	31	16.605	344	0.821	15.508	157	1.031
Alaska Knight	32	16.507	417	0.732	15.613	191	1.270
Alaska Knight	33	14.307	412	0.623	13.806	88	1.185
Alaska Knight	34	14.352	434	0.593	14.265	150	1.124
Alaska Knight	35	15.555	419	0.695	14.857	248	0.926
Alaska Knight	40	17.239	417	0.527	16.761	227	0.479
Alaska Knight	41	17.161	309	0.611	16.196	244	0.269
Alaska Knight	42	17.216	403	0.520	16.302	263	0.233
Alaska Knight	43	17.700	395	0.387	17.114	251	0.364
Alaska Knight	44	16.415	404	0.370	15.681	266	0.365
Alaska Knight	46	18.732	101	0.652	17.551	124	0.333
Alaska Knight	49	18.229	375	0.401	17.642	197	0.484
Alaska Knight	50	20.015	327	0.480	19.129	152	0.544
Alaska Knight	51	19.170	406	0.337	18.425	158	0.465
Alaska Knight	52	19.646	380	0.376	18.719	156	0.451
Alaska Knight	53	19.565	363	0.372	18.780	85	0.393
Alaska Knight	54	18.647	329	0.456	18.055	82	0.502
Alaska Knight	55	18.362	392	0.364	17.766	191	0.542
Alaska Knight	56	18.457	408	0.399	17.919	201	0.560
Alaska Knight	58	17.989	108	0.541	17.026	217	0.459
Alaska Knight	59	18.412	105	0.816	17.222	170	0.578
Alaska Knight	66	13.996	423	0.503	13.738	166	0.722
Alaska Knight	73	12.644	413	0.619	12.847	223	1.072
Alaska Knight	78	18.083	265	0.637	17.002	161	0.354
Alaska Knight	79	17.551	407	0.474	17.035	213	0.483
Alaska Knight	80	18.849	393	0.433	18.227	115	0.557
Alaska Knight	81	18.087	415	0.347	17.712	206	0.359
Alaska Knight	86	20.010	404	1.053	19.425	256	1.126
Alaska Knight	87	18.137	307	0.678	17.378	240	0.413
Alaska Knight	90	18.084	342	0.738	17.766	152	0.385
Alaska Knight	91	17.780	338	0.523	17.012	97	0.466
Alaska Knight	96	16.137	416	0.753	15.699	55	0.531

Appendix 2. Continued.

Vessel	Haul	Mean Marport net spread	Number of pings	Standard deviation Marport net spread	Mean Netmind net spread	Number of pings	Standard deviation Netmind net spread
Alaska Knight	104	13.624	417	0.529	13.222	117	0.642
Alaska Knight	106	12.771	406	0.583	12.563	80	0.908
Alaska Knight	111	13.542	419	0.545	13.274	76	0.421
Alaska Knight	114	16.052	411	0.622	15.782	81	0.261
Alaska Knight	118	16.305	417	0.759	15.529	155	0.266
Alaska Knight	119	17.092	402	0.702	16.257	275	0.274
Alaska Knight	123	15.922	401	0.632	15.334	254	0.274
Alaska Knight	124	16.108	416	0.714	15.497	228	0.274
Alaska Knight	128	17.657	332	0.602	16.885	136	0.363
Alaska Knight	129	17.952	391	0.399	17.218	122	0.349
Alaska Knight	132	17.910	408	0.586	17.034	207	0.213
Alaska Knight	133	18.306	356	0.418	17.453	36	0.419
Alaska Knight	134	18.631	387	0.572	17.755	198	0.257
Alaska Knight	135	17.367	394	0.323	16.661	59	0.371
Alaska Knight	136	16.877	419	0.507	16.133	181	0.327
Alaska Knight	137	15.240	409	0.623	14.709	223	0.294
Alaska Knight	138	16.820	421	0.757	16.430	85	0.269
Alaska Knight	139	16.127	411	0.789	15.762	39	0.348
Alaska Knight	140	16.615	418	0.791	15.985	220	0.349
Alaska Knight	143	17.243	431	0.527	16.669	235	0.335
Alaska Knight	147	17.306	413	0.640	16.764	148	0.396
Alaska Knight	148	19.025	410	0.845	18.717	50	0.675
Alaska Knight	152	18.601	385	0.739	17.943	256	0.399
Alaska Knight	153	16.091	341	1.115	15.221	109	0.329
Alaska Knight	155	17.095	413	0.607	16.555	178	0.303
Alaska Knight	158	18.266	426	0.373	17.458	268	0.235
Alaska Knight	159	18.348	431	0.247	17.558	281	0.309
Alaska Knight	160	18.272	387	0.493	17.382	258	0.196
Alaska Knight	161	18.297	411	0.339	17.676	264	0.334
Alaska Knight	162	17.737	325	0.894	17.087	216	0.301
Alaska Knight	163	17.331	405	0.256	17.194	63	0.319
Alaska Knight	165	17.450	403	0.404	17.256	43	0.333
Alaska Knight	166	17.816	1220	0.583	16.953	25	0.273
Alaska Knight	167	17.932	418	0.407	17.367	247	0.384
Alaska Knight	168	18.296	415	0.515	17.922	110	0.251
Alaska Knight	169	17.740	391	0.314	17.290	140	0.380
Alaska Knight	171	18.014	413	0.259	17.544	243	0.386
Alaska Knight	172	18.203	424	0.264	17.547	247	0.301
Alaska Knight	173	18.712	321	0.460	18.021	269	0.325
Alaska Knight	174	17.895	395	0.460	17.275	225	0.364
Alaska Knight	175	17.725	392	0.482	17.172	105	0.401
Alaska Knight	176	18.443	442	0.548	17.686	270	0.325
Alaska Knight	177	18.816	389	0.433	18.147	237	0.293
Alaska Knight	179	18.076	418	0.248	17.658	215	0.341
Alaska Knight	180	18.249	392	0.256	17.651	252	0.369
Alaska Knight	184	19.015	245	0.506	18.429	155	0.367
Alaska Knight	185	18.675	385	0.475	18.258	231	0.466

Appendix 2. Continued.

Vessel	Haul	Mean Marport net spread	Number of pings	Standard deviation Marport net spread	Mean Netmind net spread	Number of pings	Standard deviation Netmind net spread
Alaska Knight	186	19.111	399	0.357	18.417	271	0.242
Alaska Knight	187	19.241	401	0.230	18.651	120	0.506
Alaska Knight	189	19.357	399	0.274	18.654	199	0.264
Alaska Knight	190	19.224	405	0.260	18.646	180	0.388
Alaska Knight	191	18.969	413	0.243	18.420	227	0.287
Alaska Knight	192	19.376	375	0.438	18.497	220	0.348
Alaska Knight	193	19.063	418	0.255	18.339	267	0.197
Alaska Knight	194	18.655	421	0.214	18.035	275	0.275
Alaska Knight	195	19.169	422	0.255	18.427	271	0.223
Alaska Knight	196	18.570	423	0.229	18.028	253	0.326
Alaska Knight	197	18.786	404	0.257	18.106	260	0.380
Alaska Knight	199	18.577	358	0.605	18.366	249	0.708
Alaska Knight	201	19.414	405	0.804	19.152	216	0.913
Alaska Knight	202	18.134	406	0.288	17.895	228	0.484
Alaska Knight	203	17.408	414	0.329	17.210	152	0.429
Alaska Knight	204	17.761	412	0.526	16.936	265	0.180
Alaska Knight	205	17.494	398	0.594	17.042	109	0.345
Alaska Knight	206	18.748	416	0.670	18.348	142	0.705
Alaska Knight	207	17.558	394	0.396	17.460	64	0.512
Alaska Knight	211	18.887	416	0.260	18.418	96	0.501
Alaska Knight	212	18.965	368	0.304	18.372	128	0.533
Alaska Knight	213	19.327	396	0.295	18.677	143	0.396
Alaska Knight	214	18.751	399	0.212	18.198	169	0.377
Alaska Knight	215	19.017	394	0.534	18.347	133	0.269
Alaska Knight	216	19.054	389	0.381	18.299	104	0.471
Alaska Knight	218	17.101	387	0.619	16.648	46	0.733
Alaska Knight	219	14.757	380	0.553	14.827	58	0.939
Alaska Knight	221	15.886	396	0.787	15.377	178	0.543
Alaska Knight	224	16.762	396	0.646	16.072	96	1.593
Aldebaran	6	16.799	476	0.802	15.969	258	0.320
Aldebaran	10	17.518	296	0.905	16.231	240	0.320
Aldebaran	13	16.361	290	1.033	15.915	132	0.867
Aldebaran	16	18.486	415	0.911	17.939	309	0.367
Aldebaran	17	17.743	1392	1.745	17.018	240	0.417
Aldebaran	18	18.021	495	0.715	17.150	235	0.600
Aldebaran	19	16.158	508	0.689	15.589	107	0.779
Aldebaran	20	16.901	110	0.776	16.014	116	0.493
Aldebaran	22	18.130	302	0.485	17.682	153	0.987
Aldebaran	26	18.399	177	0.882	17.411	250	0.431
Aldebaran	27	17.511	173	0.896	16.172	190	0.395
Aldebaran	29	17.135	230	0.984	15.852	246	0.945
Aldebaran	34	16.332	481	0.479	15.475	308	0.452
Aldebaran	35	16.585	422	0.947	15.729	168	1.016
Aldebaran	39	16.552	446	0.912	16.144	110	0.430
Aldebaran	45	17.323	376	1.104	16.271	285	0.317
Aldebaran	46	15.718	456	0.784	14.961	275	0.330
Aldebaran	47	15.238	488	0.569	14.732	119	0.384

Appendix 2. Continued.

Vessel	Haul	Mean Marport net spread	Number of pings	Standard deviation Marport net spread	Mean Netmind net spread	Number of pings	Standard deviation Netmind net spread
Aldebaran	49	17.698	367	1.125	16.926	171	0.314
Aldebaran	50	18.438	79	1.322	17.753	99	0.378
Aldebaran	51	17.625	221	1.564	16.981	291	0.286
Aldebaran	52	18.312	175	1.085	17.428	241	0.300
Aldebaran	53	17.552	430	0.620	16.992	250	0.360
Aldebaran	56	16.850	445	0.602	16.232	199	0.341
Aldebaran	57	16.582	343	0.876	15.639	228	0.326
Aldebaran	64	15.866	313	0.879	15.027	277	0.483
Aldebaran	65	16.413	1352	0.870	15.861	77	0.321
Aldebaran	67	16.114	354	0.974	15.390	38	0.569
Aldebaran	68	15.988	223	1.634	14.736	179	0.337
Aldebaran	69	16.243	298	1.017	15.042	175	0.389
Aldebaran	71	15.689	425	0.952	14.564	208	0.378
Aldebaran	75	17.152	465	0.615	16.589	60	0.328
Aldebaran	78	17.896	341	0.930	16.987	188	0.422
Aldebaran	79	17.947	336	0.814	17.176	311	0.293
Aldebaran	80	17.704	116	0.810	17.229	285	0.364
Aldebaran	81	20.344	1708	1.593	19.316	264	1.307
Aldebaran	83	19.462	163	0.759	18.324	309	0.867
Aldebaran	84	19.457	238	0.997	18.222	261	0.895
Aldebaran	88	18.702	273	0.772	17.981	308	0.347
Aldebaran	89	18.312	365	0.563	17.286	273	0.397
Aldebaran	91	17.278	333	0.770	16.319	243	0.369
Aldebaran	92	17.541	183	0.787	16.609	215	0.468
Aldebaran	93	18.167	145	0.917	17.124	223	0.373
Aldebaran	94	17.778	232	0.628	16.862	264	0.501
Aldebaran	97	15.910	398	0.790	15.155	134	0.639
Aldebaran	98	16.469	442	0.605	15.940	147	0.590
Aldebaran	100	15.885	473	0.612	15.029	51	0.699
Aldebaran	103	15.558	495	0.652	15.150	108	0.510
Aldebaran	107	17.050	236	0.777	16.110	277	0.700
Aldebaran	108	16.108	479	0.624	15.114	280	0.463
Aldebaran	109	15.953	485	0.925	15.559	165	0.509
Aldebaran	110	14.943	476	0.758	14.399	169	0.461
Aldebaran	112	16.312	380	0.896	15.273	300	0.291
Aldebaran	113	16.417	414	0.702	16.157	64	0.604
Aldebaran	117	16.903	207	0.608	15.924	282	0.628
Aldebaran	120	15.753	505	0.475	14.992	287	0.451
Aldebaran	121	16.192	424	0.743	15.326	293	0.532
Aldebaran	122	16.765	181	0.779	15.525	298	0.304
Aldebaran	123	15.461	473	0.868	14.906	68	0.291
Aldebaran	125	17.259	511	0.732	16.679	247	0.341
Aldebaran	126	17.585	236	1.558	16.968	310	0.596
Aldebaran	127	18.282	339	0.700	17.350	176	0.714
Aldebaran	128	18.312	321	0.689	17.759	154	0.592
Aldebaran	129	17.022	423	0.832	15.972	232	0.674
Aldebaran	130	18.001	352	0.767	17.341	244	0.413

Appendix 2. Continued.

Vessel	Haul	Mean Marport net spread	Number of pings	Standard deviation Marport net spread	Mean Netmind net spread	Number of pings	Standard deviation Netmind net spread
Aldebaran	131	17.109	496	0.495	16.578	133	0.725
Aldebaran	132	16.746	453	0.728	16.111	289	0.398
Aldebaran	133	16.303	185	1.331	15.141	130	0.601
Aldebaran	135	17.352	261	0.799	16.481	266	0.537
Aldebaran	137	17.429	442	1.029	16.510	308	0.324
Aldebaran	138	19.187	348	0.753	18.600	295	0.442
Aldebaran	140	18.100	325	0.845	17.190	247	0.323
Aldebaran	141	17.806	491	0.812	17.196	166	0.502
Aldebaran	142	18.244	447	0.958	17.432	292	0.274
Aldebaran	143	17.410	468	0.968	16.517	282	0.324
Aldebaran	144	18.259	424	1.234	17.676	244	0.649
Aldebaran	145	17.871	364	1.186	16.770	282	0.308
Aldebaran	146	16.746	421	0.992	15.933	276	0.458
Aldebaran	147	18.684	408	0.791	17.915	291	0.281
Aldebaran	148	17.403	446	0.772	16.656	191	0.347
Aldebaran	149	17.903	371	0.937	17.270	249	0.540
Aldebaran	150	19.279	438	0.629	18.647	280	0.455
Aldebaran	153	16.968	126	1.885	16.114	124	0.348
Aldebaran	154	18.596	430	0.965	17.860	299	1.025
Aldebaran	155	18.943	234	0.719	17.744	147	0.675
Aldebaran	157	21.621	352	1.052	20.360	226	0.796
Aldebaran	158	17.904	482	0.568	17.090	300	0.292
Aldebaran	159	22.783	116	0.756	21.635	106	0.787
Aldebaran	160	17.973	445	0.723	17.116	228	0.281
Aldebaran	161	18.110	352	0.608	17.347	255	0.365
Aldebaran	162	18.082	492	0.378	17.229	315	0.296
Aldebaran	163	18.608	484	0.606	17.661	307	0.318
Aldebaran	164	18.242	371	0.680	17.317	291	0.365
Aldebaran	165	18.313	418	0.926	17.386	274	0.288
Aldebaran	166	20.048	245	0.695	19.178	300	0.279
Aldebaran	167	19.073	301	0.452	18.462	202	0.631
Aldebaran	168	19.484	279	0.613	18.313	309	0.413
Aldebaran	169	19.507	374	0.536	18.372	258	0.338
Aldebaran	170	19.617	391	0.537	18.608	271	0.550
Aldebaran	171	19.765	348	0.488	18.583	326	0.382
Aldebaran	173	19.405	498	0.391	18.369	252	0.648
Aldebaran	174	19.169	443	0.512	18.055	317	0.324
Aldebaran	175	18.551	486	0.474	17.922	296	0.365
Aldebaran	176	19.120	287	0.573	18.043	318	0.351
Aldebaran	177	19.934	310	0.602	18.927	335	0.342
Aldebaran	179	18.709	169	0.306	17.806	114	0.266
Aldebaran	180	19.319	416	0.511	18.372	328	0.345
Aldebaran	181	18.731	181	0.407	17.796	99	0.878
Aldebaran	182	19.271	485	0.455	18.260	184	1.292
Aldebaran	184	19.360	393	0.539	18.510	202	1.183
Aldebaran	185	19.354	418	0.514	18.328	333	0.349
Aldebaran	186	20.044	437	0.699	19.269	234	0.816

Appendix 2. Continued.

Vessel	Haul	Mean Marport net spread	Number of pings	Standard deviation Marport net spread	Mean Netmind net spread	Number of pings	Standard deviation Netmind net spread
Aldebaran	188	20.084	213	0.617	19.028	287	0.516
Aldebaran	189	20.267	459	0.359	19.513	309	0.431
Aldebaran	190	19.801	194	0.535	18.780	314	0.347
Aldebaran	191	19.325	152	0.582	18.223	333	0.290
Aldebaran	192	19.283	391	0.422	18.269	322	0.277
Aldebaran	193	19.518	359	0.451	18.644	325	0.283
Aldebaran	196	19.146	475	0.460	18.527	98	1.859
Aldebaran	197	19.793	455	0.309	18.850	156	0.853
Aldebaran	198	19.281	516	1.088	18.282	229	1.025
Aldebaran	199	17.686	526	0.528	16.844	136	1.265
Aldebaran	200	16.896	432	0.648	16.720	96	1.329
Aldebaran	201	16.531	476	0.566	15.694	144	1.224
Aldebaran	202	19.756	204	0.757	18.938	253	0.689
Aldebaran	204	17.662	198	0.551	17.206	250	0.641
Aldebaran	205	18.055	439	0.723	17.657	103	1.613
Aldebaran	206	19.608	239	1.196	18.305	96	1.770
Aldebaran	207	17.960	500	0.372	17.396	313	0.430
Aldebaran	208	18.012	342	0.660	17.090	302	0.393
Aldebaran	209	18.124	283	0.677	17.373	313	0.379
Aldebaran	210	18.036	494	0.315	17.344	317	0.220
Aldebaran	211	17.343	453	0.418	16.838	109	0.505
Aldebaran	212	18.513	130	0.569	17.228	297	0.339
Aldebaran	213	18.452	544	0.437	17.819	270	0.570
Aldebaran	214	18.813	463	0.527	17.771	324	0.283