Lurking variables and the interpretation of statistical analyses of data collected under JARPA

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ABSTRACT

This paper investigates whether reliable inferences in year trends in biological parameters can be obtained using samples collected by Japan's Special Permit Whaling Program (known as JARPA). Information on biological parameters of Antarctic minke whales is analysed using standard forms of multiple regression model. The presence of "lurking variables" is demonstrated by analysing the apparent trends in two population parameters, the sex ratio and the female length at 50% maturity, which would both be expected to be nearly constant over time. The results obtained show much higher levels of variability than would be expected in a biological population, indicating that there are unaccounted for sources of variation. Such lurking variables can arise from inter-annual variability in the locations and dates on which whales were taken, the population spatial distributions of one or more biological populations and the co-effects of seasonality by sex and reproductive state. Although apparently statistically significant trends are obtained, the statistical tests are not valid because of the lurking variables that lead to unaccounted for variance components. The design of JARPA (and JARPAII) is declared to be based on random transects. Proceeding along a track-line, even if randomly selected, is not simple random sampling – it involves a form of pseudo-replication. A simulation is used to demonstrate that standard errors calculated using the sample size underestimates the true variability for estimates derived from random transects over a spatially heterogeneous population. The simulations demonstrate that transects are the basic sampling units, not the individual animals. The design of the JARPA and JARPAII programs are thus statistically flawed and existing statistical analyses of the data are invalid. The obvious presence of lurking variables coupled with a design based on transect sampling indicate that the methods used to calculate required sample sizes in JARPA and JARPAII are also statistically invalid. JARPA/JARPAII lacks program design and execution that allows the estimation of the random variation among transects, which is essential for the application of hypothesis tests relating to monitoring trends in biological parameters. Consequently, the design of JARPA and JARPA II precludes reliable and appropriate analysis of the data collected.

KEYWORDS: ANTARCTICA, MINKE WHALES, BIOLOGICAL PARAMETERS, LONG-TERM CHANGE, ECOLOGICAL MONITORING, WHALING, STATISTICAL ANALYSIS, LURKING VARIABLES, PSEUDO-REPLICATION

INTRODUCTION

Since 1987 Japan has conducted the Japanese Whale Research Program under Special Permit in the Antarctic (JARPA/JARPAII). One of the objectives of JARPA was "Elucidation of the effect of environmental changes on cetaceans" (GOJ, 1995). In JARPAII this objective was also stated in terms of ... "monitoring trends in biological parameters" (GOJ, 2005).

Following an analysis of trends in body condition published by Konishi *et al*. (2008) de la Mare (2011) demonstrated a number of pitfalls in analysing blubber thickness data and requested access to the relevant data to explore whether existing analyses of the data "captured all the main features of the data" (IWC, 2011). Unfortunately a satisfactory agreement could not be reached with the Institute for Cetacean Research for access to the data. Consequently I have been unable to undertake further analyses of the body condition data as recommended by the Scientific Committee.

However, some JARPA data are available in the IWC's catch database (IWC, 2010) (listed in Table 1). In this paper I examine whether common forms of multiple linear regressions models using these data lead to reliable inferences about trends in biological parameters. The spatial and temporal sampling patterns for the data are the same as for the data on body condition data analysed by Konishi *et al*. (2008).

Regression models are needed for analysing the JARPA data not only for statistical inference, but to correct for the heterogeneous manner in which the data were collected. Whales are taken by a single operation throughout the several months of the whaling season. Consequently, they are taken on different dates at different places during the whaling season. The effects of date and place are particularly important because the migratory behaviour of whales throughout the whaling season is related to size, age, sex and pregnancy (Horwood, 1990). Thus a statistical model is necessary, but may not be sufficient, to account for the effects of date and location when making inferences about possible year trends.

CHARACTERISTICS OF THE JARPA MINKE WHALE DATA

The first question is whether the data collected under JARPA have features that indicate that they would be susceptible to the effects of 'lurking variables'. A lurking variable is defined to be a variable that has an important effect on the dependent variable and yet is not included in the predictor variables under consideration (Box, 1966; Joiner 1981). Here the term is used to refer both to unobserved variables which could have fixed or random effects, or variables that are included in the models but have random effects that cannot be estimated due to the manner in which the data were collected.

In JARPA minke whales were taken south of 60°S and east or west of longitude 130°E in alternate years as shown in Figs 3 and 1. In 1995 the region sampled in the western half (odd years) was extended further west to include half of IWC Area III, and in 1996 half of Area VI was added to the eastern region (even years). There was no longitudinal overlap between the odd and even years (see Fig. 1). The changes in program design lead to a westward trend in the mean longitude in the western region and an eastward trend in the eastern region.

In the JARPA cruise reports data are summarised in terms of strata based on half Areas also divided in Areas IV and V into northern and southern strata. Table 2 gives the strata names and boundaries used in the analyses here. Because animals move between strata during their annual migration and in response to stochastic variations in krill abundance, the JARPA strata are not strata in the usual statistical sense that a given animal will always be present in only one stratum.

Fig 2 shows a plot of mean longitude by year and stratum. Despite the general trend for the mean longitude to have moved to the west for the western region, within each stratum there has been a trend for the mean longitude to move eastwards Table 3a shows that these trends are statistically significant and are roughly 0.5° of longitude per year, or of the order of 10° of longitude over the JARPA period. For the Eastern region analysis shown in Table 3b, the overall trend in longitude is not significant but the trends in three of the four strata are. In this case the strata VIW and VWN have an easterly trend in the sample longitudes, but stratum VWS moving westwards by roughly 15°. The restricted longitudinal range for the catches during the first two seasons (the JARPA ‘feasibility studies’) is evident for both regions.

It is not possible from these data alone to determine whether these shifts within the strata are due to shifts in the abundance of whales, shifts in the sea-ice or shifts in the sampling strategy or some combination of these.

Fig 3 shows that both means and ranges of latitudes sampled are substantially different for the eastern and western regions. The mean latitudes by year in each stratum (Fig. 4) can vary by one or two degrees of latitude, which is probably due primarily to inter-annual variability in the ice-edge combined with the effects of variation in the dates when catches were taken in each stratum.

Fig 5 shows the numbers caught in most strata varies substantially from year to year, and in some cases, such as VWN and VEN, showing some clear trends. Stratum IIIE has virtually constant catches each year, as does stratum VIW after 1998.

Fig. 6 shows that there are systematic changes over the years on the means and ranges of dates within the season when the whales were caught. In stratum PB, not only is there a systematic shift in mean date, but the range of dates do not even overlap after the shift. The mean dates in Stratum VWN and VWS also show clear trends and have numbers of years where there is no overlap in the sampling dates. Fig. 7 summarises the distributions of sampling dates for each stratum; it is clear that the distribution of sampling dates are very heterogeneous across the strata. Statistical inference in a regression model used to estimate the trends in a dependent variable depends on the contrast (range of values) in independent variables such as date or location. The variance of the independent variables is an appropriate measure of the contrast. Fig. 8 shows the realised variance in sampling date for each stratum compared with the variance that would be attained with uniform sampling by date. In most strata the variances are uniformly low across all years, and so the ability for a regression model to correct for the effects of date on dependent variables such as blubber thickness within strata will also be low.

The basic analyses of the characteristics of the JARPA data demonstrate trends in the conduct of the program. These trends create conditions where lurking variables will undermine analyses of the data.

EVIDENCE FOR THE EFFECTS OF LURKING VARIABLES

The question is whether there is evidence to support the proposition that lurking variables are present. A definitive answer to this question would require the true values and trends of any dependent variables we analyse to be known. A second approach that leads to an indicative answer would be to simulate the data collection process, in which case the “true” trends are known, and apply the estimation methods, as demonstrated in de la Mare (2011) and later below. The third possibility is to analyse the trends in dependent variables that would be expected to be constant or which if changing, would do so only slowly. If regression analyses using such dependent variables demonstrate unexpected trends or variations, then we can conclude that the results are affected by lurking variables. Two such parameters can be estimated from the publicly available JARPA data, namely the sex ratio and the length at which 50% of females are sexually mature (the maturity status of males is not included in the IWC catch database).

The presence of lurking variables is demonstrated when a dependent variable that should be constant, or nearly constant, exhibits statistically significant trends or has confidence intervals that are too narrow, that is, do not overlap at a frequency consistent with their calculated coverage probability. I tested for these effects using the same general linear modelling approach used in other analyses of JARPA data, such as in Bando *et al.* (2006) and Konishi *et al.* (2008). This does not imply that these are the appropriate forms of analysis for valid statistical hypothesis tests, as will be demonstrated later. Following the recommendations of Burnham and Anderson (1998), model selection here will be based on Akaike’s information criterion (AIC) (Akaike, 1974); automatic stepwise regression algorithms are not used. Concerns about “data-dredging” and the validity of significance tests after model selection are ignored. All analyses are implemented using R (R Development Core Team, 2011) and the scripts are available on request.

ANALYSIS OF MINKE WHALE SEX RATIO

In a baleen whale biological population the sex ratio (expressed here as the proportion of females) is expected to be very close to 0.5. The only mechanisms for this ratio to vary in a closed mammalian population are either a change in the sex ratio at birth or a differential change in mortality of either sex. In an open population, sex selective immigration or emigration would also affect the sex ratio. An unbiased estimate of sex ratio also requires estimates of abundance in each stratum or a design that ensures sampling probabilities are the same in each stratum. This aspect of the analysis is ignored here, although stratum abundance is an obvious candidate for a lurking variable.

The basic properties of the data should be explored before deciding on statistical models. Fig. 9 shows the proportion of females in the catch by year and stratum, with error bars showing the approximate 95% confidence intervals based on a binomial model. Clearly the sex ratios are different in the different strata, often statistically significantly different from 0.5 and variable from year to year. Not surprisingly, the individual strata have not provided representative samples from a whale biological population. The bottom right-hand plot gives the sex ratios by year for the data combined across strata. The trajectories are plotted separately for the western region (odd years) and eastern region (even years). Both combined trajectories indicate variation in the apparent sex ratio over the years and they are often significantly different from 0.5. The mean sex ratio for the entire dataset is 0.466, with a binomial standard error of 0.006, and hence also apparently significantly different from 0.5.

One possible source of variation in the sex ratios is the sampling date within each season hereafter referred to as Day. Day here is given from an origin of November 30, i.e. 1 = December 1. Fig. 10 shows the sex ratios, with approximate 95% confidence intervals, by stratum and date pooled across years. The bottom right-hand plot is sex ratio by Day for all the data. The combined plot indicates that Day should be an important explanatory variable for the sex ratio. However, the plots for the separate strata show that information is missing on the patterns by Day of sex ratios for most strata. This will be primarily due to the operating pattern of the whaling expedition and partly influenced by the seasonal distribution of the whales themselves.

The data also illustrate that some of the whales present in one stratum on a given day must have been present in a different stratum a different date. Consider the stratum IVES, which shows a pattern of variation where the sex ratio appears high early in the season. The sex ratio appears to fall and then increases again in a dome shape that has a downward limb towards the end of the season. This probably indicates the differential influx of males early in the season, followed by either an influx of females in the second half of the season (days 60 to 80) or the departure then of some males, or both. However, the animals arriving or departing would be present in some other stratum outside those dates. Thus, the observed sex ratios in the strata are not independent observations over the season. This indicates another source of lurking variables that arises from the behaviour of the whales interacting with environmental variability, and in turn interacting with heterogeneity in the operating pattern of the whaling expedition.

Sex ratio model with Year as categorical variable

The basic form of linear model to fit to sex ratio data is a generalised linear model (GLM) (McCullagh and Nelder, 1983) using a logit transform – often termed a logistic regression model. The first model explored will involve treating year as a categorical variable, thus allowing each year to have a different estimated sex ratio. Fig. 11 shows the sex ratio predicted from the simplest GLM where sex ratio is a function of Year only. This of course should be, and is, identical to the lower right-hand plot on Fig 9. If the confidence intervals in Fig. 11 were valid then we would expect that all but one or two out of the 18 would include 0.5; whereas the half the years have confidence intervals that do not include 0.5, which therefore means that the confidence intervals are too narrow.

The next analysis attempts to correct for the effects of sampling heterogeneity by finding a model that gives a low AIC, as shown in Table 4. The model with the low AIC includes Year, Stratum - with interaction terms for Latitude and Longitude, a second degree polynomial for Day and Length (if fitted last). The analysis of deviance (Table 5) shows that all the independent variables are apparently highly statistically significant. Interestingly, length would be expected to be a predictor of the sex ratio because females are larger than males. However, length only appears to be important when fitted last; the heterogeneity in the other variables masks the effect of length. The predicted sex ratios for the model shown in Figs 12 and 13 have not noticeably, if at all, reduced the variability in the estimated sex ratios. Given that these variations in sex ratio are infeasible at the population level, we can conclude that there are sources of variability not taken into account in this form of analysis. Even a form of analysis aimed at correcting for the effects of sampling heterogeneity fails to reduce variability, thus establishing the presence of lurking variables.

Sex ratio model with Year as numeric variable

JARPA/JARPAII describes some of their objectives in terms of monitoring trends in biological parameters (GOJ, 2005). To attempt to estimate trends in biological parameters over time Bando *et al.* (2006) and Konishi *et al.* (2008) have treated Year as a numeric variable. The next model fits the sex ratio with Year as a numeric independent variable, thus enabling the fitting of the year effects in sex ratio as a linear or higher order polynomial. Table 6 shows the AIC values for various models including essentially the same independent variables as in the preceding analysis, but with categorical Year being replaced with a second order polynomial on Year as a numeric variable. The analysis of deviance (Table 7) shows that the independent variables are all apparently highly statistically significant. However, this model has a much higher AIC than the categorical Year model, and so the model with the most support is that the sex ratio exhibits high inter-annual variability rather than a smooth trend. The predicted values of sex ratios are shown for four strata in Figs 14 and 15.

ANALYSIS OF MINKE WHALE FEMALE LENGTH AT MATURITY

In many animals (including mammals) it is generally considered that the size at sexual maturity is relatively invariant (Charnov, 1991), including whales (FAO, 1977). Changes in growth rates of animals are assumed to change the age at which they reach sexual maturity rather than the size. Thus, large changes in the mean length of sexual maturity in JARPA samples are more likely to represent the effects of lurking variables than real changes in the parameter. Length at maturity can be estimated by a GLM (logistic regression) with the proportion mature as the dependent variable and length as an independent variable.

Fig. 16 shows the raw changes in the proportion of females that are mature (as a proportion of total females) by stratum and year. The lower right-hand plot shows the ratio pooled over strata. Clearly there are substantial differences between strata and considerable inter-annual variability. Fig. 17 shows the proportion of mature females calculated by Day of season, pooled over years and stratum. This suggests that there are clear trends within season of the proportion mature in the samples. Fig. 18 shows the daily variation of proportion mature within strata (pooled over years). Similarly to the sex ratio there are consistent dates for the various strata over the years when observations are not collected. For the entire data set a GLM gives an estimate of the female mean length at maturity of 8.19 metres.

Female maturity model with Year as a categorical variable

Fig 19 shows the results of fitting a GLM with Year as a categorical variable. This plot shows the apparent proportions of animals predicted to be mature at the fixed length 8.19 m (the “grand mean”) in each year. These proportions would be expected to be about 0.5, but the figure clearly shows considerable inter-annual variability and some cases where the differences are apparently statistically significantly different from 0.5. Fig. 20 shows the predictions calculated from the same GLM as the length at 50% maturity for each year. The apparent length at 50% maturity is also highly variable, with predicted values ranging from roughly 7.9 m to 8.5 m and with some apparently statistically significantly different from the grand mean of 8.19 m.

The next analysis uses AIC to find a better fitting model as shown in Table 8, with the analysis of deviance for the lowest AIC model shown in Table 9. Fig. 21 shows the predicted proportion mature at 8.19 m from the low AIC GLM, which corrects for the effects of Stratum, Day and Longitude. Fig. 22 shows the corresponding predictions in terms of length at 50% maturity. The corrections have not reduced the variability in the length of 50% maturity and also indicate a substantial effect due to Stratum. After corrections the range of length at 50% maturity is 7.6 m to 8.6 m in the strata IVWS and VES. Thus the variability is greater than with the uncorrected estimates and some predicted values continue to have apparently statistically significant differences from the grand mean.

Female maturity model with Year as a numeric variable

Finally, Year is treated as a numerical variable and the AIC is used to find a reasonable model as shown in Table 10, with the analysis of deviance given in Table 11. The effect of Year is fitted as a second order polynomial and Stratum, Day and Longitude are also selected. There is negligible difference in the AICs of the models with Year as a categorical variable and Year as a numeric variable and so both models appear to be supported. Figs 23 and 24 show that Stratum effects are substantial and that the range of lengths at 50% maturity is substantial at 7.8 m to 8.3m.

Given that length at 50% maturity is unlikely to be highly variable in a natural population, the analyses presented here are consistent with the results of sex ratio analysis in demonstrating the presence of lurking variables.

THE LIKELY LURKING VARIABLES

The obvious candidates for lurking variables are the effects of inter-annual spatial variation in abundance from one or more biological populations with co-effects of distribution and seasonality by sex, size, maturity and reproductive state. These variations may be partly driven by sea ice and weather conditions, the sequential nature of sampling and other operational considerations (for example limits on numbers of whales that can be processed each day). Environmental variability will also affect prey distribution and behaviour which will in turn lead to variability in whale foraging areas, feeding behaviour and the dates of arrival at and departure from those areas. These variables interact with another source of random variation that arises from the random placement of transects. Although the analyses above give apparently statistically significant trends, the statistical significance tests will not be valid because of the unaccounted for variance components.

Variance component models and the effects of random transects

The appropriate form of analysis needs to take into account that the distribution of animals is not spatially uniform, will vary both within years and between years and that the sampling design is based on random transects. When sampling is based on transects it is not valid to assume that animals encountered along transects are independent samples (Millar and Anderson, 2004). Animals along a given transect will tend to be more similar to their neighbours than they are to animals far away. Thus the number of degrees of freedom relevant for statistical analysis is not the total sample size. Each transect is the basic sampling unit and different transects will have different expected values for any spatially heterogeneous statistic collected along each one. The randomisation of transects is one of the lurking variables contributing to the apparently high levels of variability in sex ratios and lengths at maturity. Even repeating the same transect track-line at different dates or in different years will exhibit variability because of the redistribution of the whales due to migration and environmental variations such as prey availability.

A statistic from random transects has a composite statistical distribution that arises from the sampling variability on each transect combined with the distribution of the expected values of the statistic from the (statistical) population of all possible transects. The number of possible random transects in a region is practically unbounded when the region is substantially larger than the area covered by any one transect. Unbiased estimation requires that transects are selected at random, that is, each transect has an equal, or estimable, probability of being selected.

An illustration of some consequences of the variability arising from transect sampling is demonstrated by means of simulation. The simulation is based on a single region of 100x100 arbitrary units. The two sexes of whales are distributed according to the density contours shown in Fig 25. These density contours are mixtures of three bivariate normal distributions for each sex but this is simply for the mathematical convenience of creating them. The sex ratio along any one straight line transect is found by taking a simulated set of catches (with replacement) of males and females using the basic catch and effort simulation model as used in de la Mare (2012), with handling time = 1.2 hours, length of operating day = 0.7 days and with the total sample size adjusted by varying the number of catcher vessels and operating days (the results are not sensitive to these details). Some animals of each sex are found outside the region and the true sex ratio in the region is not 0.5. The random transects were selected from uniform distributions for the left and right hand *y* values and thus each transect traverses the full region. Each transect is completed in the specified number of operating days. The table also shows the standard error calculated directly from the distribution of the mean sex ratios from the sample of transects. Fig. 26 shows the distribution of the estimates for the case where the average sample size per transect was in excess of 2000, and so this gives a close approximation of the distribution of estimates that arises from the variability from random transect placement alone. The nearest comparison that can be made with real data is shown in Fig. 27, which shows the distribution of sex ratios found in the various strata across years. The distribution shown in Fig. 26 is thus unlikely to have overstated the possible variability due to random transect placement.

Table 12 gives the means and standard errors calculated assuming binomial sampling along 1000 random transects through the region. The table shows that increasing the sample size reduces the estimated standard error when it is calculated assuming pure random sampling from a binomial distribution. However, the true standard error (the standard deviation of the distribution of estimates obtained) is virtually independent of sample size (some effect is becoming apparent when the sample size is as low as 66). This demonstrates 'pseudo-replication' (Hurlbert, 1984, Miller and Anderson, 2004). The next analysis, (shown in Table13) shows the effect of increasing the number of transects while keeping the same total sample size. Increasing the number of transects reduces the true standard error, even though the total sample size is unchanged.

The next set of analyses, shown in Table 14, examines the calculation of the probabilities of Type I error (rejecting the null hypothesis when it is true) using a (generalised) linear model to detect a linear trend. This is consistent with the analyses used in JARPA for monitoring trends in biological parameters. Table 15 shows the results from fitting a logistic regression model to 1000 replicates of 20 years of single transects drawn from the same distributions of abundance as in fig 25. There is no trend in the distribution of abundance or density over time. Thus finding an apparently statistically significant non-zero slope in the regression represents a Type I error. For a valid statistical model, if the size of the test is set at $\alpha = 0.05$, in 1000 trials there should be around 50 significant estimates. Table 14 clearly shows that statistical tests calculated using the sample size understate the probability of a Type 1 error by a considerable margin (in this example by 6 to 16 fold). The results show the apparent paradox that increasing the sample size actually increases the probability of making a Type I error (if validly calculated it would be constant). This is because the calculated standard error declines with increasing sample size, while the real standard error is largely unaffected.

Calculating the probability of a Type II error (accepting the null hypothesis when it is false) is also directly related to the estimated standard error of the statistic of interest. The analyses here show that reducing the standard error requires increasing the number of transects. Therefore the determinant of the precision of the estimates (and therefore power) is not primarily the sample size (once greater than a low number), but the number of transects. Thus statistical analyses of these data need to be based on mixed effects models, and that at least one of the grouping (random effects) variables will need to be based on "Transects" that can be treated as independent replicates. Table 15 shows the results from fitting a mixed effects GLM using categorical year as a random effect to estimate the variance component arising from the random placement of transects. A mixed effects model considerably reduces the probability of making a Type I error to near the nominal level. The remaining discrepancy is likely due in this case to the distribution of transect random effects (see Fig 26) being more heavy-tailed than a normal distribution.

Applying mixed effects models to the data to estimate biological parameters such as sex ratio and female length at maturity depends on whether the realised design of JARPA has transects that can be treated as independent replicates within the various strata. Figs 28 and 29 show four examples of JARPA track-lines based on the catch locations in the IWC database. These were selected to illustrate two cases where there are reasonably clear transects, and two others where the identification of reasonable replicate transects would be problematic. In all four cases there are track-lines that do not provide obvious replicate transects in all strata or in a given stratum in all years (all the JARPA and JARPAII track-lines are shown in Appendix 1). This makes it very difficult to add "Transect" as a replicated independent categorical variable to the dataset in a form suitable to apply standard mixed effects models to the JARPA data. However, estimating the random variation among replicated transects is essential for the application of hypothesis tests relating to monitoring trends in JARPA and JARPAII biological parameters. Consequently, the design and execution of JARPA/JARPA II includes flaws that are unable to be corrected through appropriate analysis

CONCLUSION AND DISCUSSION

The analyses of IWC submitted, publicly available JARPA data to estimate variability and trends in sex ratio and length at 50% maturity reveal flaws in the design of JARPA such that analyses of the results are not reliable. Analyses of two variables that should be constant, or only slowly changing, show the results to be highly variable and to have apparently statistically significant trends where none would be expected. These findings indicate the presence of lurking variables. The apparently spurious trends that arise in these two biological parameters indicates that trends apparent in the estimates of other biological parameters, such as body condition, could have also arisen from the influence of lurking variables. Put simply, the appearance of spurious trends in parameters that should be nearly constant casts doubt on whether apparent trends in other parameter estimates represent real trends.

One of the important lurking variables will be the variability arising from the placement of random transects. Simulations show that the important determinant of statistical analysis is the number of replicate transects, not simply the sample size in terms of numbers of animals taken. Hypothesis testing based on the sample size in terms of number of animals is invalid; such tests need to be based primarily on the degrees of freedom arising from the number of replicate transects. The inconsistent design and execution of JARPA and JARPA II precludes reliable and appropriate analysis of the data collected.

This result also has implications for the calculation of sample sizes in power analyses. The analyses of sample sizes calculated for JARPA and JARPAII are based on inappropriate statistical models because they assume that the standard error depends on sample size in terms of numbers of animals (see GOJ, 2005, Appendix 6). The relevant calculations need to be based on the number of independent transects required, not simply the sample size. The analyses of sample sizes in the JARPAII program are invalid because they do not take into account the variability that arises from the interaction between the random placements of transects and the spatial and temporal variations in abundance and other biotic characteristics of the populations.

In relation to the monitoring of biological parameters under JARPA, the 2006 Scientific Committee Review (IWC, 2008) stated:

> *Finally, the Workshop **agreed** that the JARPA dataset provides a valuable resource to allow investigation of some aspects of the role of whales within the marine ecosystem. With <u>appropriate analysis</u>, this has the <u>potential</u> to make an important contribution to the Scientific Committee's work in this regard, as well as the work of other relevant bodies such as CCAMLR.* (Emphases added.)

JARPA/JARPAII can only fulfil this potential if data were collected in a way that allows for statistically appropriate analysis. The lack of consistent replicate transects in the design and execution of JARPA/JARPAII precludes appropriate analysis and therefore this potential cannot be realised.

The analyses here demonstrate that there is no substitute for direct investigation of the raw data in determining the appropriateness of methods of analysis and conclusions. Such investigations require that the data be freely available to members of the Scientific Committee.

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Table 1. JARPA data included in the IWC catch database

Date
Location of capture (latitude and longitude to nearest minute)
Length
Sex
Maturity (only females have been reported)
Female condition
Number of foetuses
Sizes of foetuses

Table 2. Definition of spatial strata based on the information contained in the JARPA cruise reports. The names are mostly based on statistical half Areas and designated W {west} or E {east} and also divided N {north} and S {south}. VES includes parts of Area VI and VW but these are in the contiguous Ross Sea and so are not divided. Longitudes are all specified as east of 0°.

Stratum name	Boundaries			
	Western (°)	**Eastern (°)**	**Northern (°)**	**Southern (°)**
IIIE	35	70	-60	Coast
PB (Prydz Bay)	70	80	-66	Coast
IVWN	70	100	-60	-64
IVWS (outside PB)	70	100	-64	Coast
IVEN	100	130	-60	-64
IVES	100	130	-64	Coast
VWN	130	165	-60	-65
VWS	130	165	-65	Coast
VEN	165	190	-60	-69
VES	160	215	-69	Coast
VIW	190	220	-60	-69

Table 3a. Linear model coefficients for the Western region Longitude

Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	843.8955	238.6230	3.537	0.000411 ***
Year	-0.3943	0.1194	-3.303	0.000967 ***
StratumIVEN	-853.0952	282.8108	-3.016	0.002576 **
StratumIVES	-1500.0544	255.2448	-5.877	4.59e-09 ***
StratumIVWN	-1249.1835	273.4185	-4.569	5.08e-06 ***
StratumIVWS	-2082.4241	276.3750	-7.535	6.26e-14 ***
StratumPB	-1017.2190	336.6354	-3.022	0.002532 **
YearNo:StratumIVEN	0.4561	0.1416	3.222	0.001287 **
YearNo:StratumIVES	0.7810	0.1277	6.115	1.08e-09 ***
YearNo:StratumIVWN	0.6406	0.1368	4.681	2.96e-06 ***
YearNo:StratumIVWS	1.0576	0.1383	7.647	2.67e-14 ***
YearNo:StratumPB	0.5184	0.1685	3.076	0.002116 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.886 on 3352 degrees of freedom
Multiple R-squared: 0.8818, Adjusted R-squared: 0.8814
F-statistic: 2272 on 11 and 3352 DF, p-value: < 2.2e-16

Table 3b. Eastern region Longitude

Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	63.03892	123.49701	0.510	0.609771
Year	0.05756	0.06184	0.931	0.352085
StratumVES	-261.42384	152.16623	-1.718	0.085887 .
StratumVIW	-567.62194	284.22285	-1.997	0.045895 *
StratumVWN	-750.02599	214.85411	-3.491	0.000488 ***
StratumVWS	1814.25896	193.93884	9.355	< 2e-16 ***
YearNo:StratumVES	0.13232	0.07621	1.736	0.082598 .
YearNo:StratumVIW	0.29593	0.14214	2.082	0.037418 *
YearNo:StratumVWN	0.36080	0.10768	3.351	0.000816 ***
YearNo:StratumVWS	-0.92357	0.09711	-9.511	< 2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.021 on 3343 degrees of freedom
Multiple R-squared: 0.8544, Adjusted R-squared: 0.854
F-statistic: 2179 on 9 and 3343 DF, p-value: < 2.2e-16

Table 4. Sex ratio model selection with Year as a categorical variable. The term poly(Day, 2) indicates an orthogonal polynomial of degree 2.

Model term added	AIC
Constant	9282.35
+Year	9154.21
+Stratum	8519.57
+Day	8503.09
+poly(Day,2)	8490.28
+Latitude:Stratum	8270.89
+Longitude:Stratum	8224.27
+Length	**8213.08**

Table 5. Analysis of deviance table for the selected sex ratio model with Year as a categorical variable.

Term	Degrees of freedom	Deviance	Residual degrees of freedom	Residual deviance	P(>|Chi|)
NULL			6716	9280.30	
Year	17	162.14	6699	9118.2	< 2.2e-16 ***
Stratum	9	652.64	6690	8465.6	< 2.2e-16 ***
poly(DayNo, 2)	2	33.29	6688	8432.3	5.910e-8 ***
Latitude:Stratum	11	241.40	6677	8190.9	< 2.2e-16 ***
Longitude:Stratum	11	68.62	6666	8122.3	2.237e-10 ***
Length	1	13.19	6665	8109.1	2.819e-4 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

Table 6. Sex ratio model selection with Year as a numeric variable. The terms poly(Year, 2) and poly(Day, 2) indicates orthogonal polynomials of degree 2.

Model term added	AIC
Constant	9282.35
+Stratum	8593.81
+Year	8582.76
+poly(Year,2)	8567.09
+Day	8542.91
+poly(Day,2)	8527.98
+Latitude:Stratum	8307.15
+Longitude:Stratum	8264.25
+Length	**8258.25**

Table 7. Analysis of deviance table for the selected sex ratio model with Year as a categorical variable.

Term	Degrees of freedom	Deviance	Residual degrees of freedom	Residual deviance	P(>|Chi|)
NULL			6716	9280.3	
Stratum	10	708.54	6706	8571.8	< 2.2e-16 ***
Poly(Year,2)	2	30.72	6704	8541..1	2.136e-7 ***
poly(Day, 2)	2	43.11	6702	8498.0	4.349e-10 ***
Stratum:Latitude	11	242.82	6691	8255.2	< 2.2e-16 ***
Stratum:Longitude	11	64.90	6680	8190.3	1.126e-9 ***
Length	1	8.00	6679	8182.3	0.00467 **

Table 8. Length at maturity model selection with Year as a categorical variable

Model term added	AIC
Constant	4207.47
+Length	1724.07
+Year	1716.10
+Length:Stratum	1704.57
+Day	1701.34
+Longitude	1695.74
+poly(Longitude,2)	**1695.70**

Table 9. Analysis of deviance table for the selected length at maturity model with Year as a categorical variable.

Term	Degrees of freedom	Deviance	Residual degrees of freedom	Residual deviance	P(>|Chi|)
NULL			3128	4205.5	
Length	1	2485.40	3127	1720.1	< 2.2e-16 ***
Stratum	10	25.49	3117	1694.6	0.00450 **
Year	16	34.34	3101	1660.2	0.00489 **
Day	1	4.48	3100	1655.8	0.0342 *
Poly(Longitude,2)	2	10.80	3098	1645.0	0.00450 **
Length:Stratum	10	31.26	3088	1613.7	0.000532 ***

Table 10. Length at maturity model selection with Year as a numeric variable

Model term added	AIC
Constant	4207.47
+Length	1724.07
+poly(Year,2)	1715.95
+Length:Stratum	1705.63
+Day	1697.93
+Longitude	**1694.94**

Table 11. Analysis of deviance table for the selected length at maturity model with Year as a numeric variable.

Term	Degrees of freedom	Deviance	Residual degrees of freedom	Residual deviance	P(>|Chi|)
NULL			3128	4205.5	
Length	1	2485.40	3127	1720.1	< 2.2e-16 ***
Stratum	10	25.49	3117	1694.6	0.00450 **
Poly(Year,2)	2	6.63	3115	1687.9	0.0363 *
Day	1	8.39	3114	1679.6	0.00378 **
Longitude	1	5.55	3113	1674.0	0.0185 *
Length:Stratum	10	31.08	3103	1642.9	0.000569 ***

Table 12. Effects of sample size and transect replication on the estimates of simulated sex ratios derived from 1000 replicates of years with random transects.

Number of transects in each year	Days per transect	Number of catcher vessels	Mean sample size	Mean proportion female	Mean nominal Std Error	Actual Std Error
1	13[1]	1	66	0.563	0.058	0.117
1	25	1	132	0.563	0.041	0.107
1	25	2	264	0.562	0.028	0.107
1	25	4	527	0.565	0.021	0.105
1	25	8	1059	0.556	0.015	0.103
1	25	16	2119	0.563	0.011	0.104

1. Length of operating day reduced from 0.7 to 0.673 to keep total operating time constant

Table 13. Effects of sample size and transect replication on the estimates of simulated sex ratios derived from 1000 replicates of years with random transects.

Number of transects in each year	Days per transect	Number of catcher vessels	Mean sample size	Mean proportion female	Mean nominal Std Error	Actual Std Error
1	25	4	527	0.565	0.021	0.105
2	25	2	528	0.561	0.021	0.075
4	25	1	527	0.562	0.021	0.055
8	13[1]	1	527	0.562	0.022	0.042

1. Length of operating day reduced from 0.7 to 0.673 to keep total operating time constant

Table 14. Effects of sample size and transect replication on the estimates of simulated year trends in sex ratios derived from 1000 replicates with 20 years of random transects, estimated with GLM.

Number transects in each year	Days per transect	Number of catchers	Mean sample size	Mean GLM nominal Std Error	GLM actual Std Error	GLM Probability of Type 1 error
1	13[1]	1	66	0.0097	0.0186	0.313
1	25	1	132	0.0068	0.0171	0.430
1	25	2	264	0.0048	0.0168	0.572
1	25	4	520	0.0034	0.0160	0.669
1	25	8	1057	0.0024	0.0162	0.758
1	25	16	2113	0.0017	0.0167	0.847

1. Length of operating day reduced from 0.7 to 0.673 to keep total operating time constant

Table 15. Effects of sample size and transect replication on the estimates of simulated year trends in sex ratios derived from 1000 replicates with 20 years of random transects, estimated with GLMs with and without random effects based on transects. The last row has the number of transects each year selected randomly from a discrete uniform distribution {1 – 4}.

Number transects in each year	Days per transect	Number of catchers	Mean sample size	Mean GLM nominal Std Error	GLM actual Std Error	GLM Probability of Type 1 error	Mean random effects nominal Std Error	Random effects actual Std Error	Random effects Probability of Type 1 error
1	25	4	520	0.0034	0.0160	0.669	-	-	-
2	25	2	528	0.0034	0.0118	0.564	0.0114	0.0121	0.077
4	25	1	528	0.0034	0.0088	0.461	0.0083	0.0089	0.080
8	13[1]	1	529	0.0034	0.0065	0.300	0.0062	0.0065	0.075
Random 1-4	25	2	548	0.0030	0.0112	0.575	0.0114	0.0126	0.081

1. Length of operating day reduced from 0.7 to 0.673 to keep total operating time constant

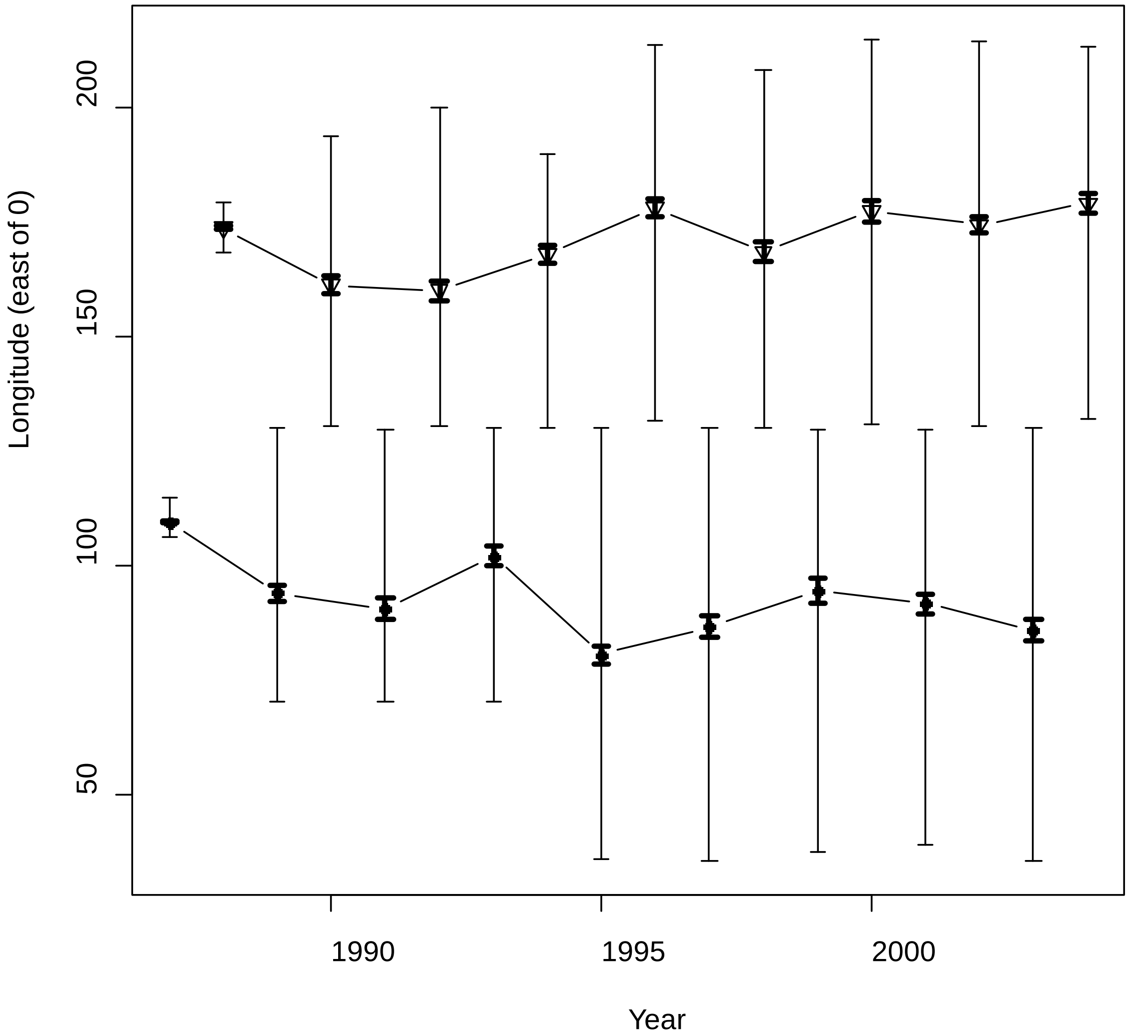


Fig 1. Means and ranges of Longitudes for the catches taken under JARPA. The heavy error bars are the approximate 95% confidence intervals for the means (± 2 standard errors); the light error bars show the ranges.

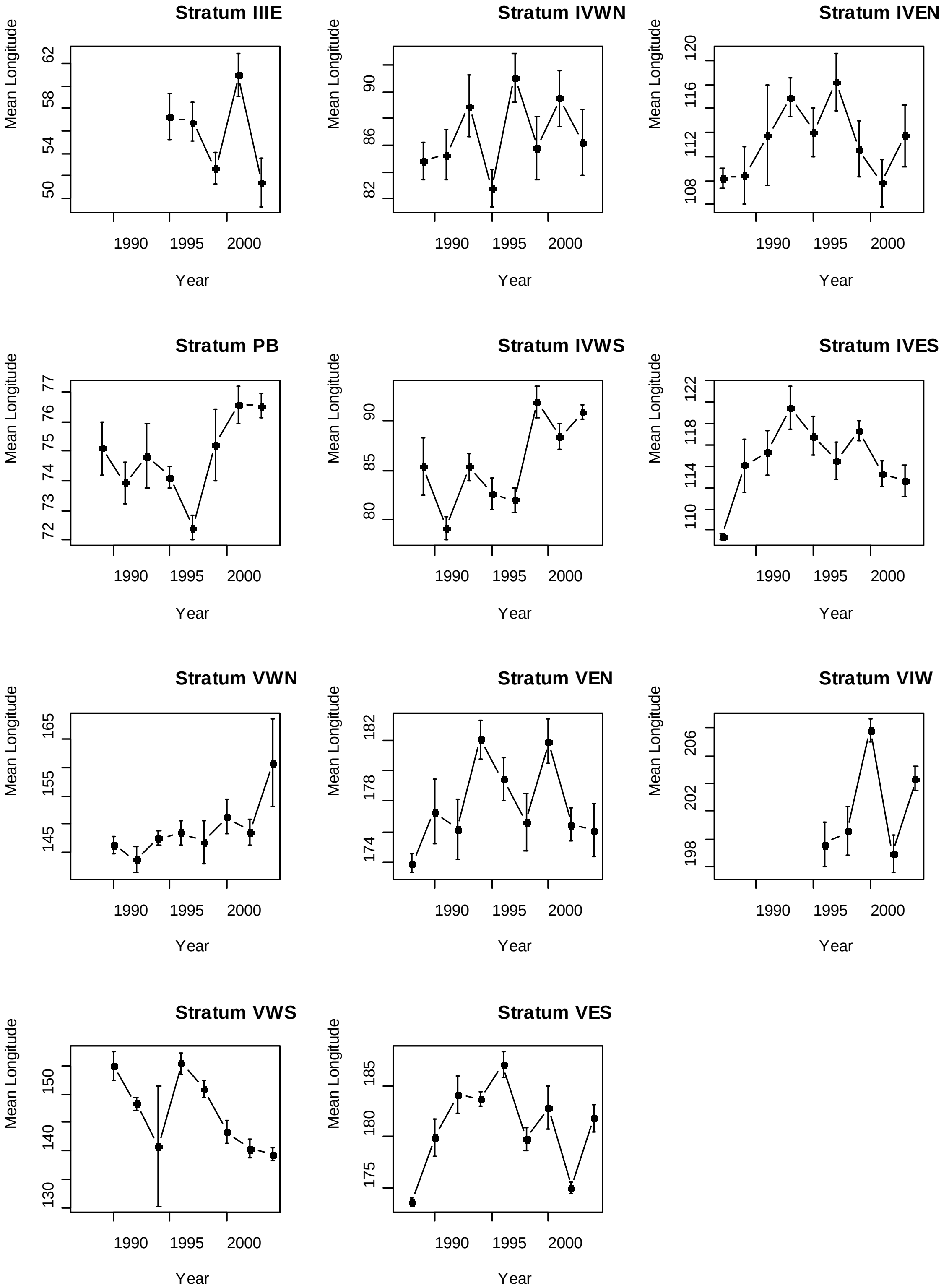


Fig 2. Mean longitude by year and stratum. The error bars represent the approximate 95% confidence intervals of the mean (± 2 standard errors).

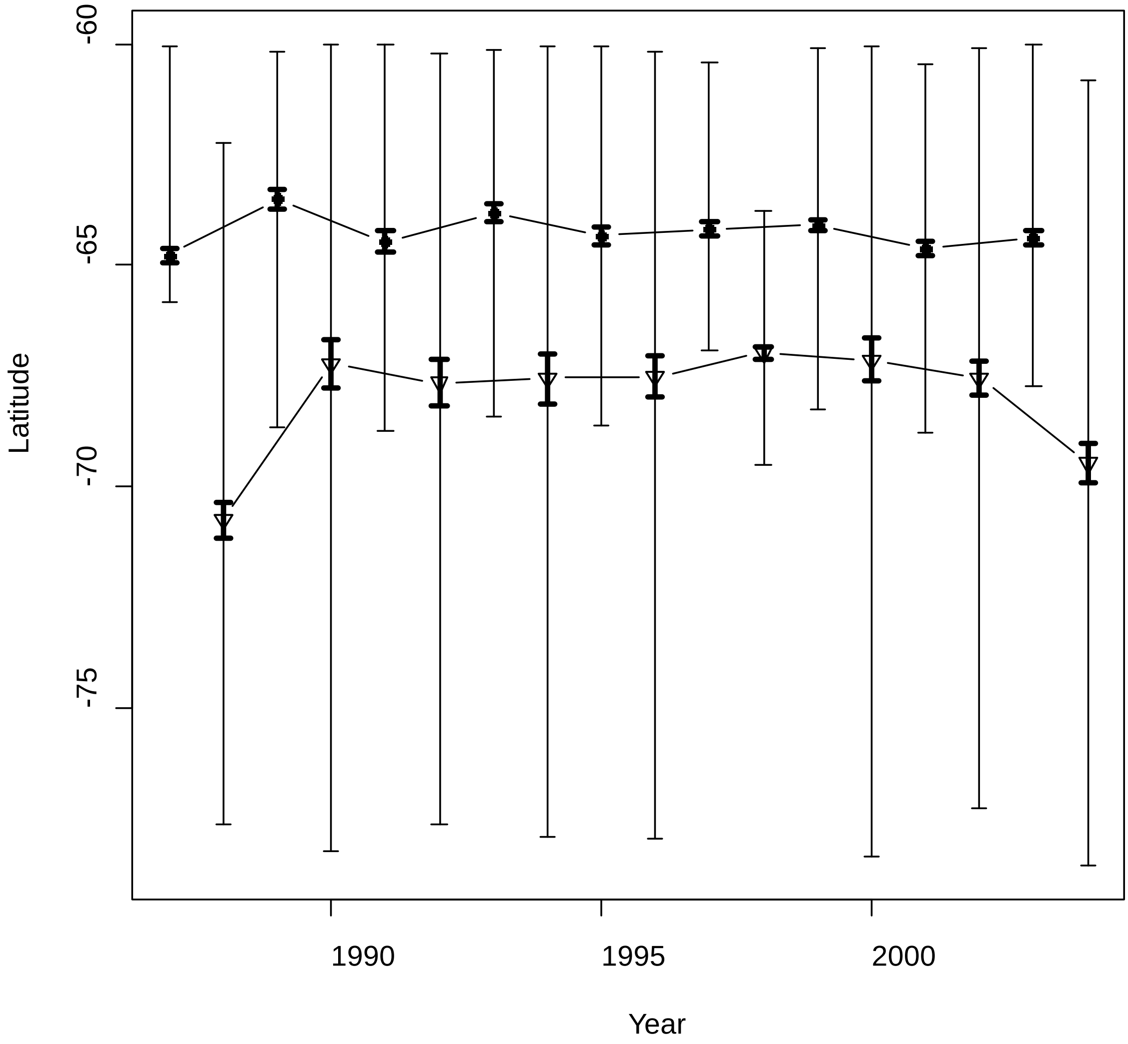


Fig 3. The distribution of latitudes sampled is different in the odd and even years. Heavy error bars approximate 95% confidence intervals (± 2 standard errors), light error bars show range

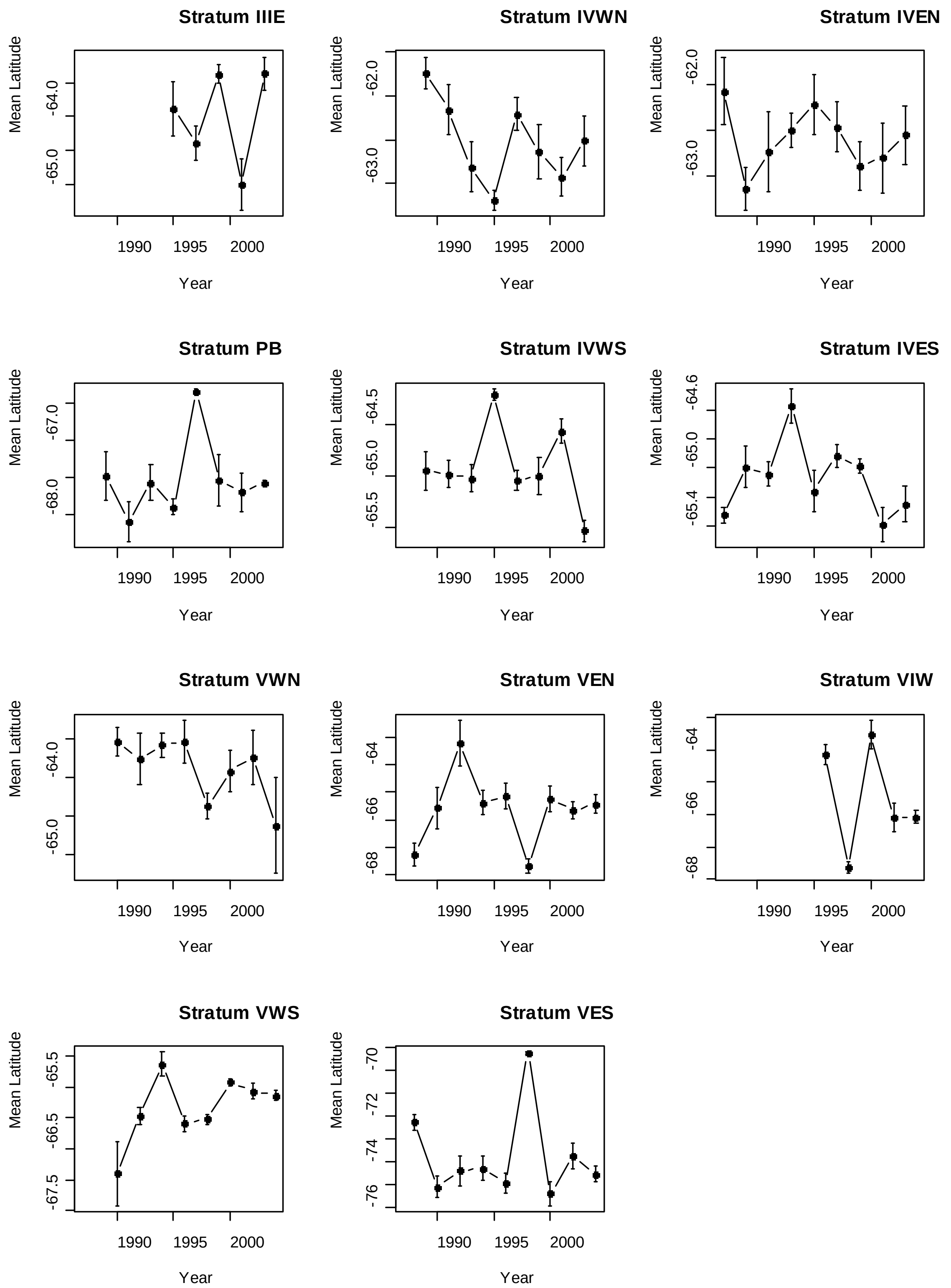


Fig. 4. Mean latitudes of catches by year and stratum, error bars are approximate 95% confidence intervals (± 2 standard errors) .

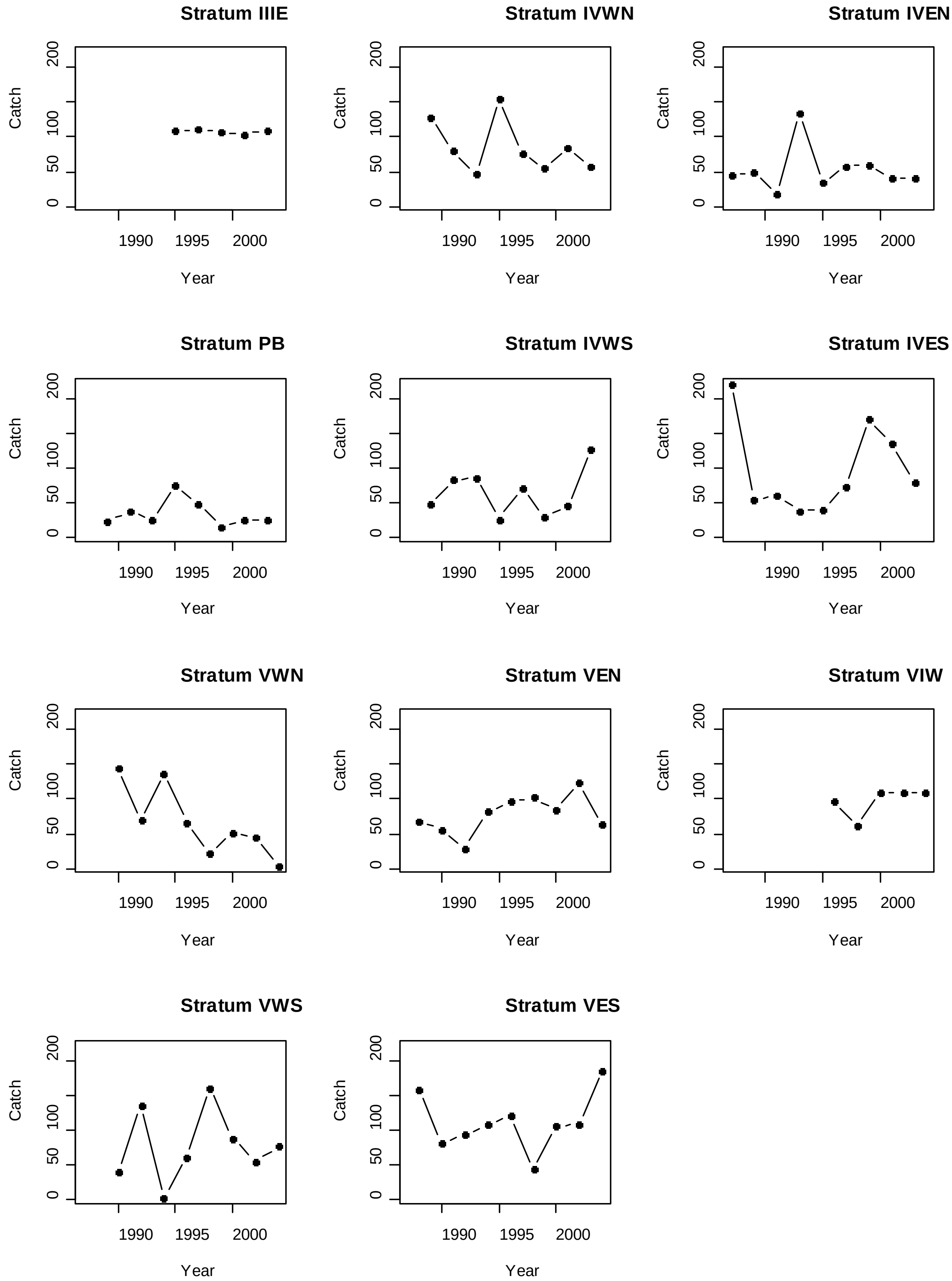


Fig 5. Numbers of whales taken in each stratum by year.

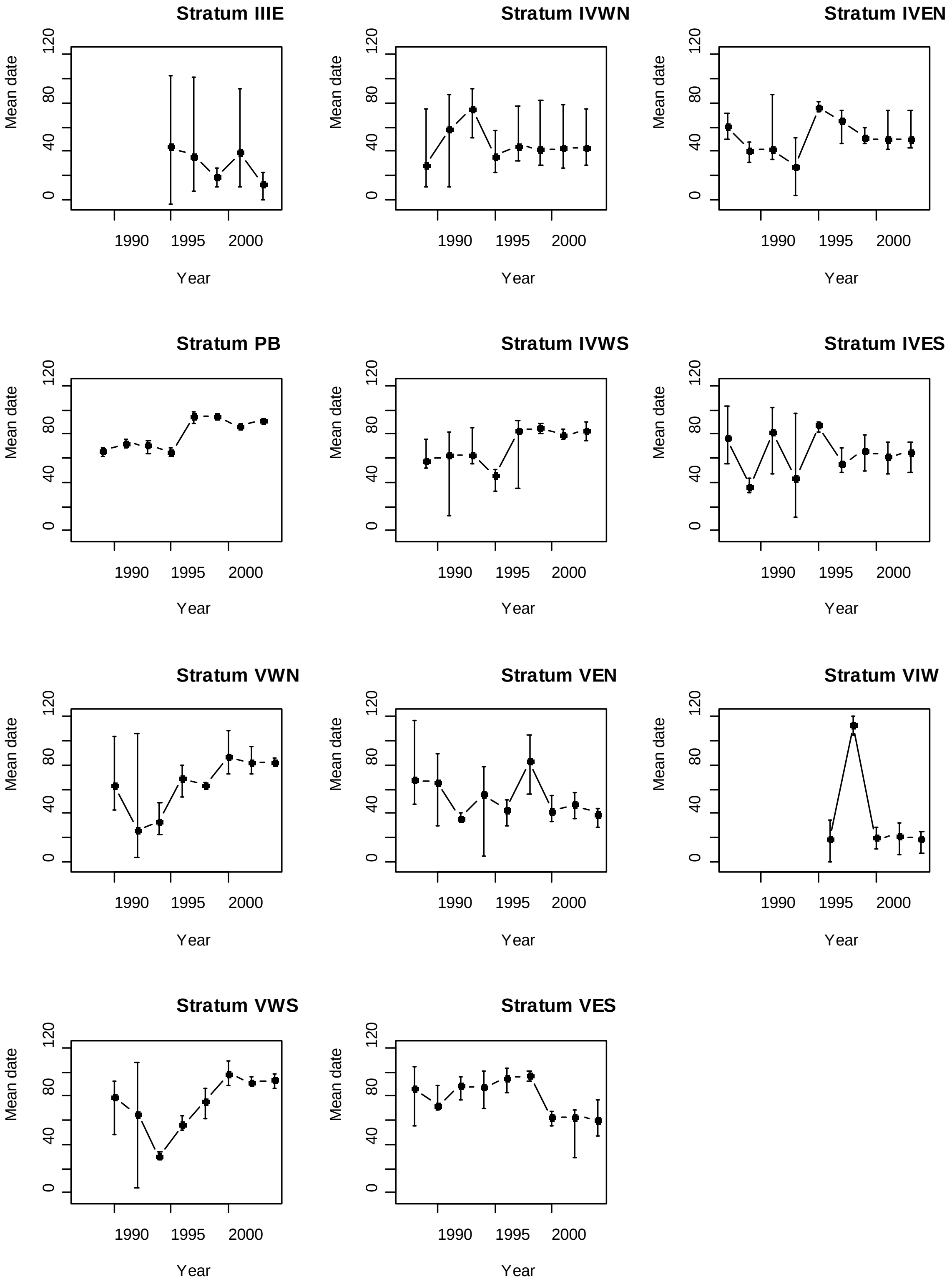


Fig 6. Means and ranges of dates of catches by year and stratum, error bars are approximate 95% confidence intervals (± 2 standard errors).

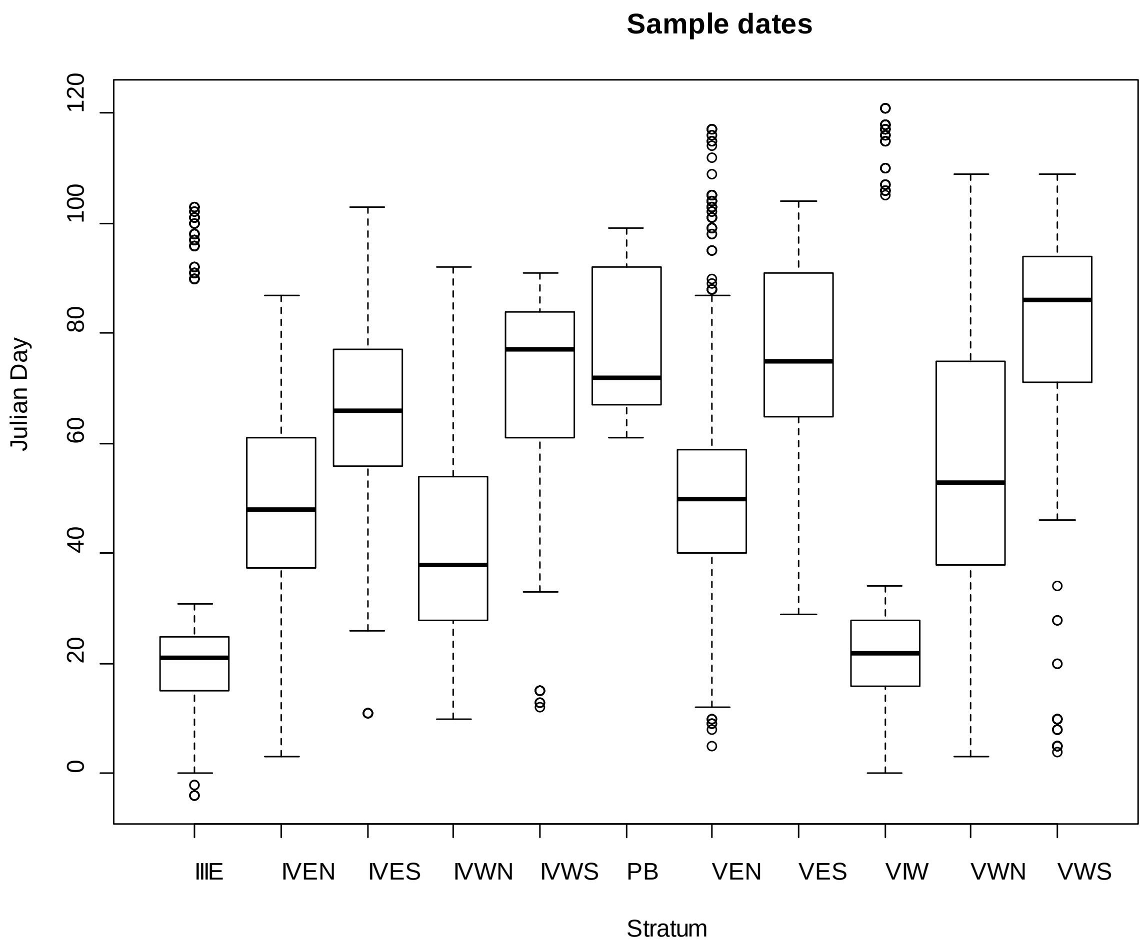


Fig 7. Dates of sampling in each stratum pooled over years (Day 1 =Dec 1)

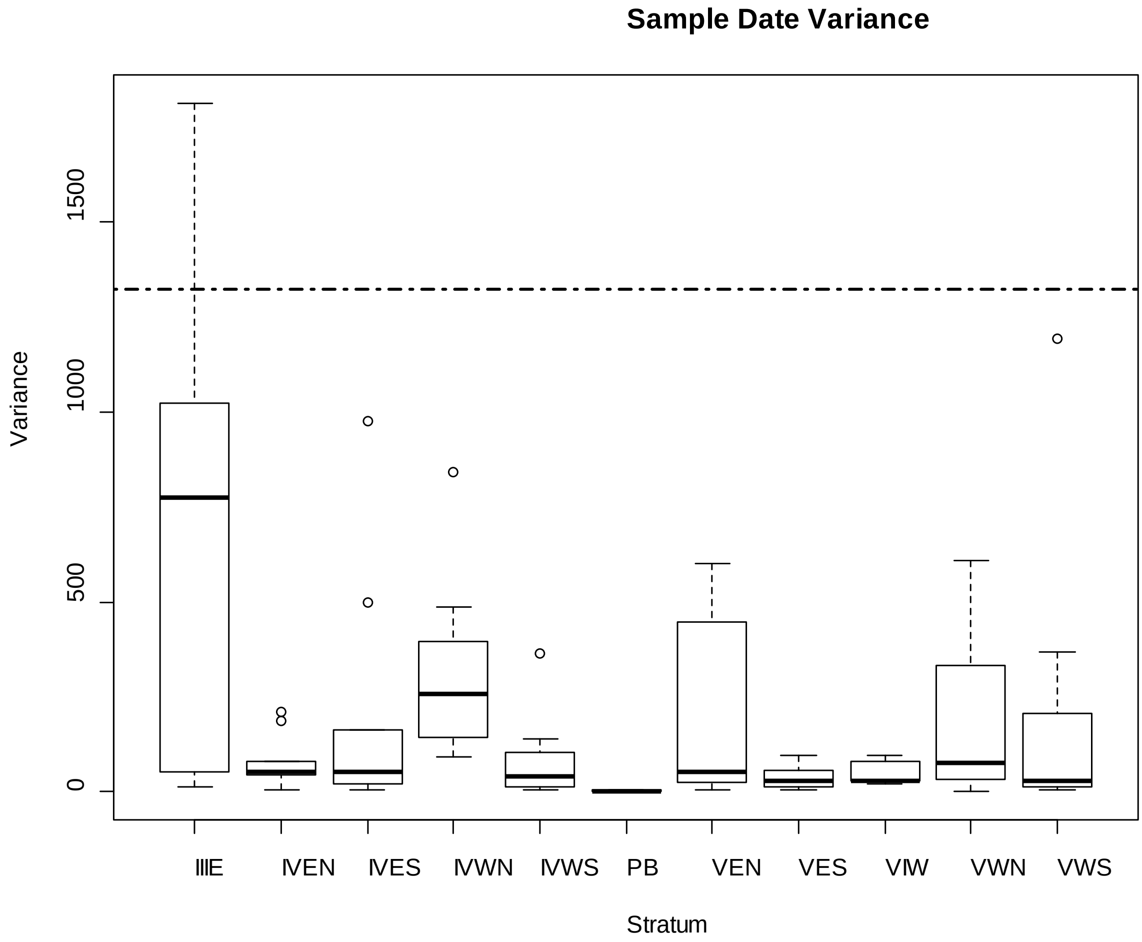


Fig 8. Variance in sampling date over years by stratum. The horizontal dashed line shows the variance that would be attained with uniform sampling of dates across the whaling season.

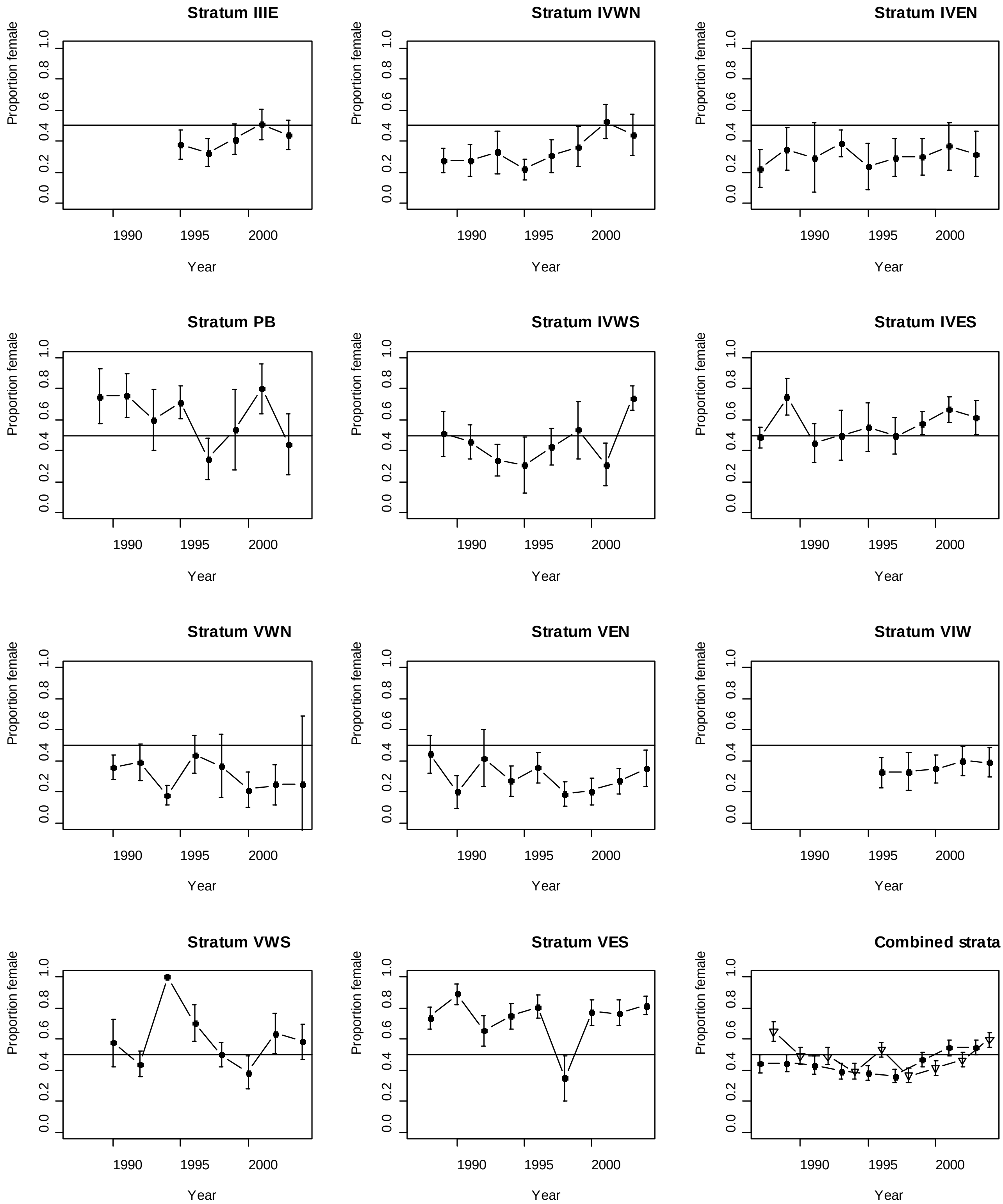


Fig 9. Proportion female (sex ratio) by Stratum and Year, the error bars represent the approximate 95% confidence intervals for the proportion (± 2 standard errors).

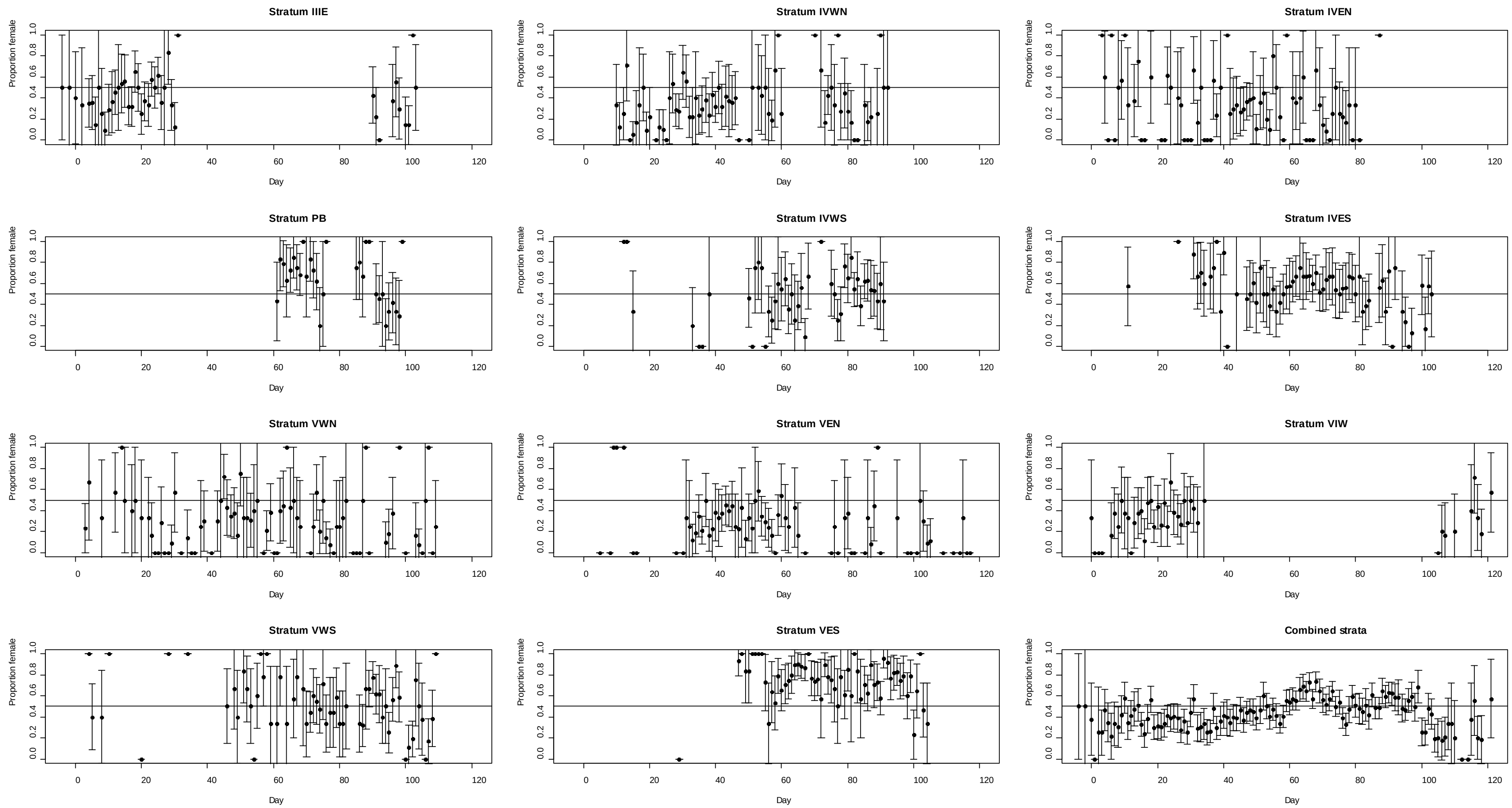


Fig. 10. Sex ratios by stratum and season date (Day, 1 = Dec 1), , the error bars represent the approximate 95% confidence intervals for the proportion (± 2 standard errors).

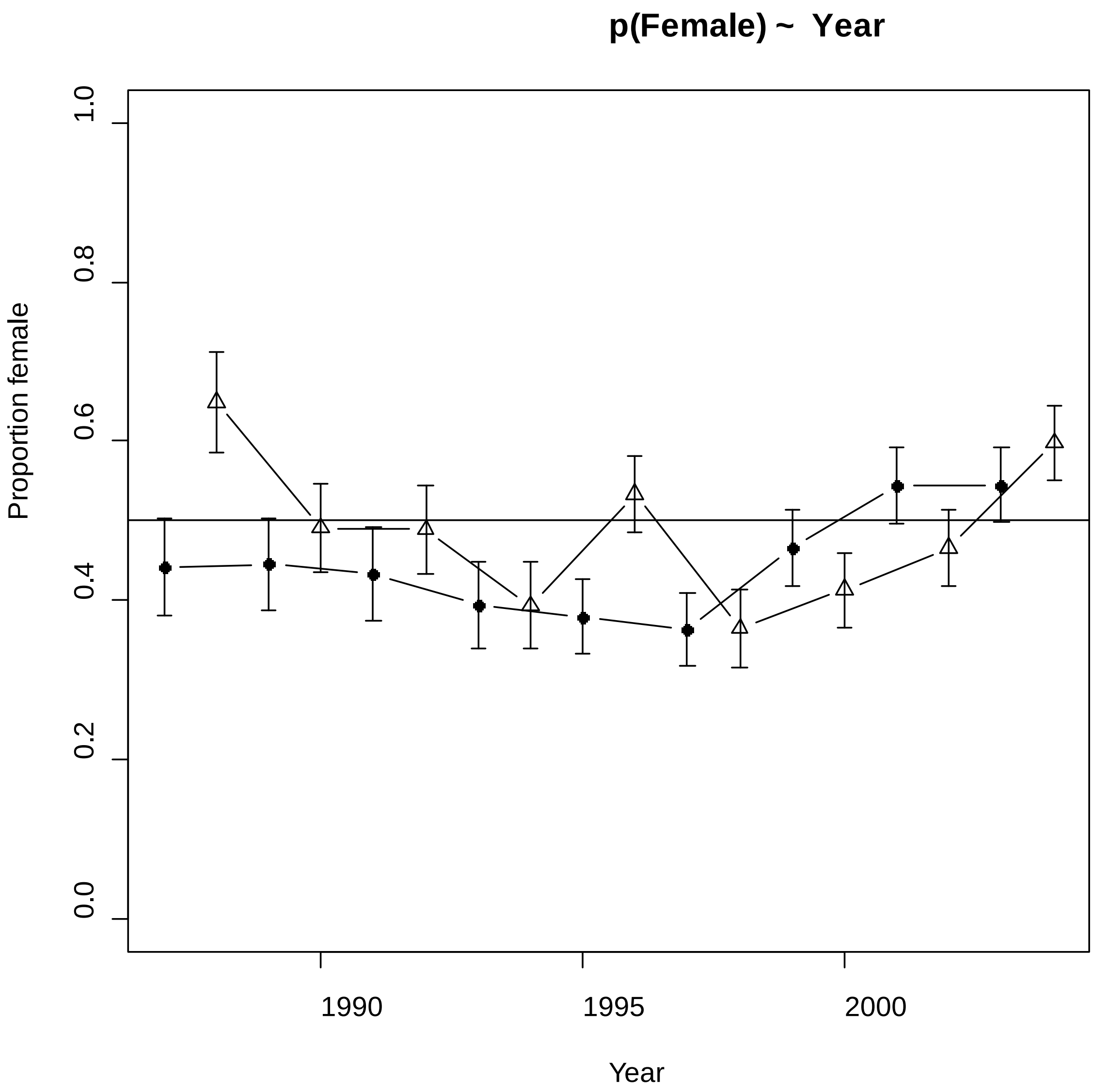


Fig. 11. Sex ratio predicted from a GLM with year as factor. The last four points on the lower trace exceed the feasible population change with sex ratio at birth set at 100% female.

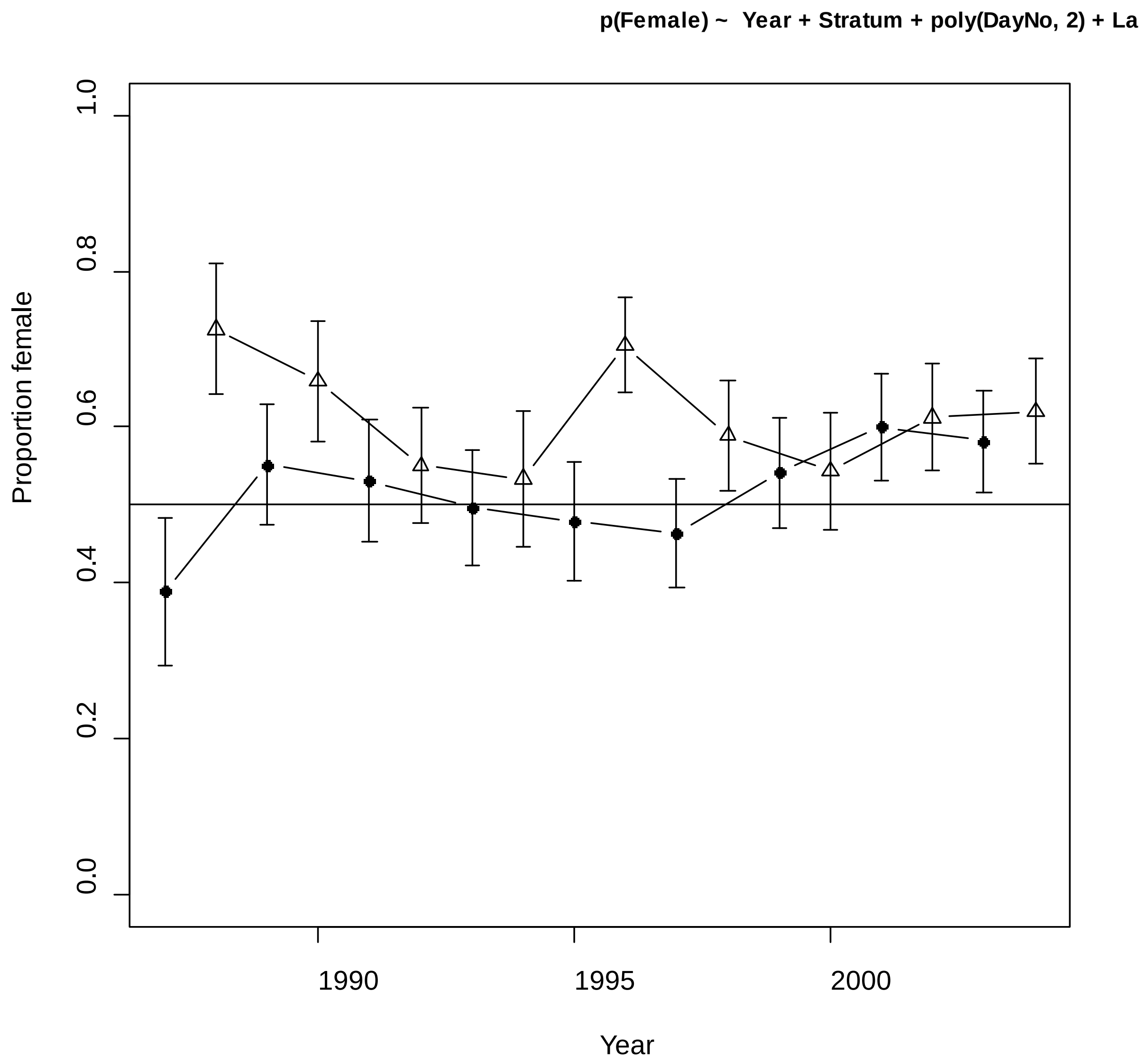


Fig. 12. Sex ratio predicted from model with substantially lower AIC (= 8213.08) for the strata IVWS (odd years) and VWS (even years). Mean position for IVW S is Lat = -65.06, Long = 85.75, and for VWS is Lat = 65.90, Lon = 147.58.

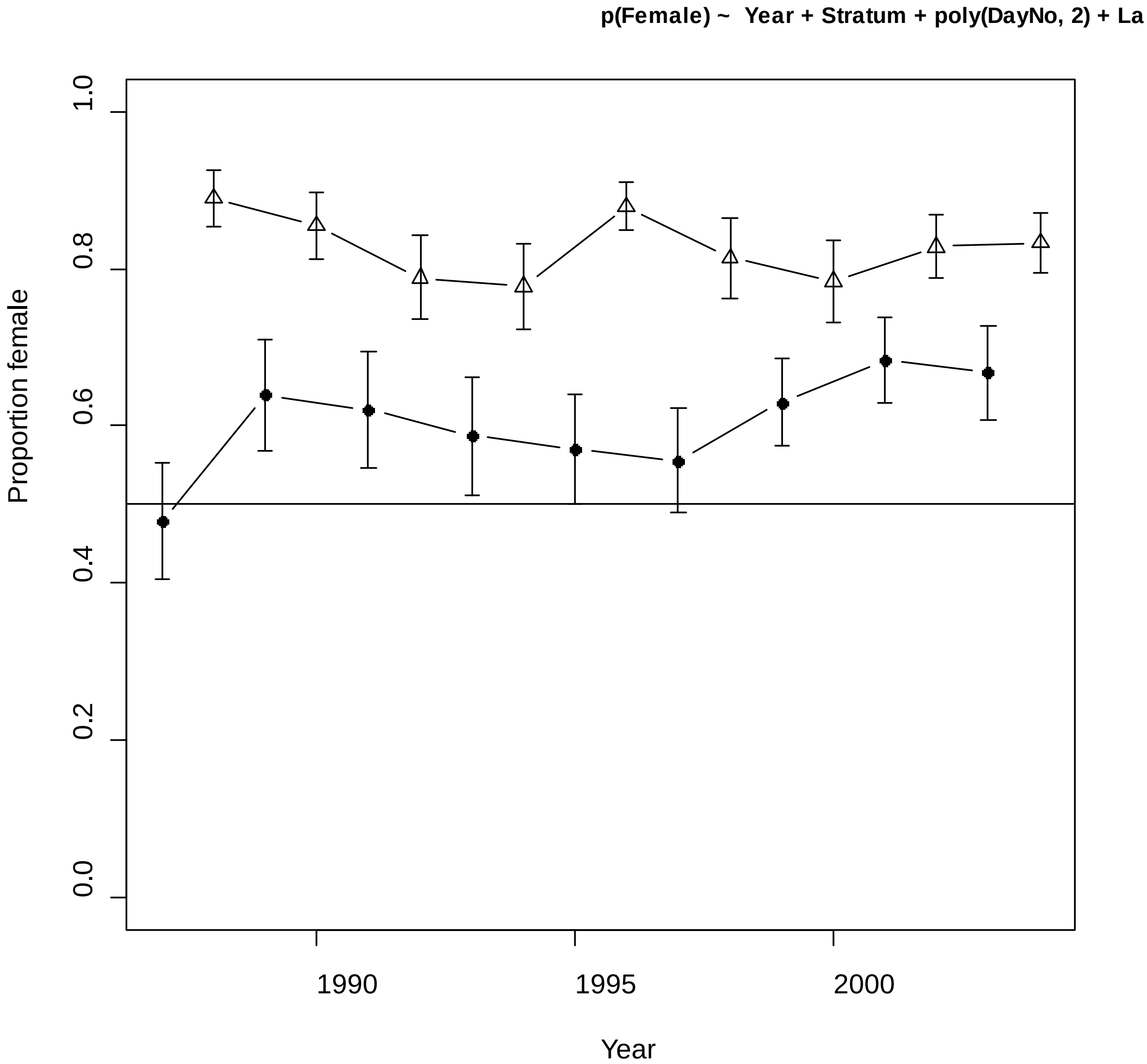


Fig. 13. Sex ratio predicted from model with Year as a categorical variable with low AIC (= 8213.08) for the strata IVES (odd years) and VES (even years). Mean position for IVE S is Lat = -65.15, Long = 115.24, and for VES is Lat = -74.01, Lon = 180.68.

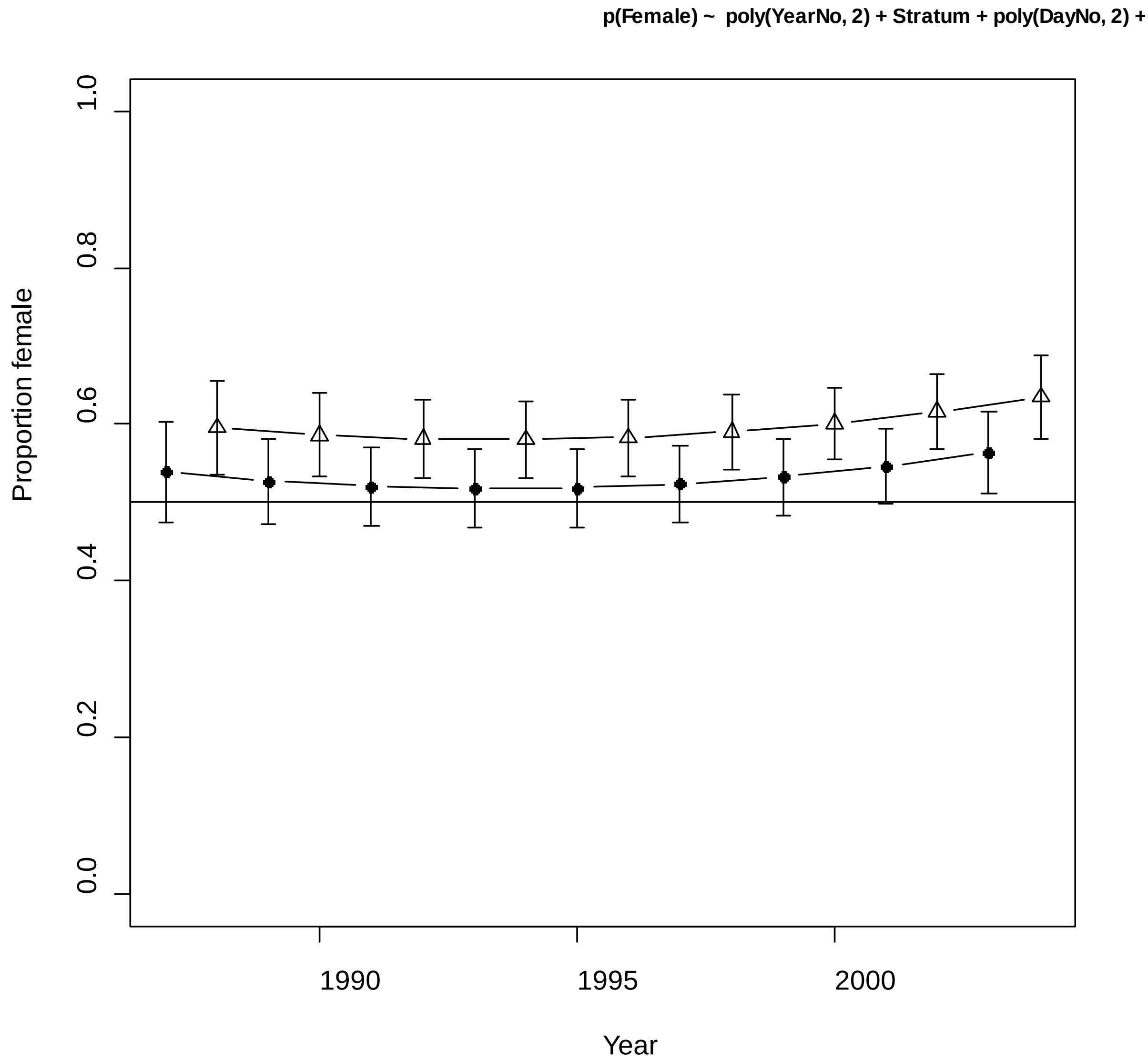


Fig. 14. Sex ratio predicted from model with Year as numeric variable with AIC = 8258.25 for the strata IVWS (odd years) and VWS (even years). Mean position for IVW S is Lat = -65.06, Long = 85.75, and for VWS is Lat = 65.90, Lon = 147.58.

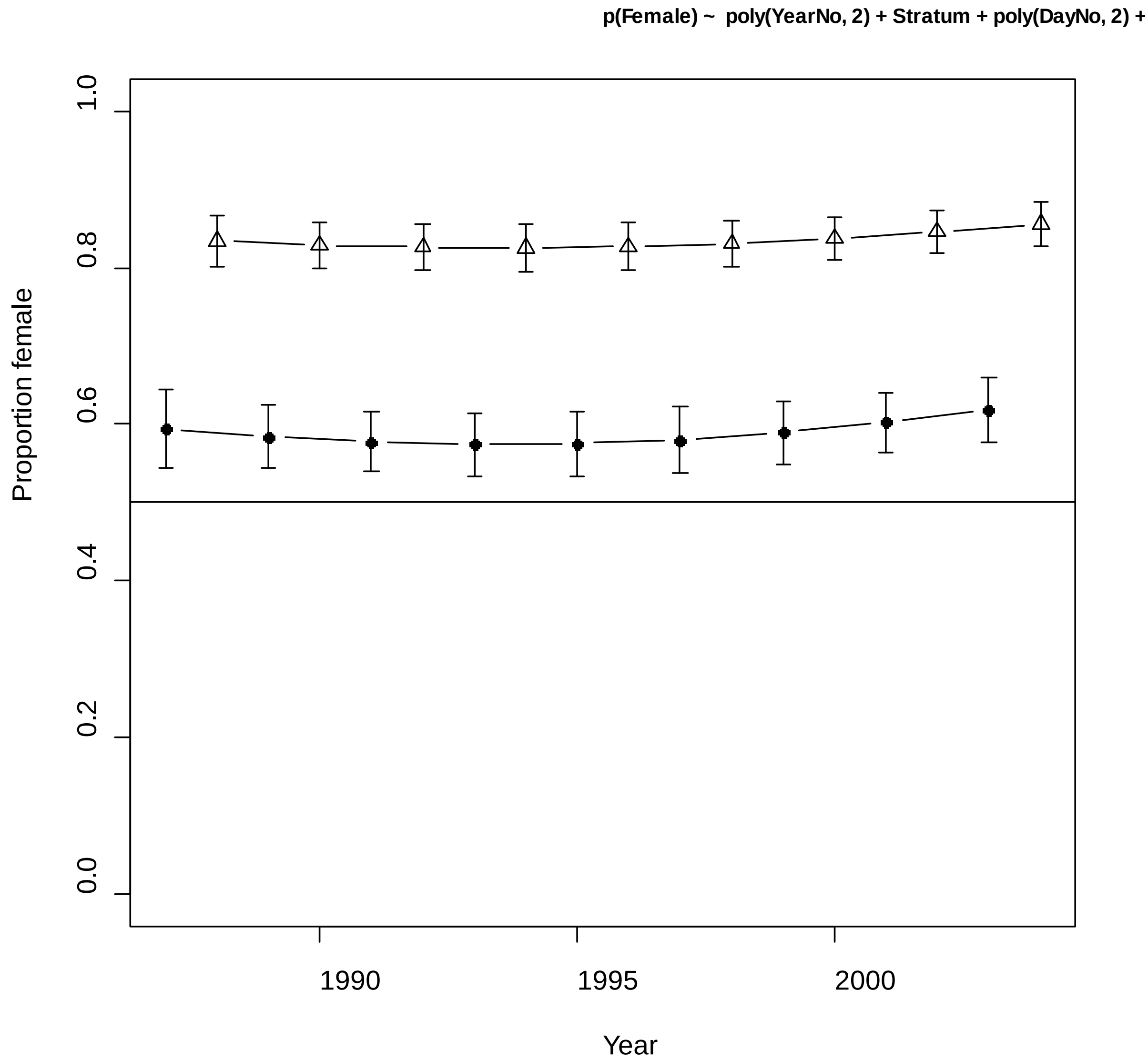


Fig. 15. Sex ratio predicted from model with Year as numeric variable with AIC = 8258.25 for the strata IVES (odd years) and VES (even years). Mean position for IVES is Lat = -65.15, Long = 115.24, and for VES is Lat = -74.01, Lon = 180.68.

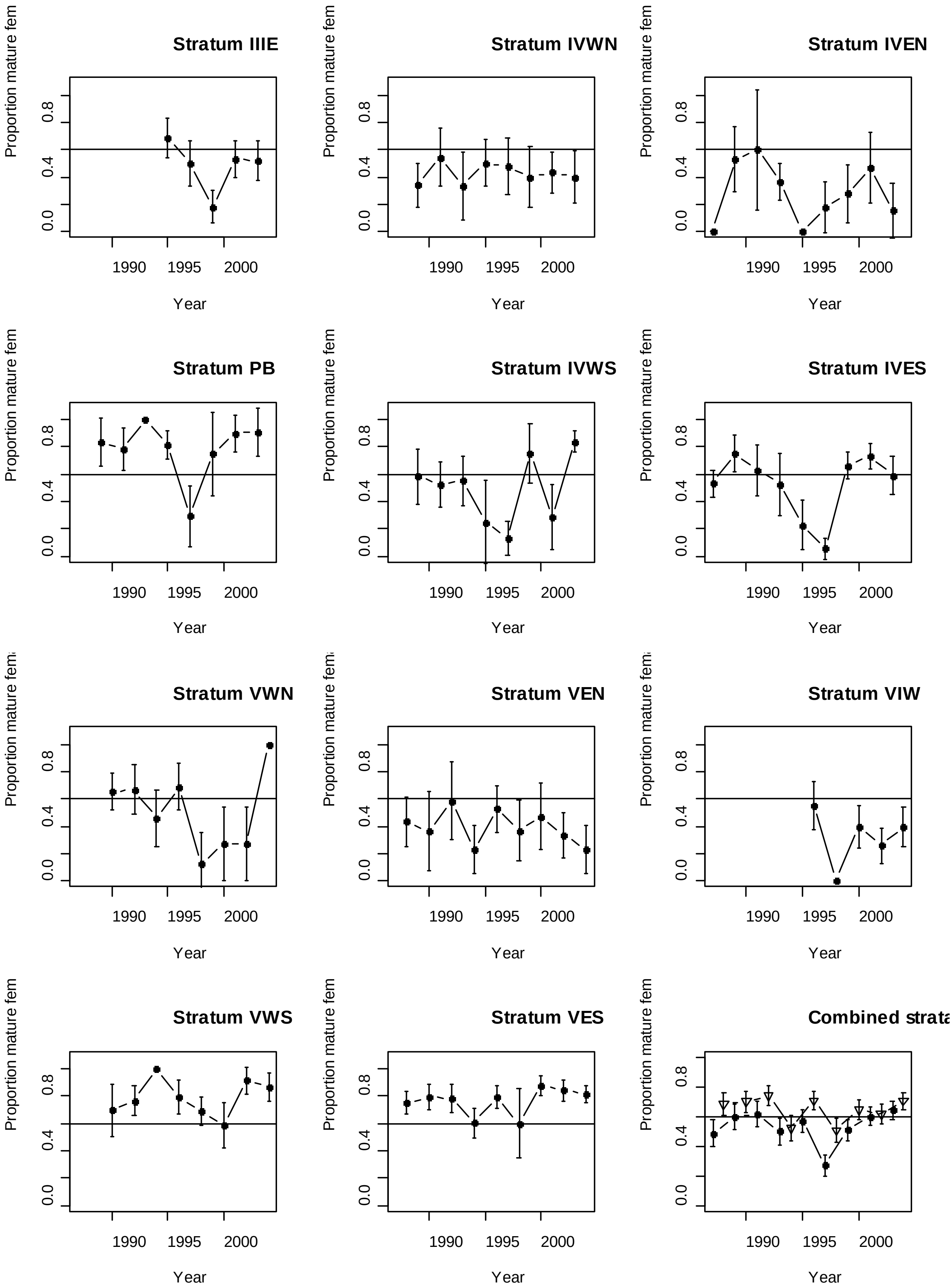


Fig. 16. Uncorrected estimates of proportion of females that are mature by year and stratum. Horizontal line is the grand mean (0.603), error bars are ~95% binomial confidence intervals.

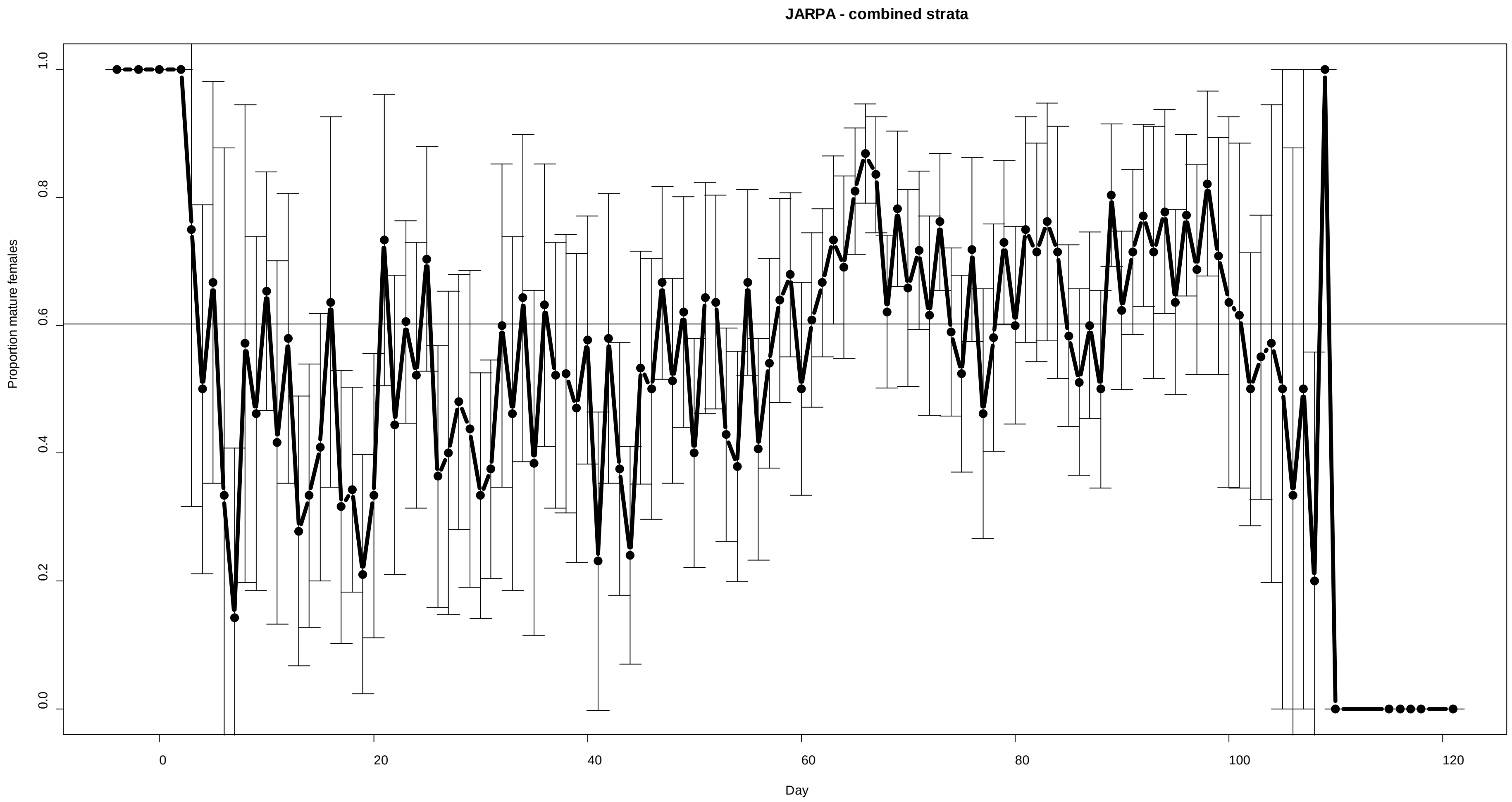


Fig. 17. Uncorrected estimates of proportion of females that are mature by day of season, pooled over years and strata. Error bars are ~95% binomial confidence intervals.

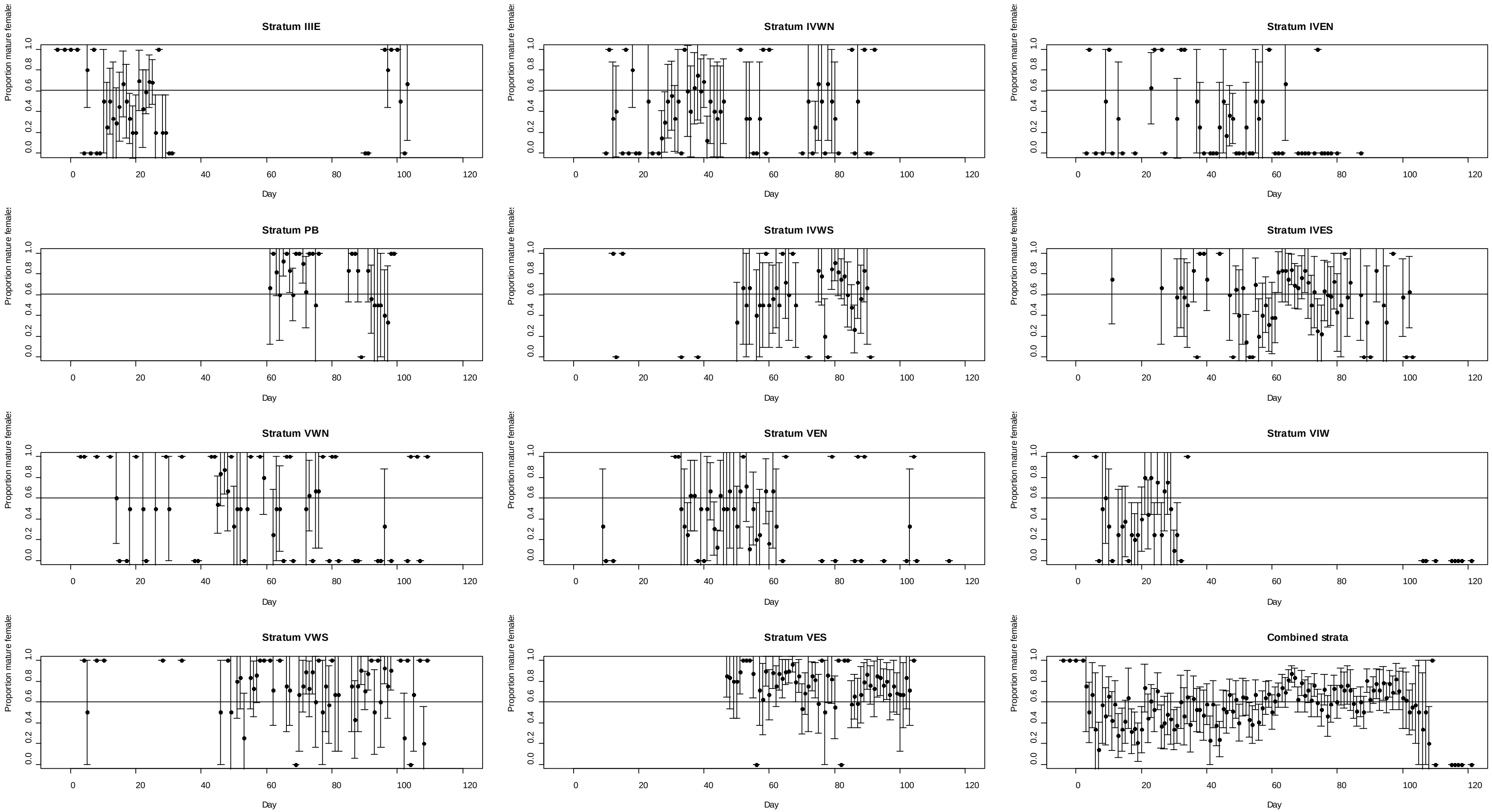


Fig. 18. Uncorrected estimates of proportion of females that are mature by day of season for each stratum, pooled over years. Error bars are ~95% binomial confidence intervals.

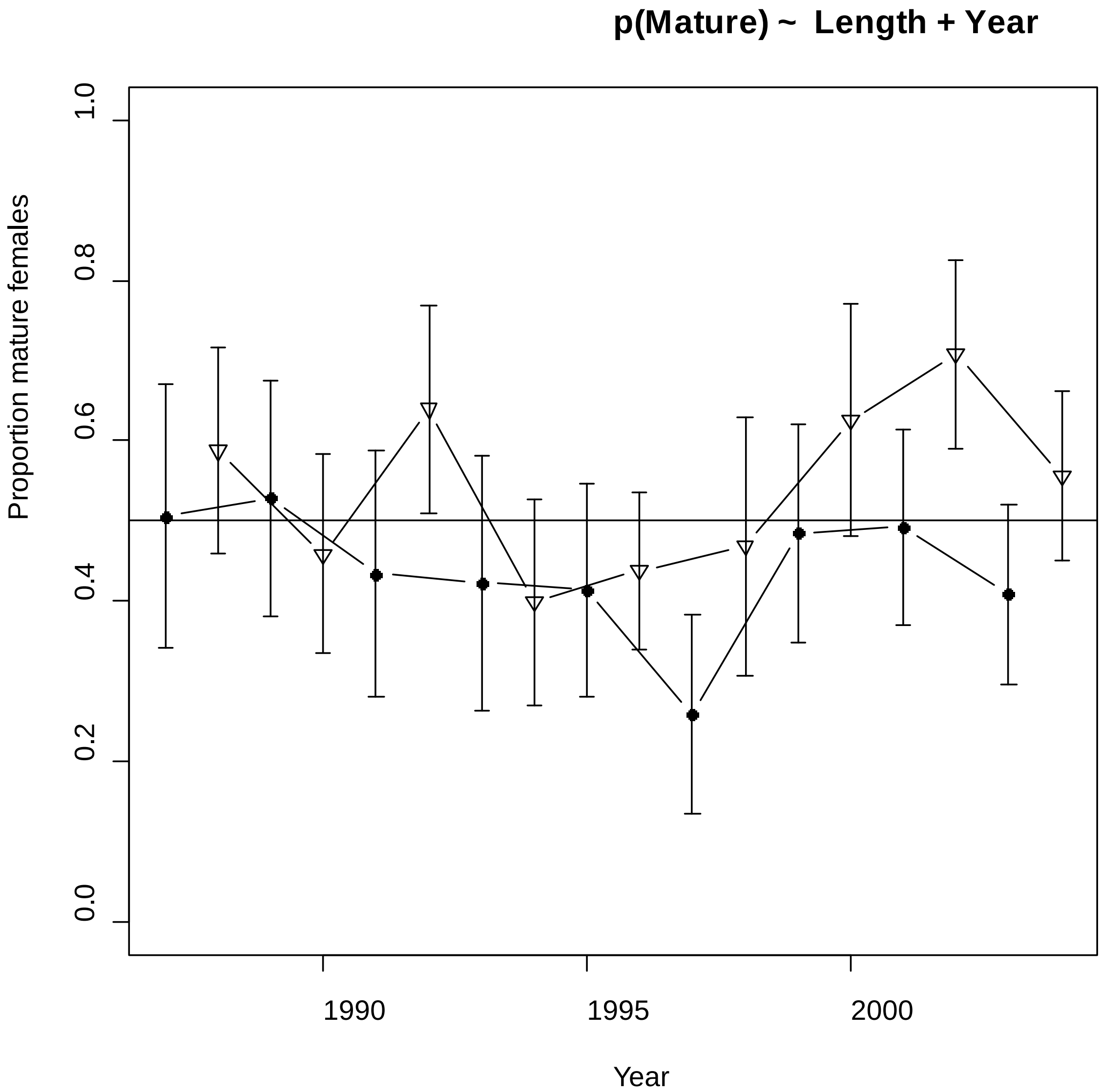


Fig. 19. Predicted proportion of females mature from a model (AIC = 1716.1) with Year as categorical variable at the length = 8.19m (where the mean probability of being mature is expected to be ~0.5).

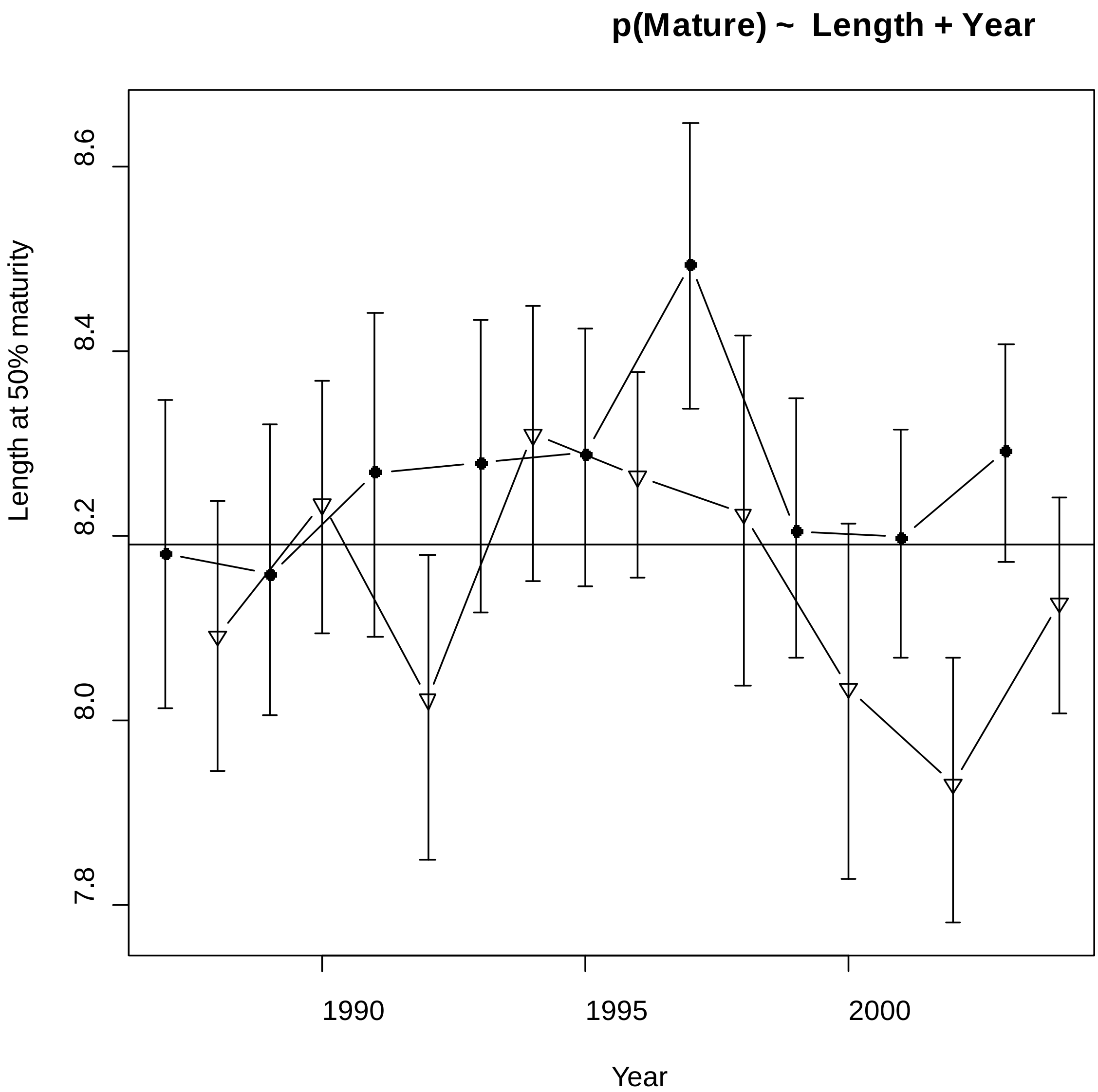


Fig. 20. Length at 50% maturity predicted using a model with year as a categorical variable. Horizontal line is the grand mean, the error bars are the estimated confidence intervals from 1000 bootstrap replicates.

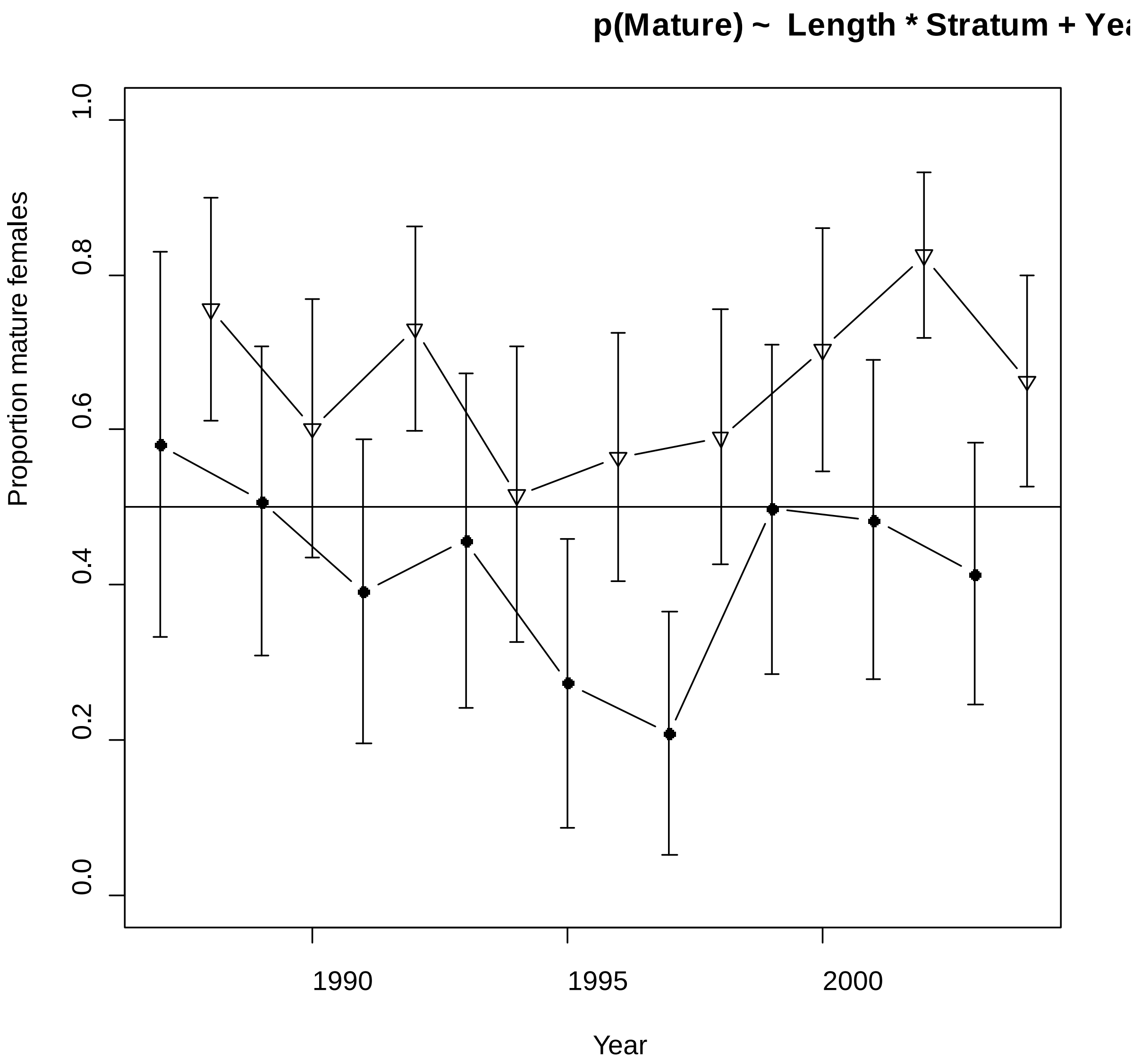


Fig. 21. Predicted proportion of females mature from a model with a low AIC (= 1695.7), with Year as categorical variable at the length = 8.19m for the strata IVWS (odd years) and VWS (even years). Mean position for IVW S is Lat = -65.17, Long = 86.97, and for VWS is Lat = -66.01, Lon = 146.53.

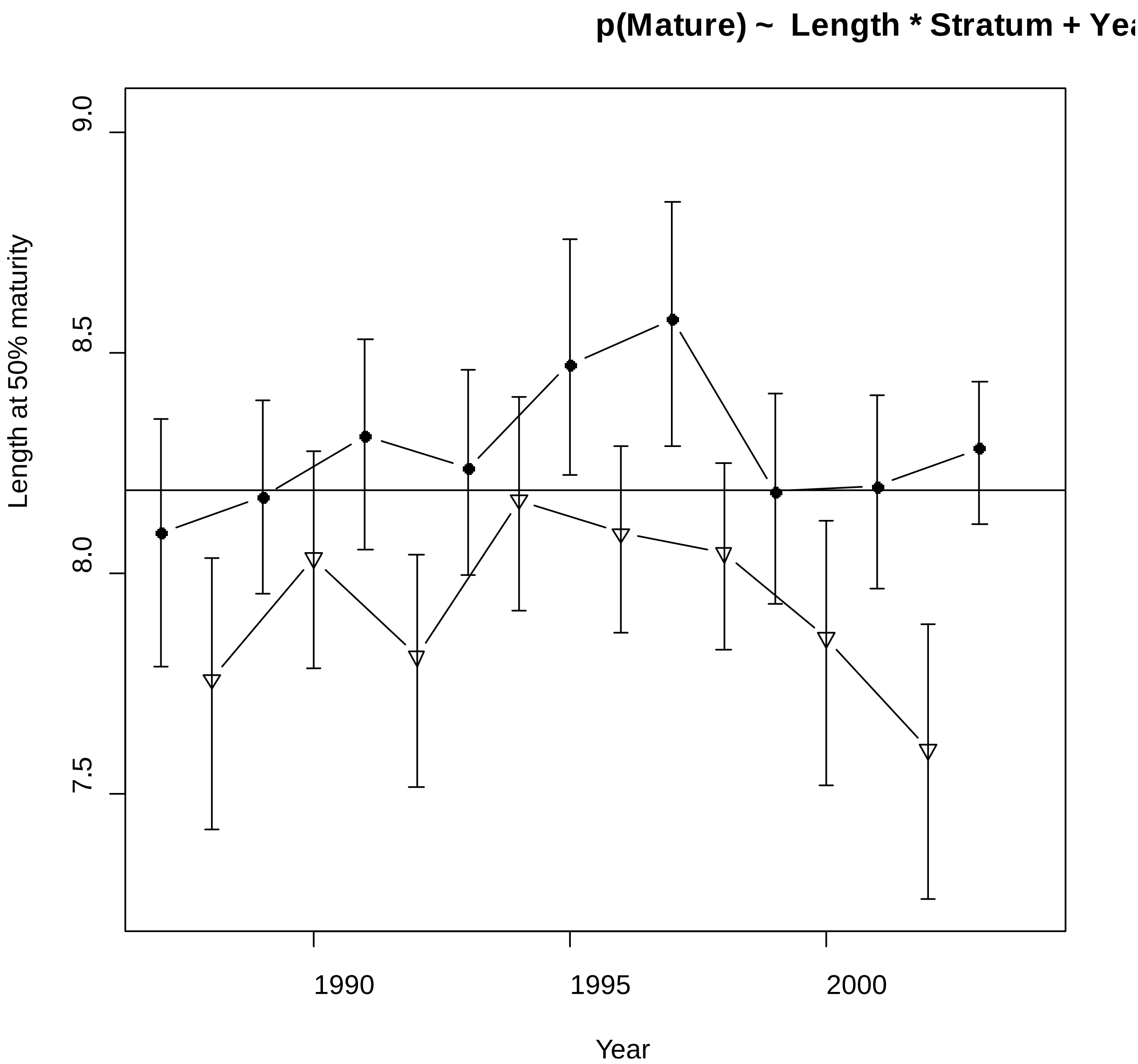


Fig. 22. Length at 50% maturity predicted using the model with a low AIC (= 1695.7), with year as a categorical variable for the strata IVWS (odd years) and VWS (even years). Horizontal line is the grand mean, the error bars are the estimated confidence intervals from 1000 bootstrap replicates.

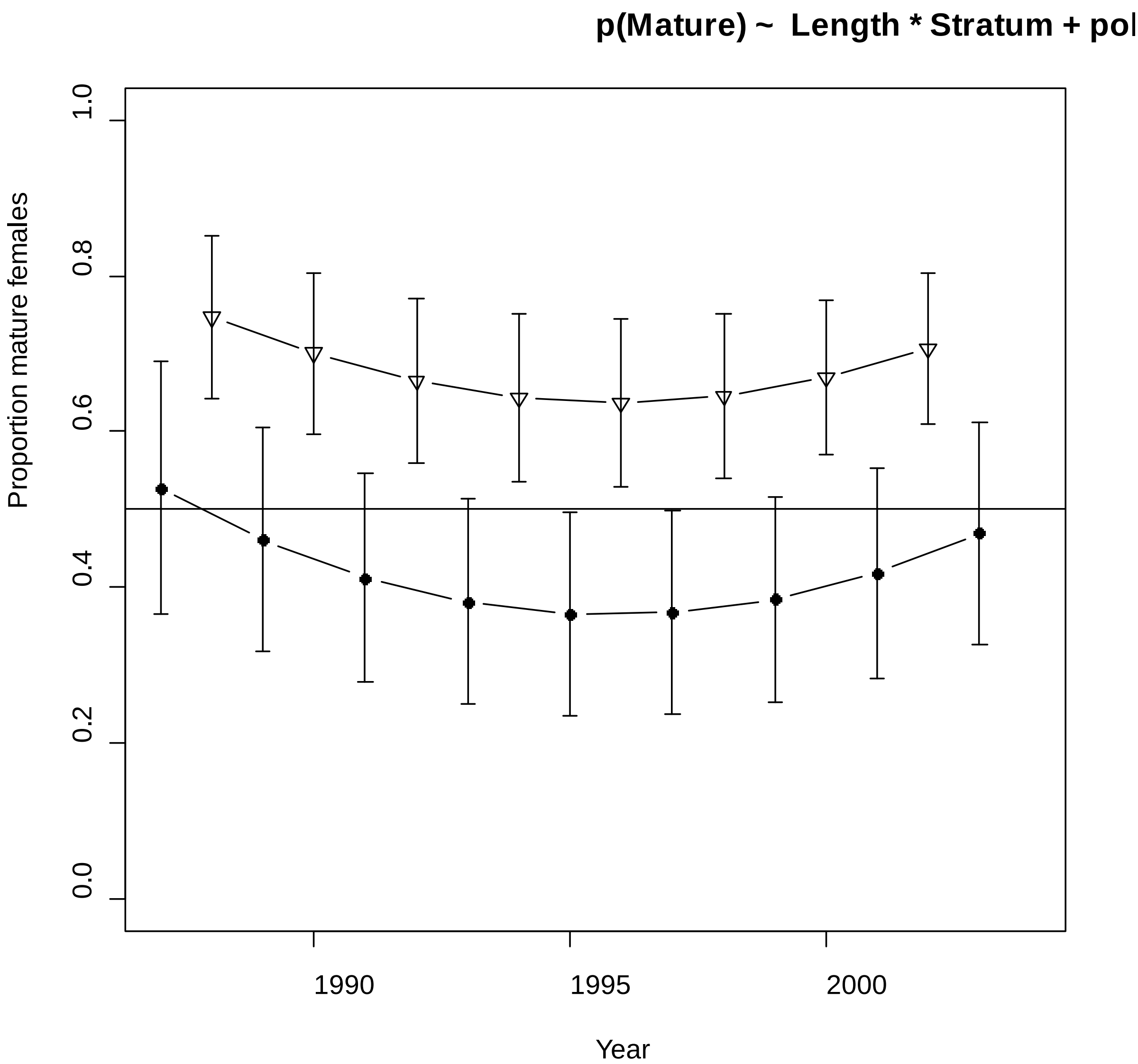


Fig. 23. Predicted proportion mature in each year in Stratum IVWS at the length = 8.19m (where the mean probability of being mature is 0.5), predicted with year as a second order polynomial. AIC = 1694.94 for the strata IVWS (odd years) and VWS (even years). Mean position for IVW S is Lat = -65.17, Long = 86.97, and for VWS is Lat = -66.01, Lon = 146.53.

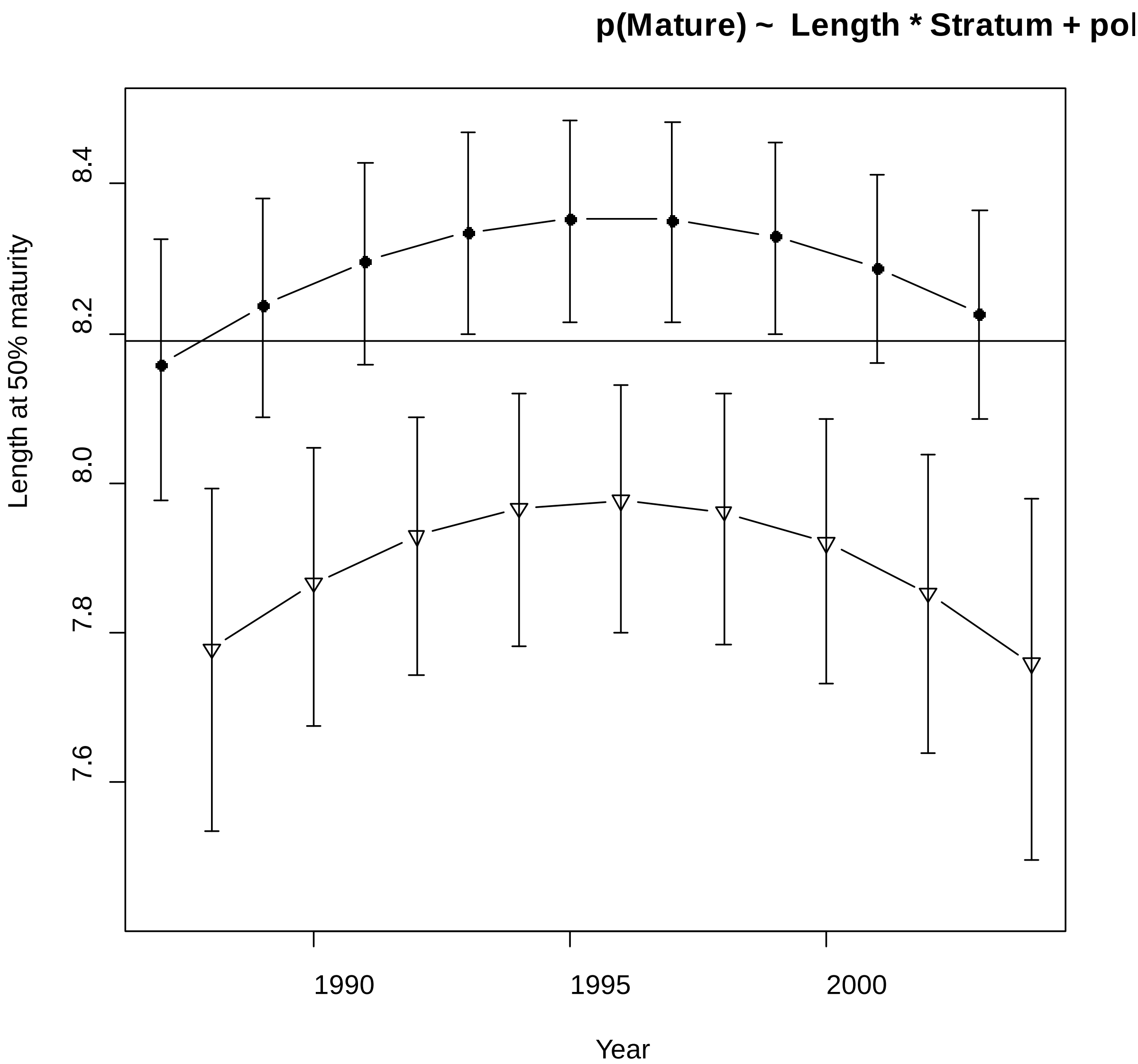


Fig. 24. Length at 50% maturity predicted using the model with a low AIC (= 1694.94), with year as a second order polynomial for the strata IVWS (odd years) and VWS (even years). Horizontal line is the grand mean, the error bars are the estimated confidence intervals from 1000 bootstrap replicates.

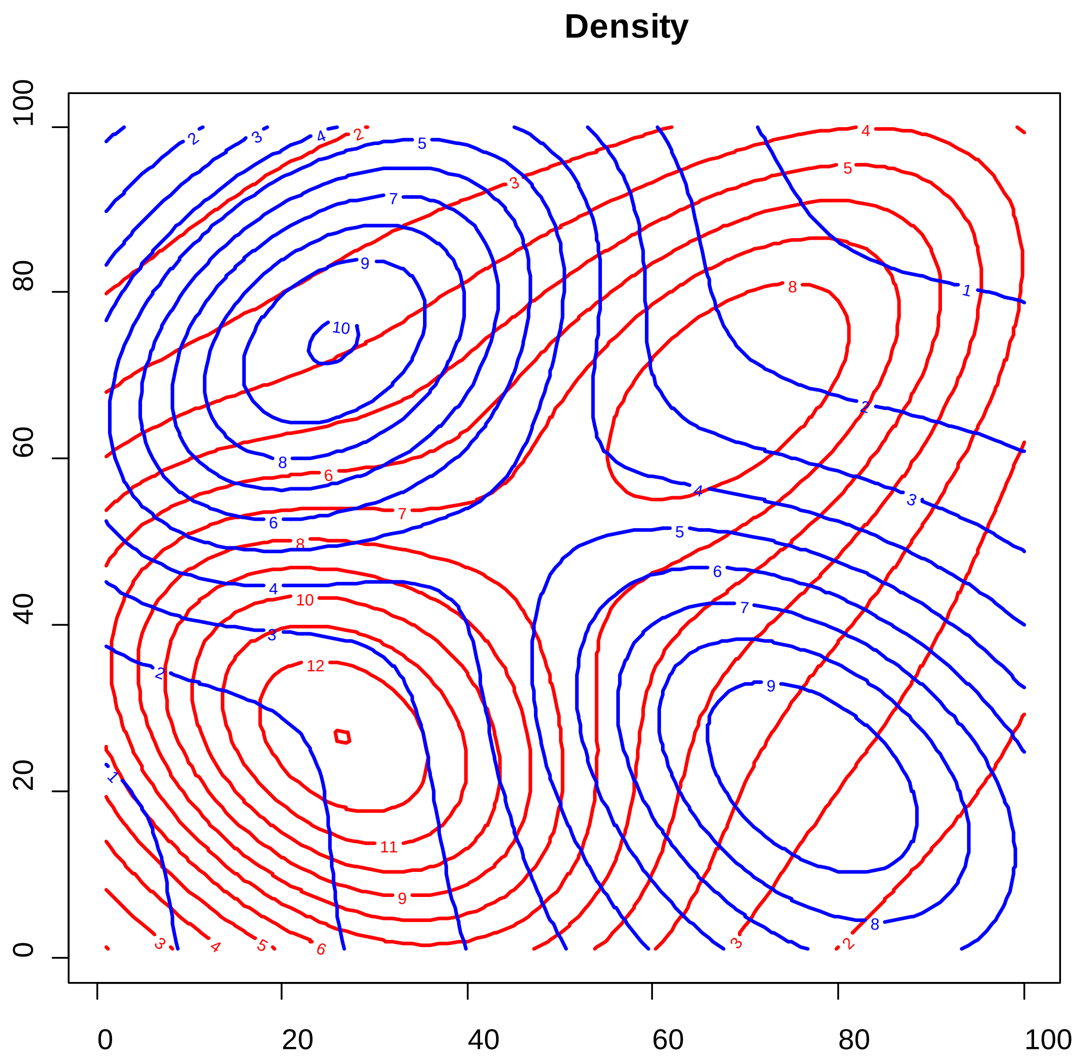


Fig. 25. Density contours for a segment of a hypothetical population, female densities (red contours) males (blue). There is a degree of spatial separation of the sexes.

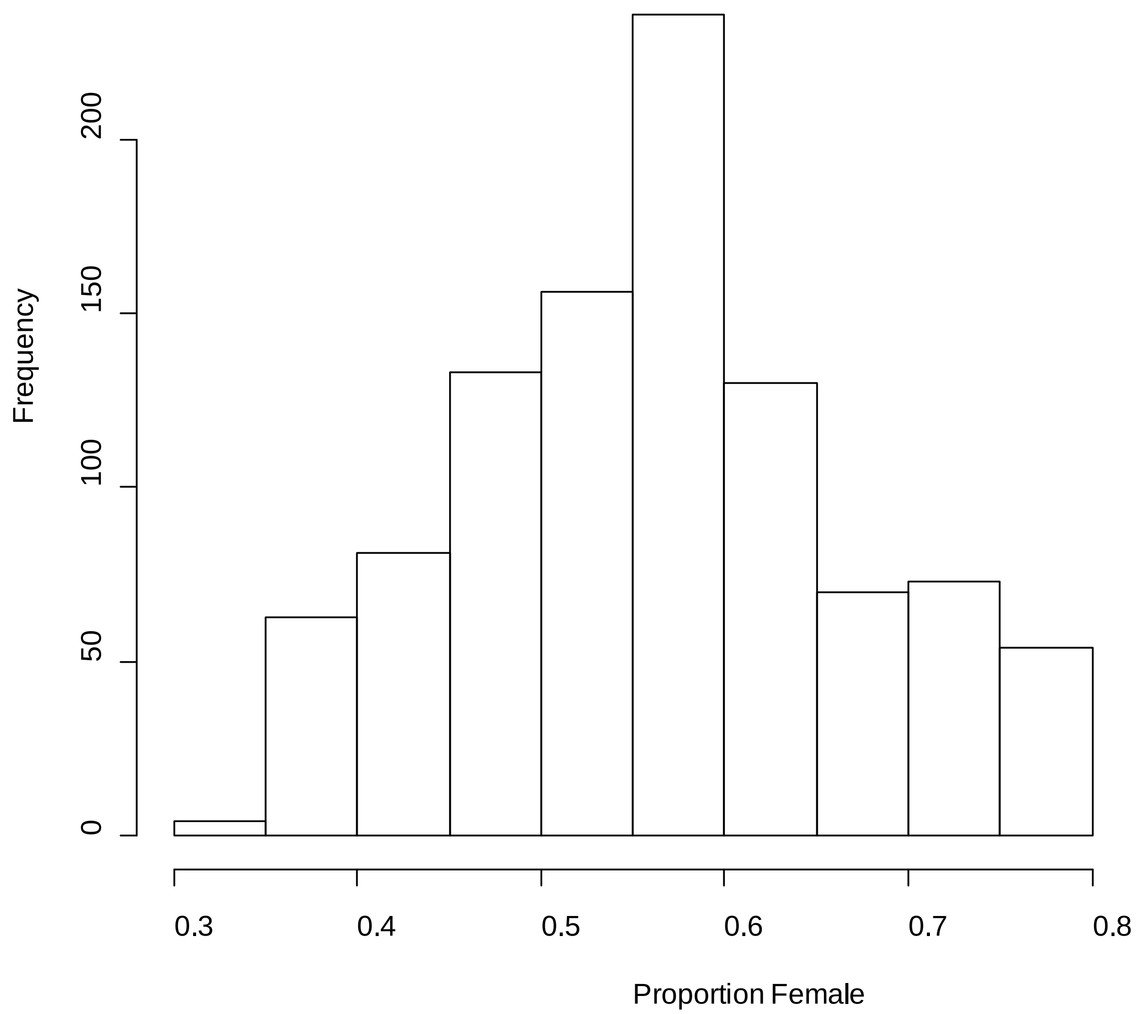


Fig. 26. Distribution of sex ratio estimates from 1000 replicates of single transects with an average sample size of 2119 per transect.

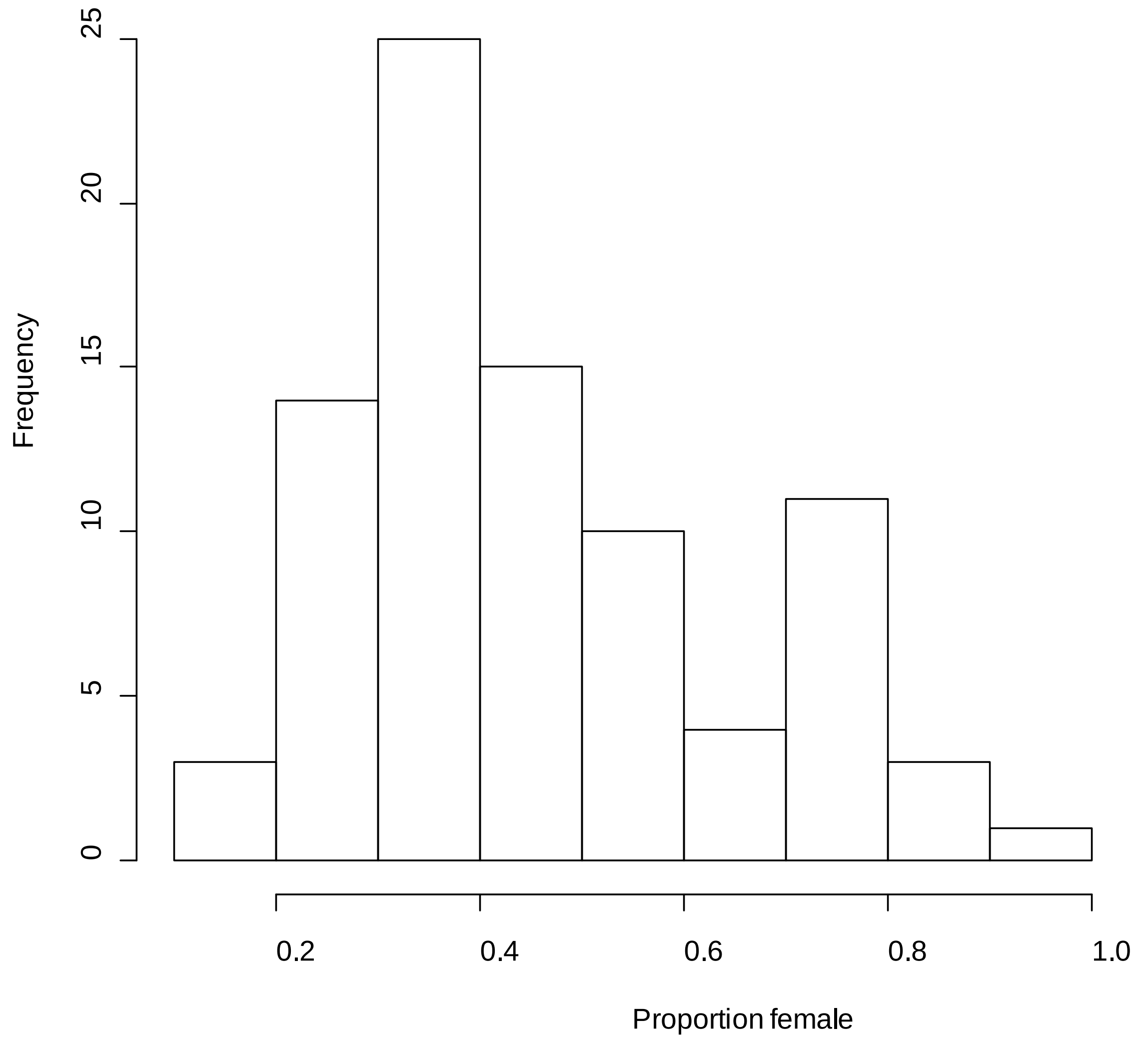
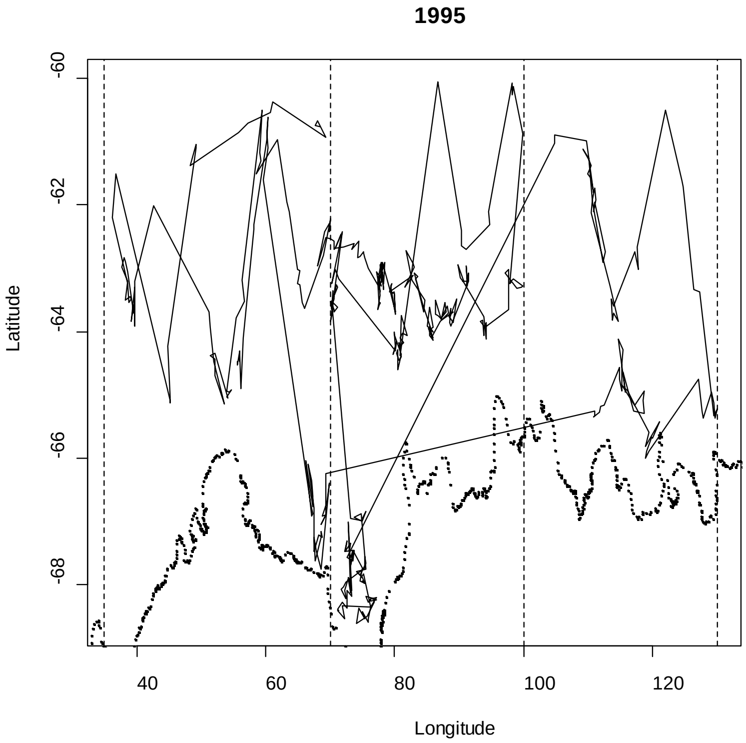


Fig. 27. Distribution of JARPA sex ratios obtained in each stratum and year.



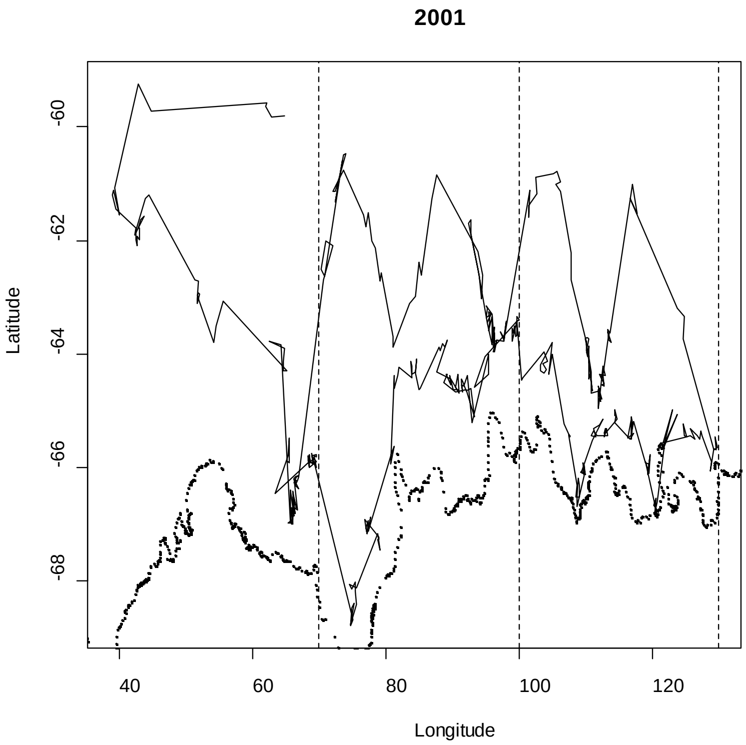
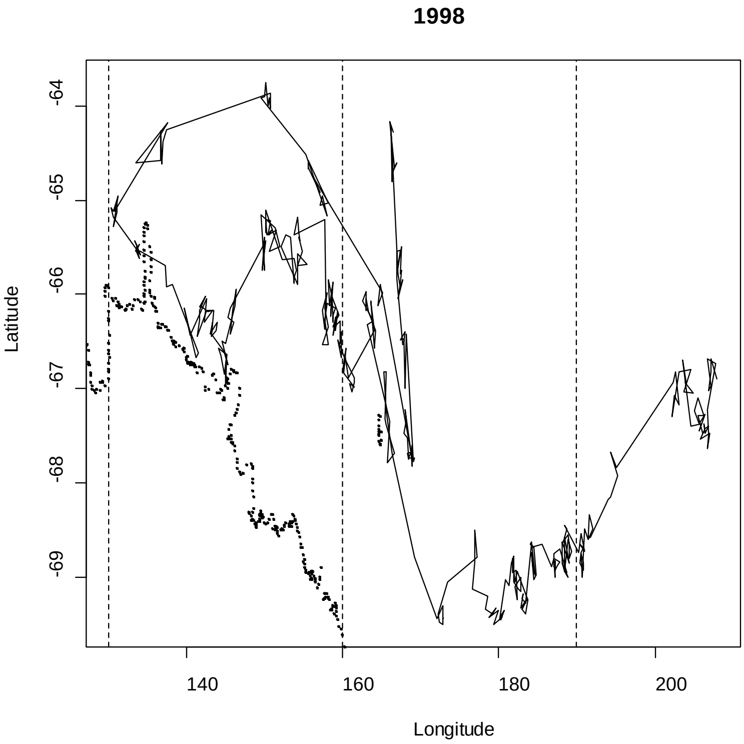


Fig. 28. Examples of tracks of whaling expedition derived from catch locations in the IWC catch database for the western region in the years 1995 and 2001. The dashed lines are the half Area boundaries. The series of dots represent the coastline. Some of the long lines may be transits, not transects.



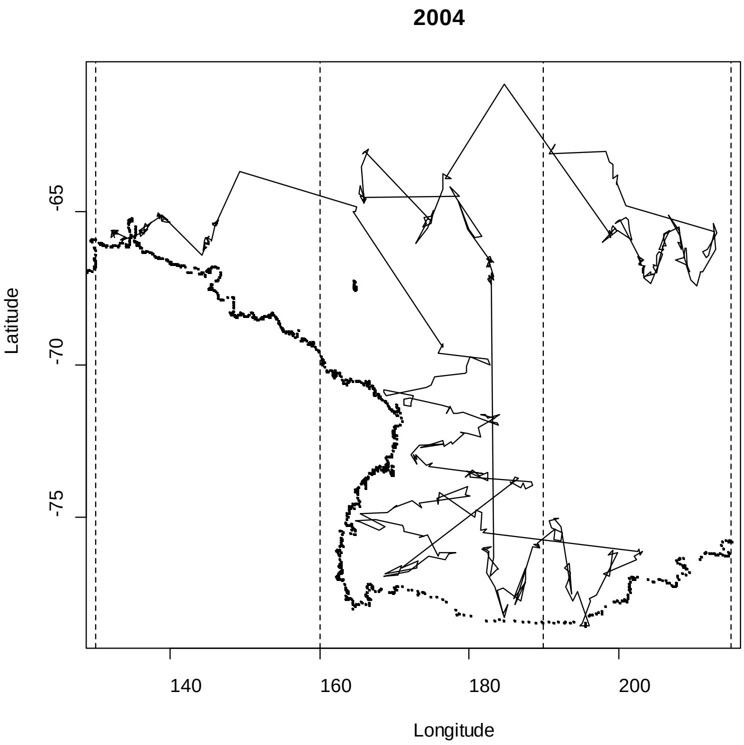
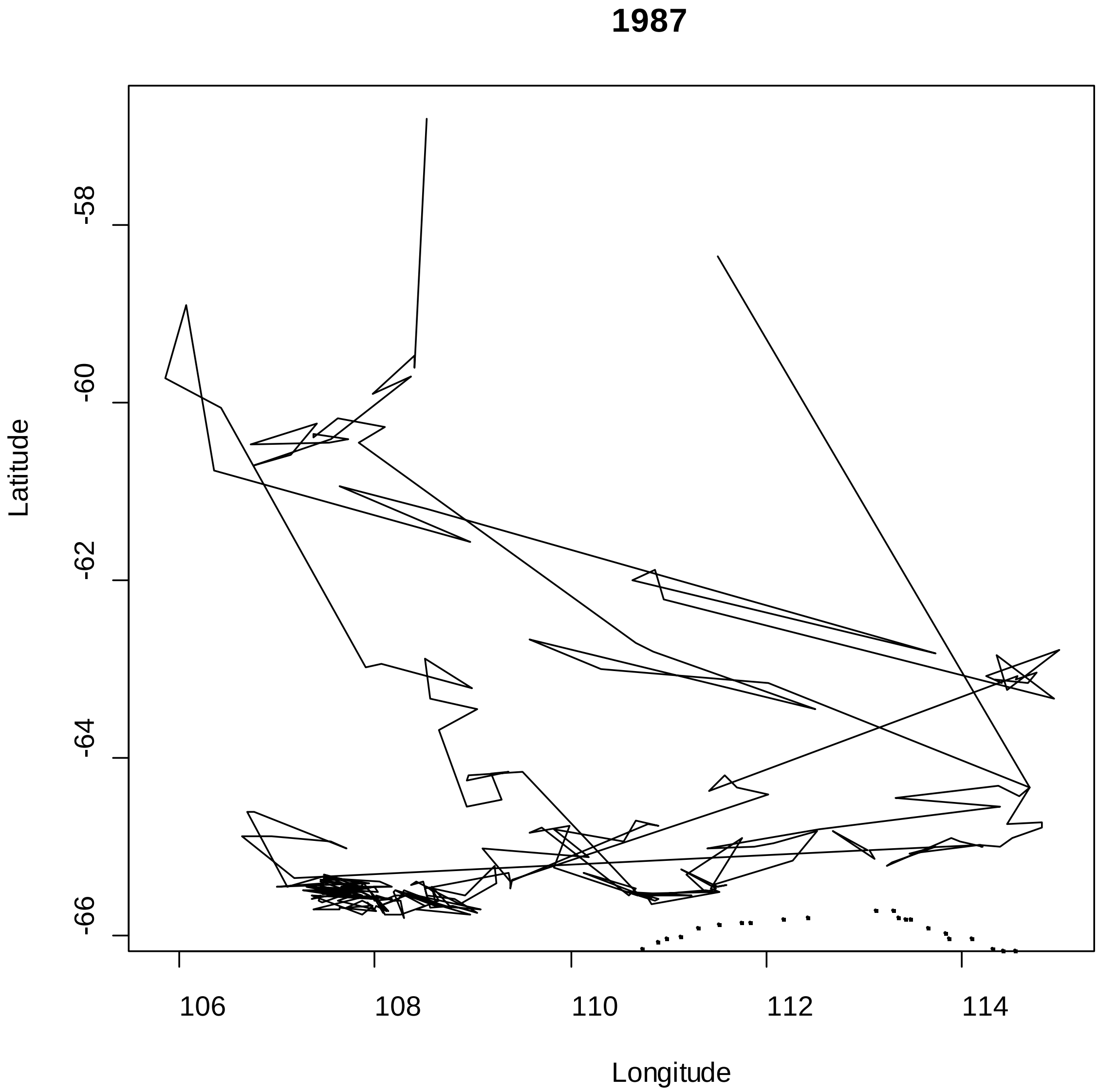
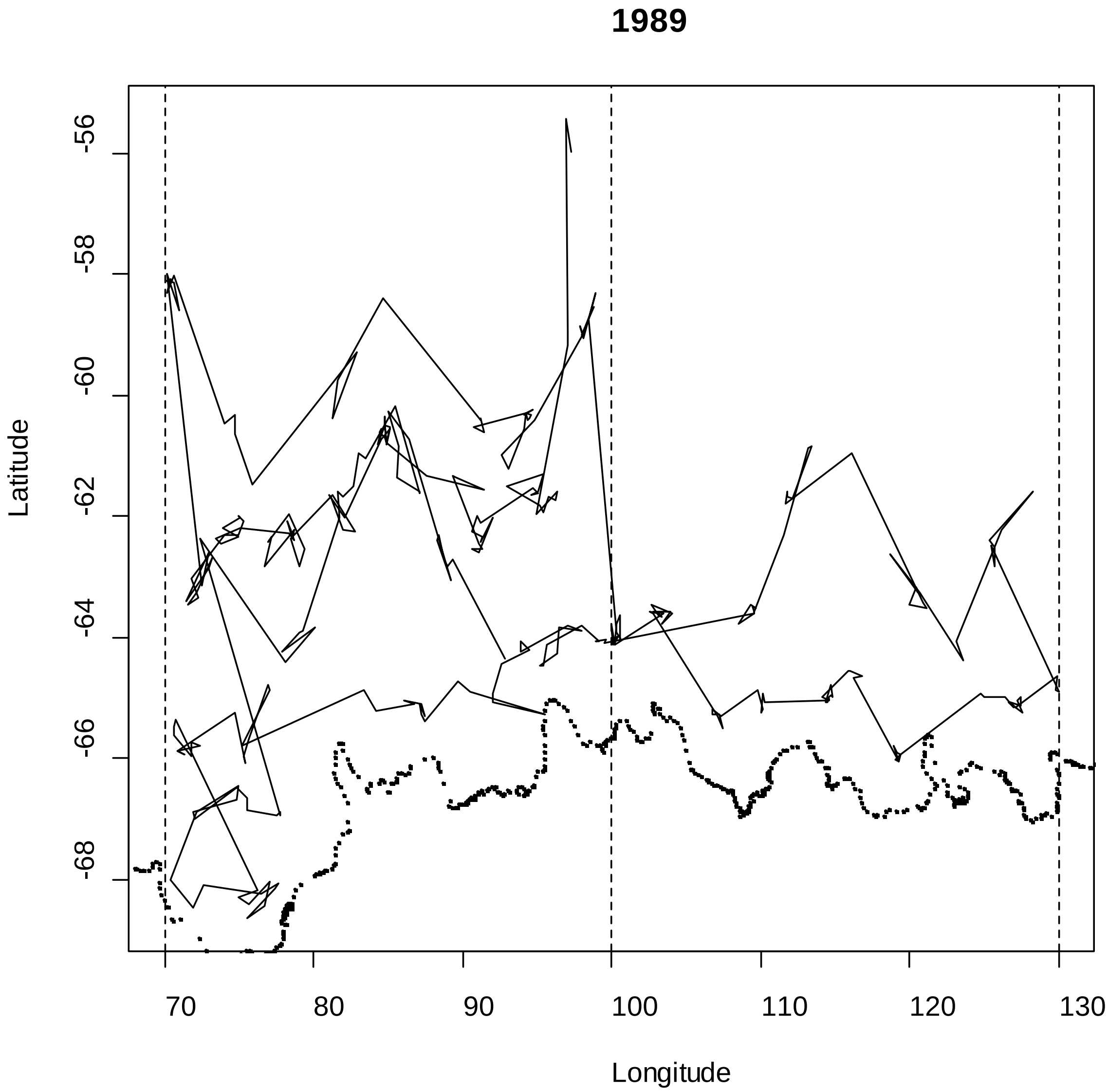


Fig. 29. Examples of tracks of whaling expedition derived from catch locations in the IWC catch database for the Eastern region in the years 1998 and 2004. The dashed lines are the half Area boundaries. The series of dots represent the coastline. Some of the long lines may be transits, not transects.

Appendix 1

Track lines of all the JARPA and JARPAII operations from 1987 to 2009 based on catch locations from the IWC catch database (IWC, 2010). The dashed lines are the half Area boundaries. The series of dots represent the coastline. Some of the long lines may be transits, not transects.

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Latitude
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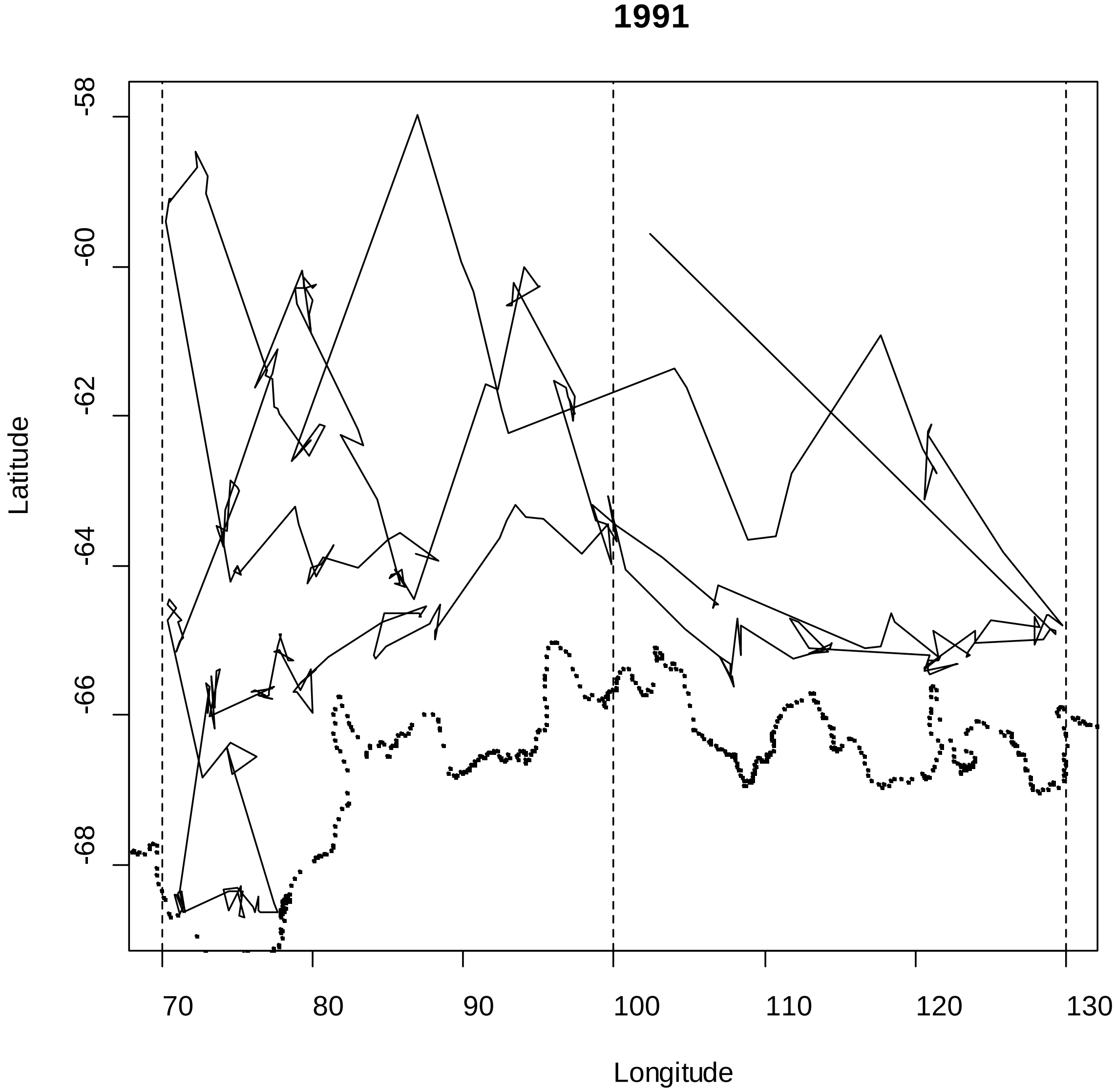
-62
-64
-66
-68
70
80
90
100
110
120
130
Longitude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Latitude
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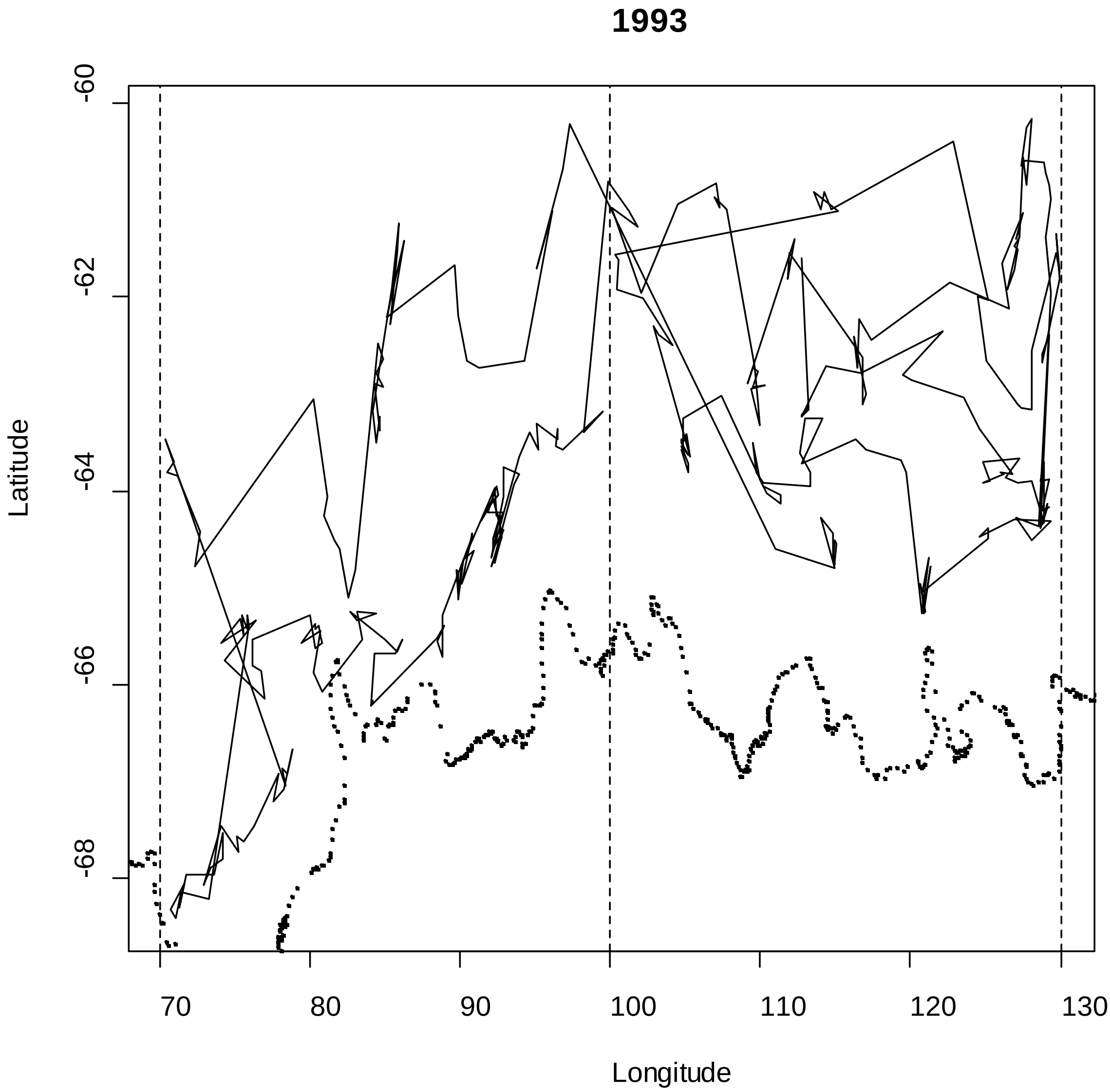
110
120
130
Longitude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Latitude
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-64
-66
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Longitude
70
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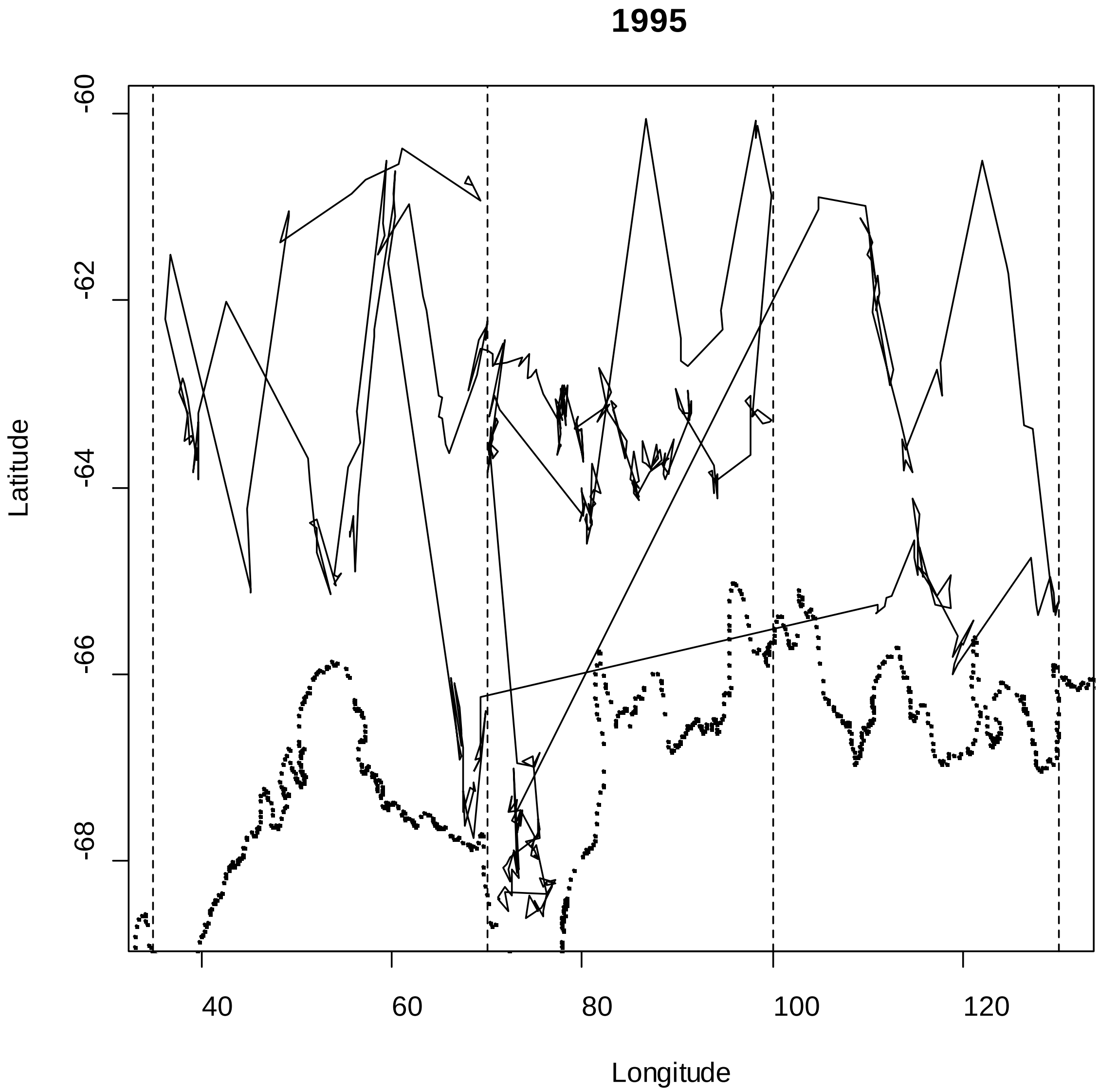
100
110
120
130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Latitude
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60
80
100
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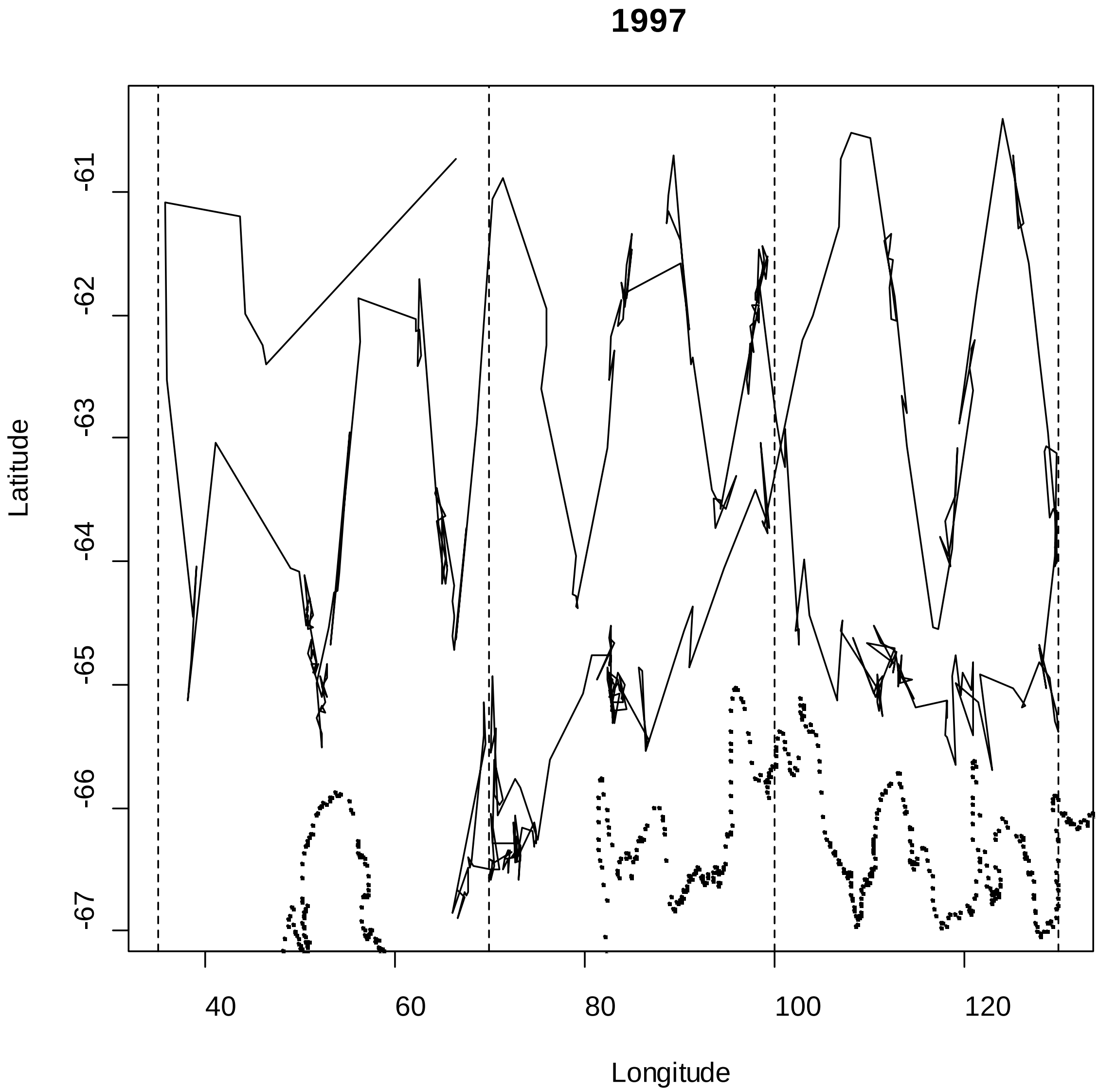
Longitude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Latitude
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60
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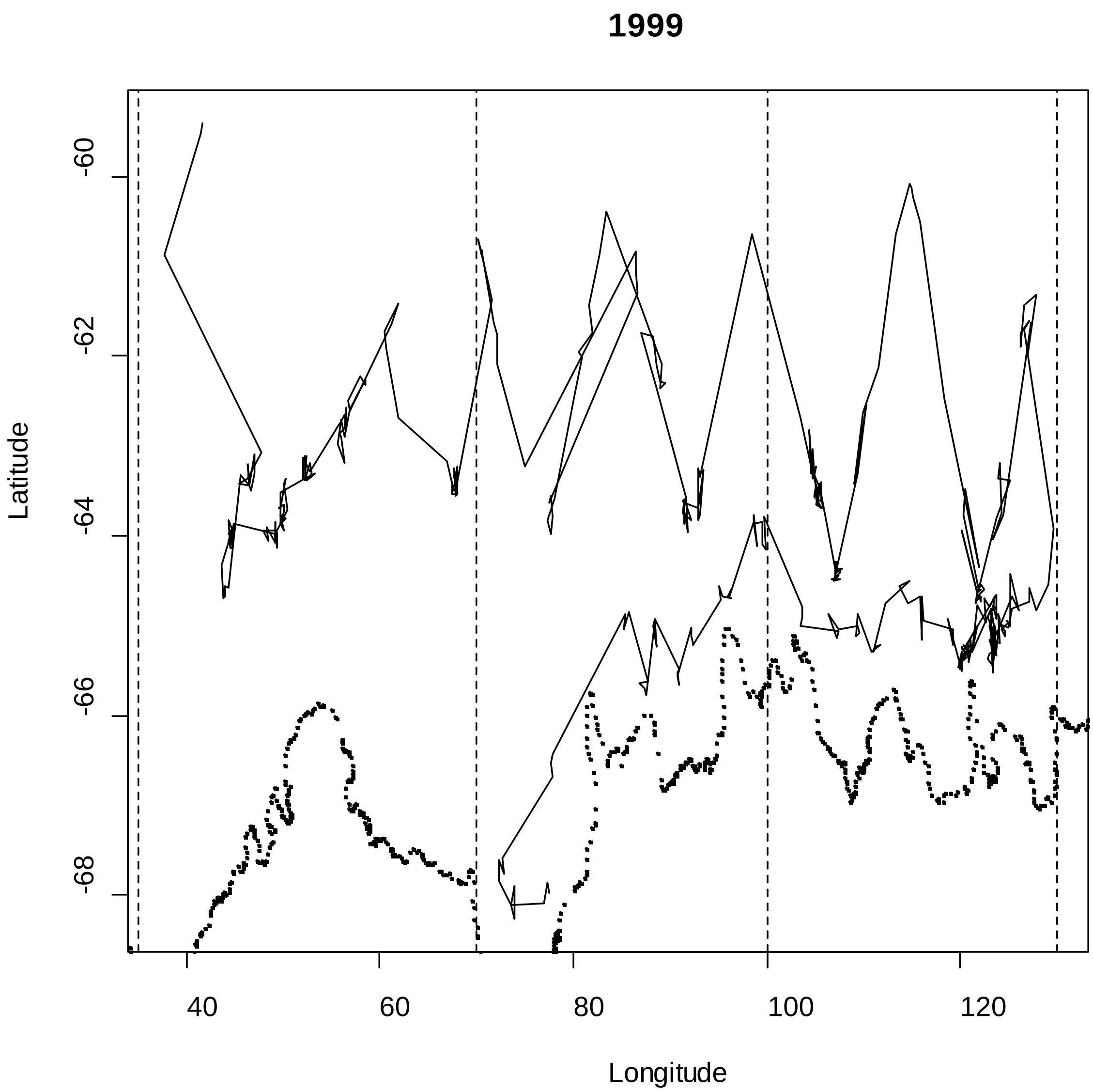
Longitude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60
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100
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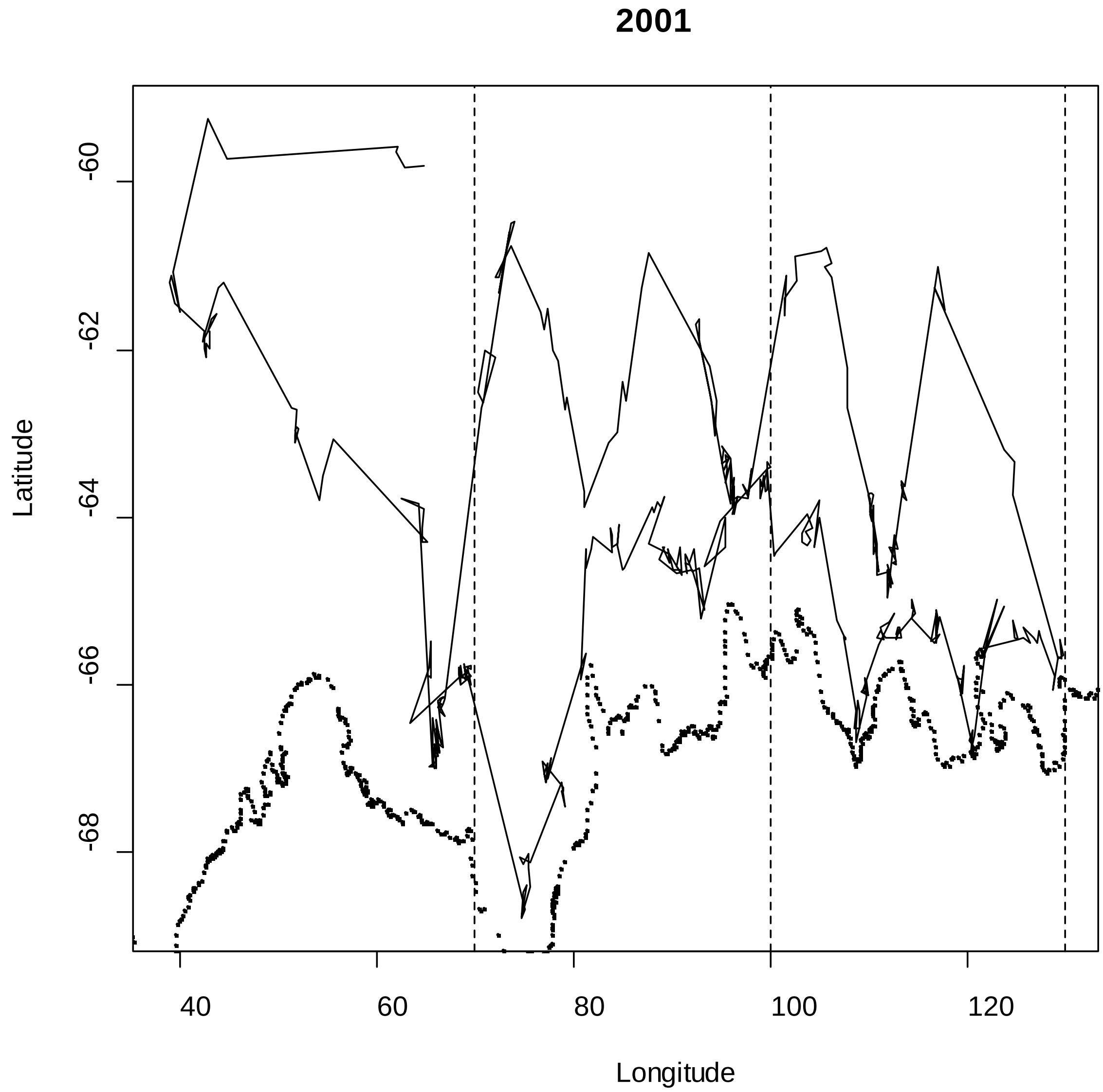
Longitude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Latitude
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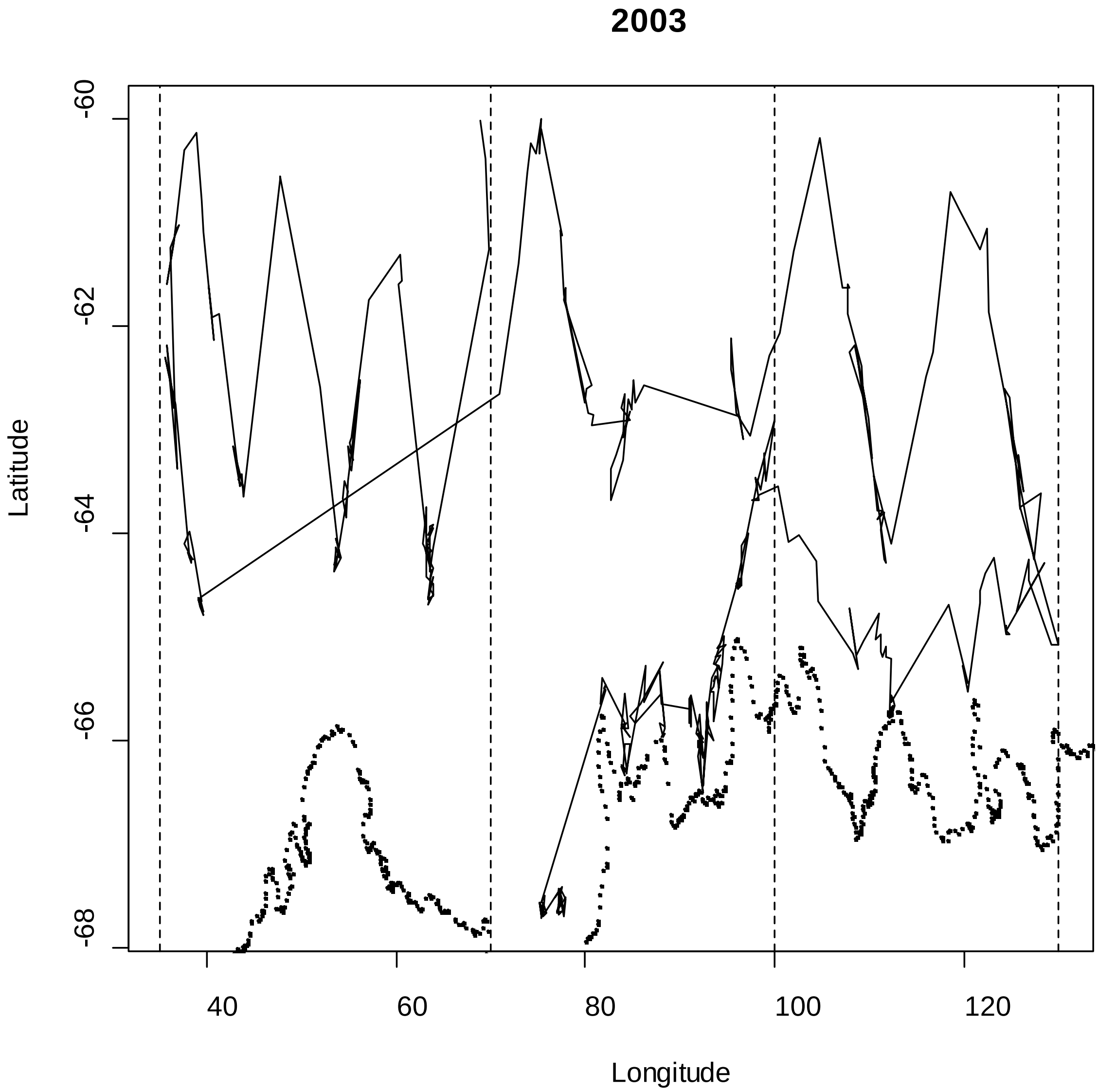
Longitude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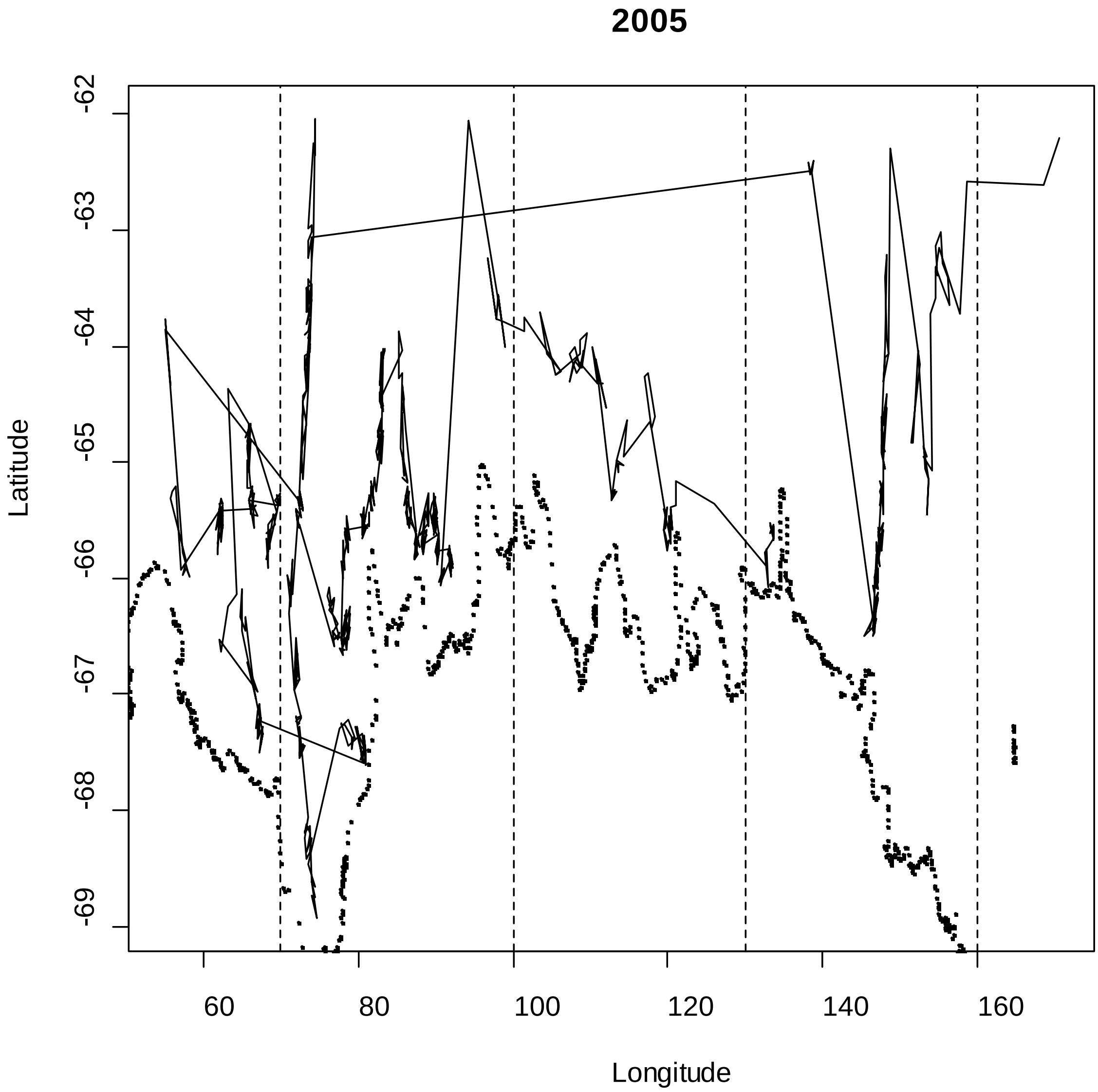
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Latitude
Longitude
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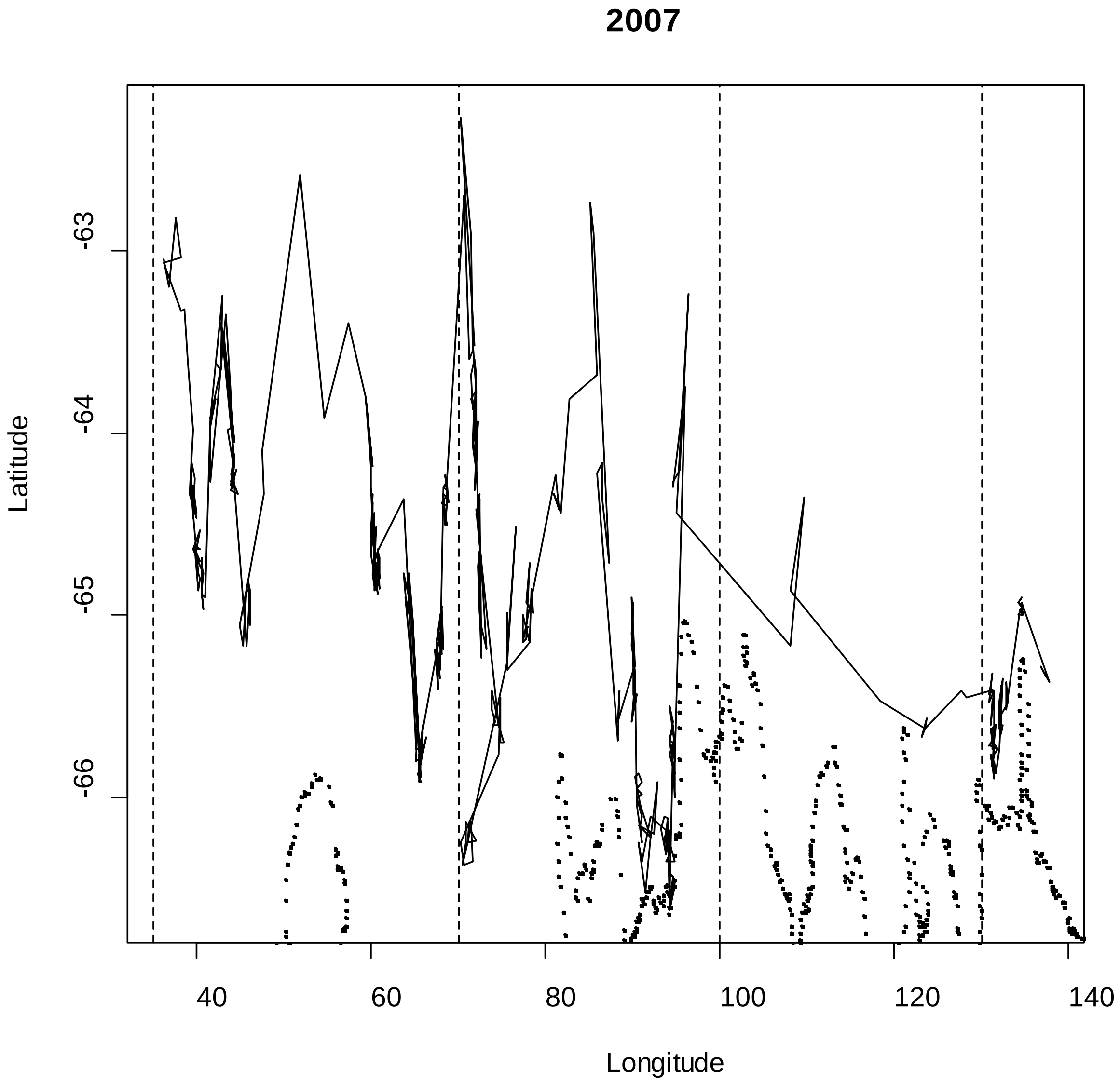
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Latitude
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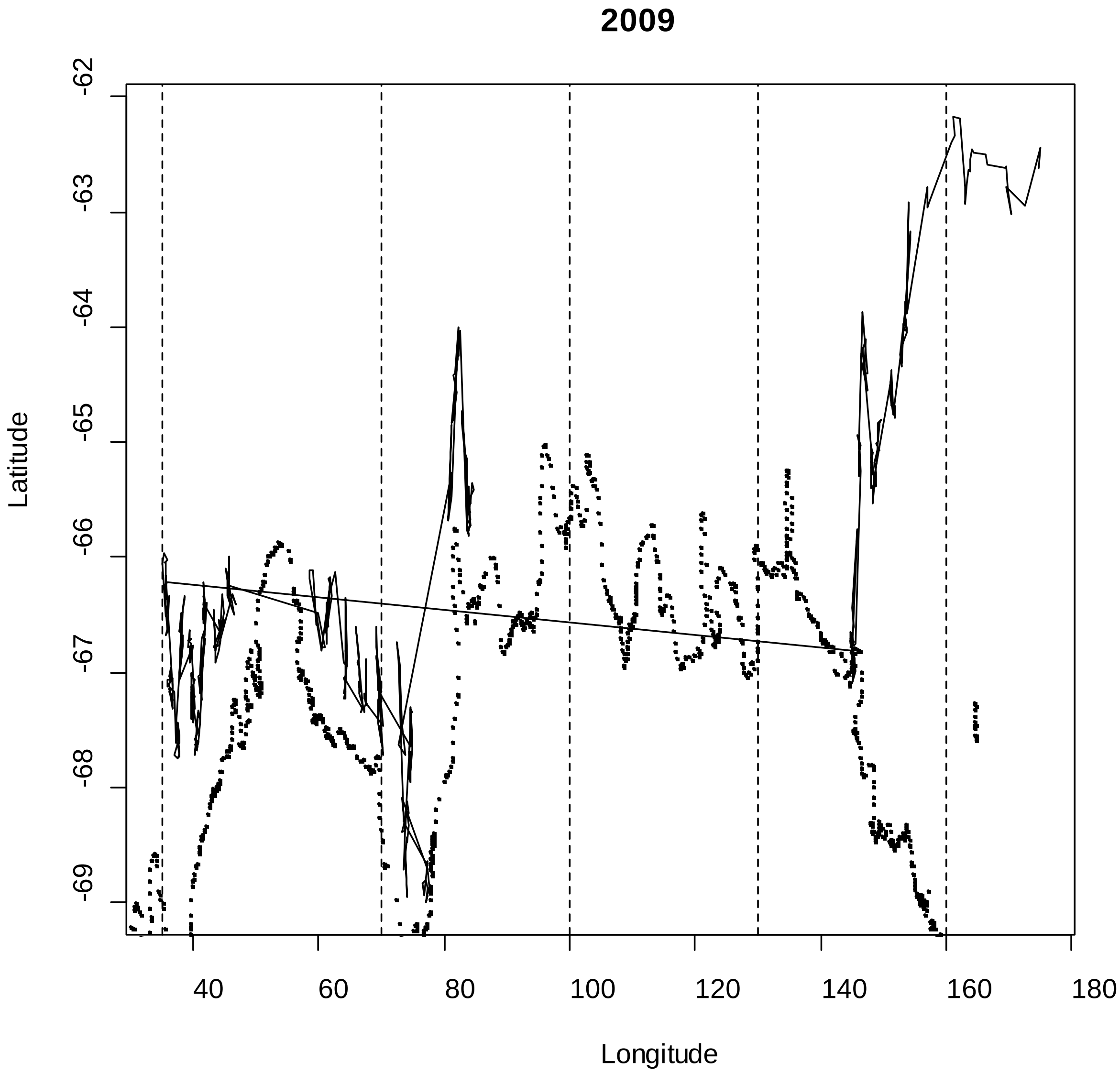
Longitude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Latitude
Longitude
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120
140
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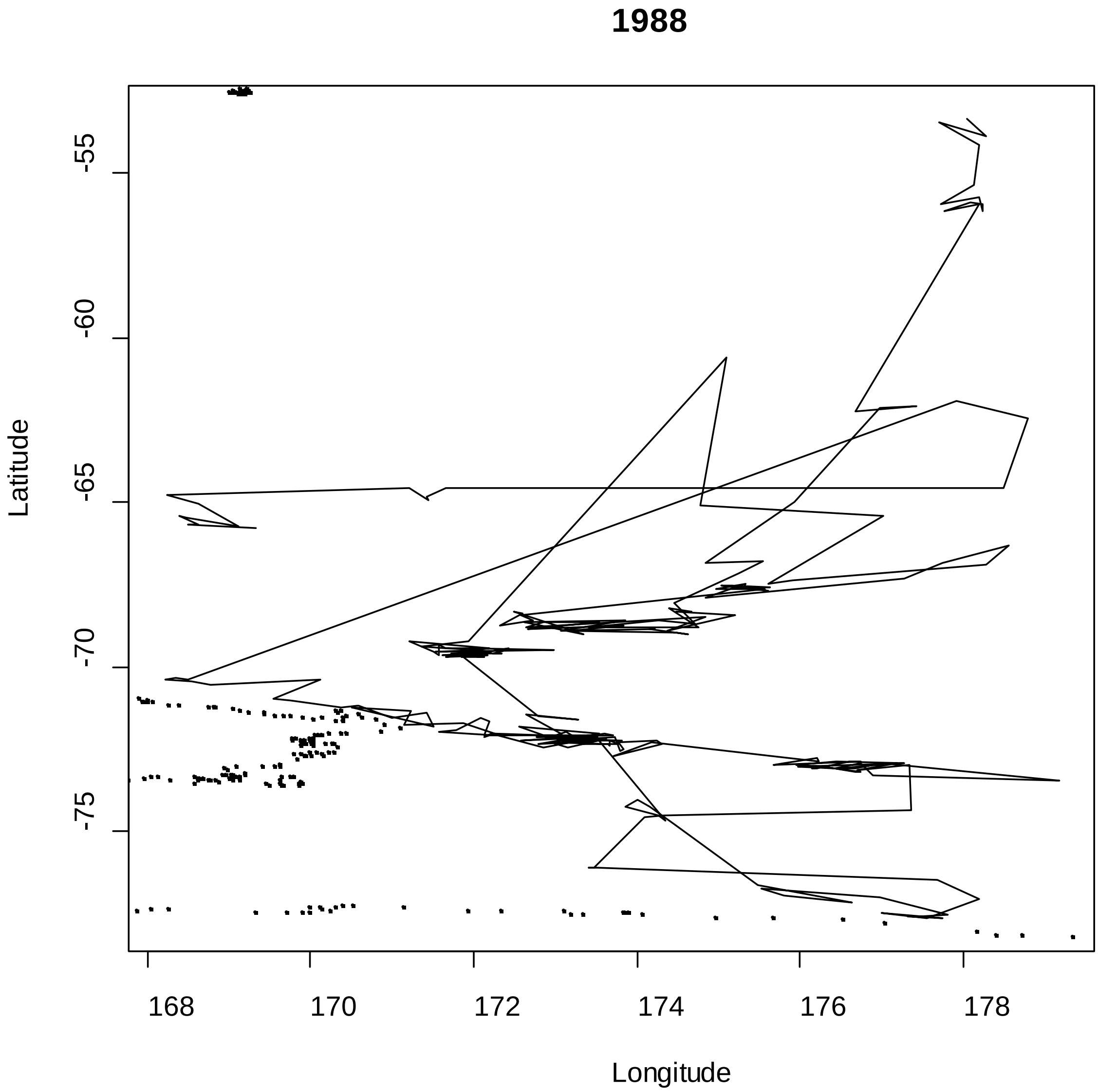
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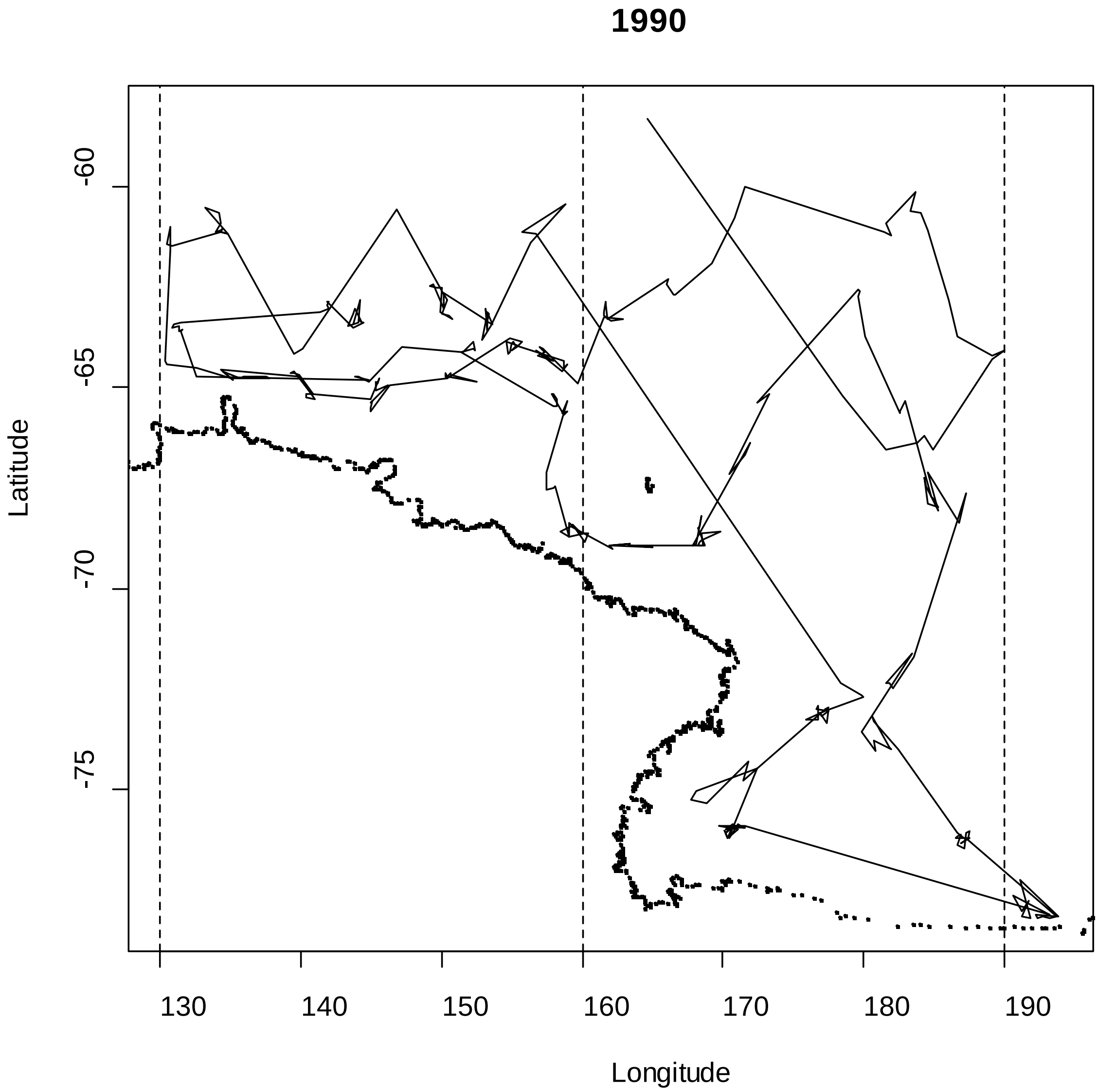
172
174
176
178
Longitude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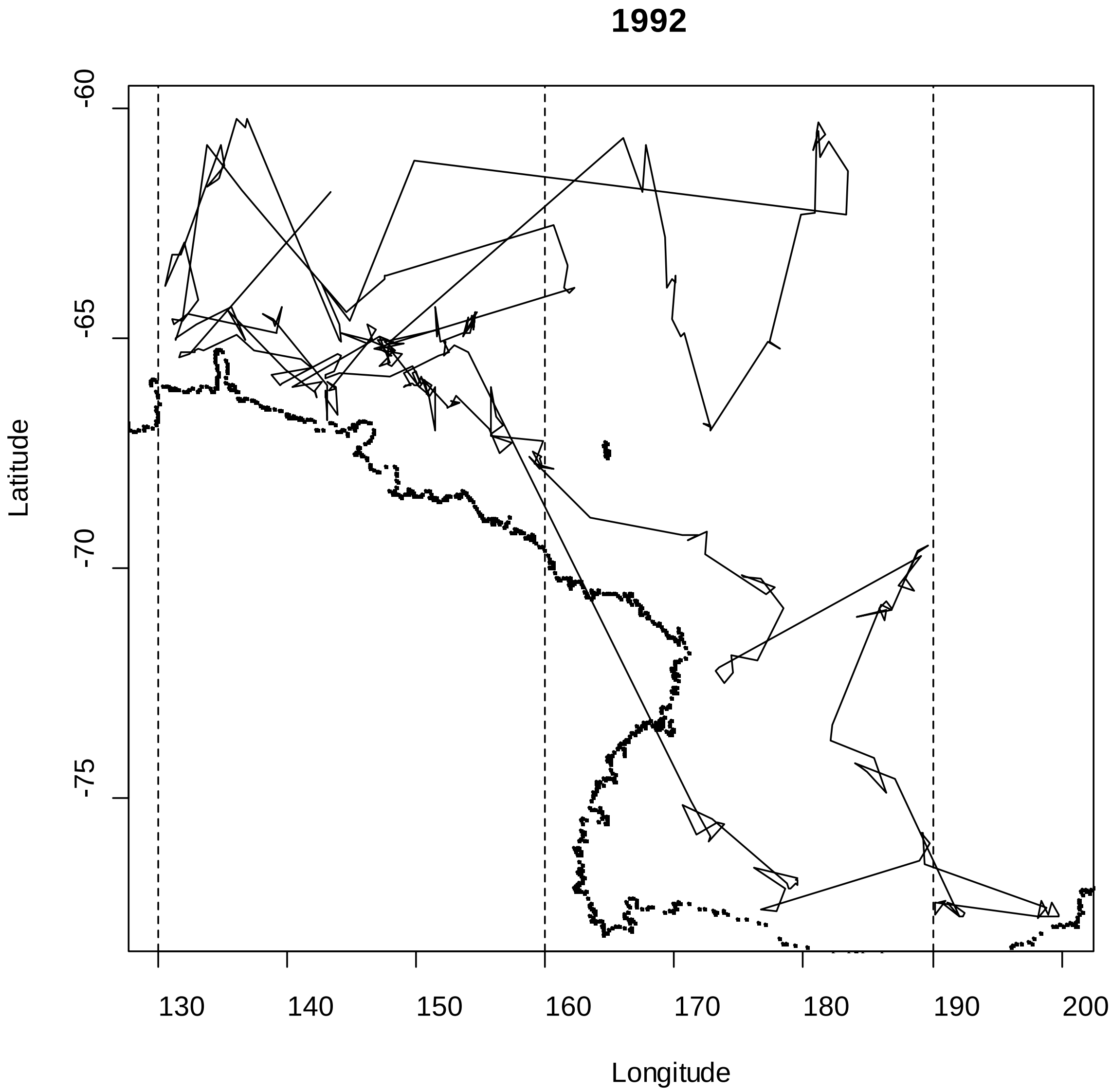
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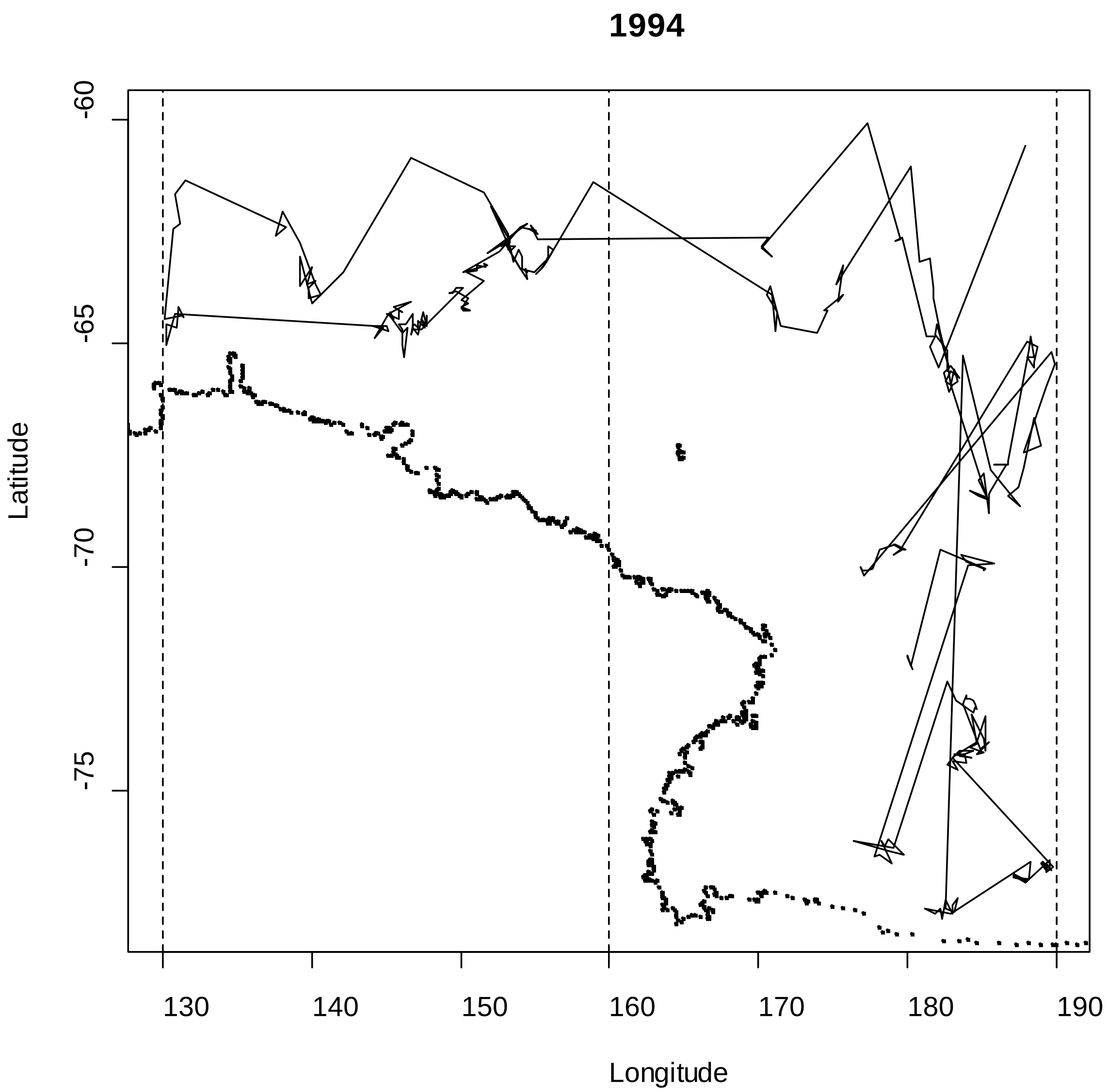
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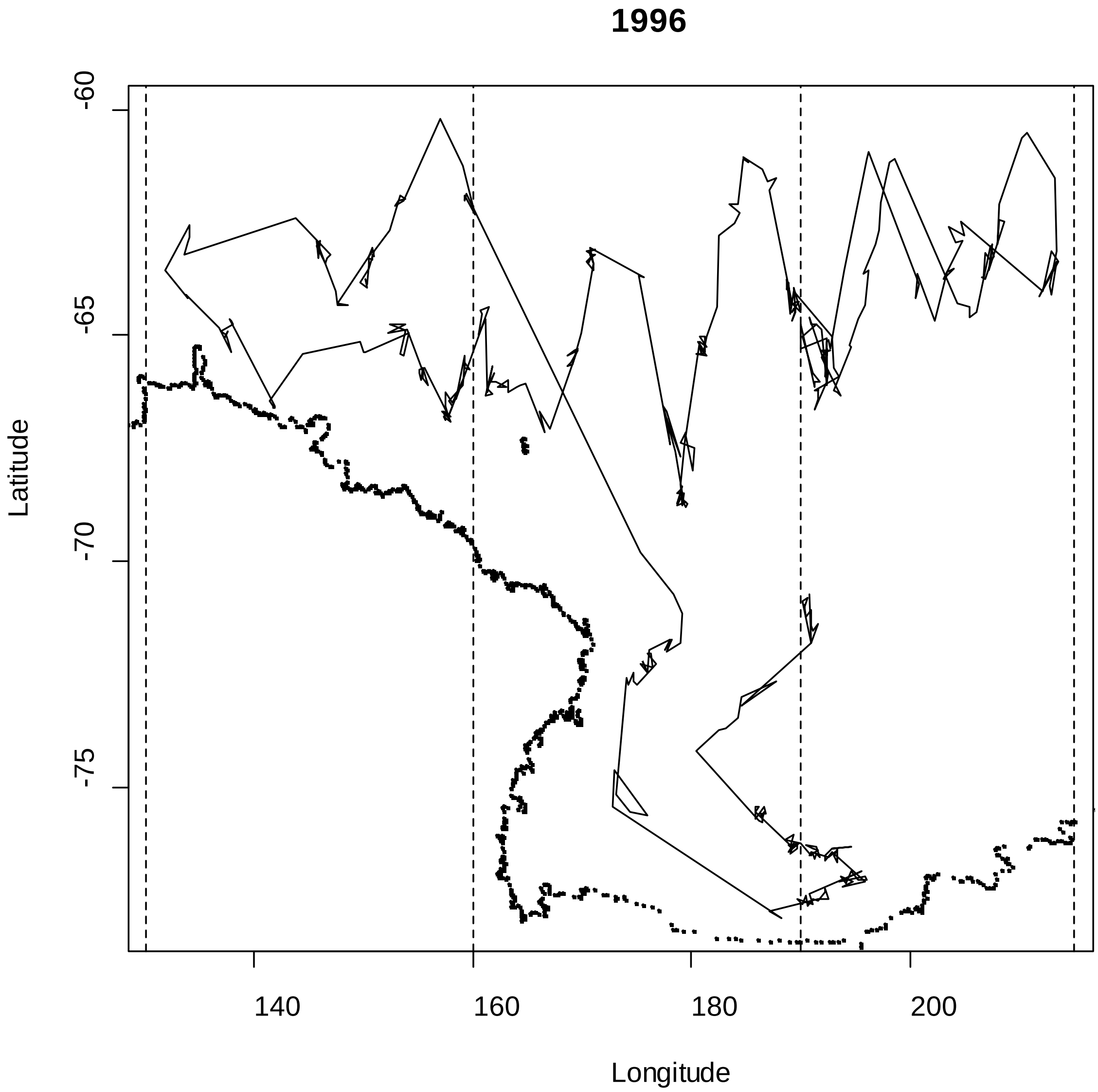
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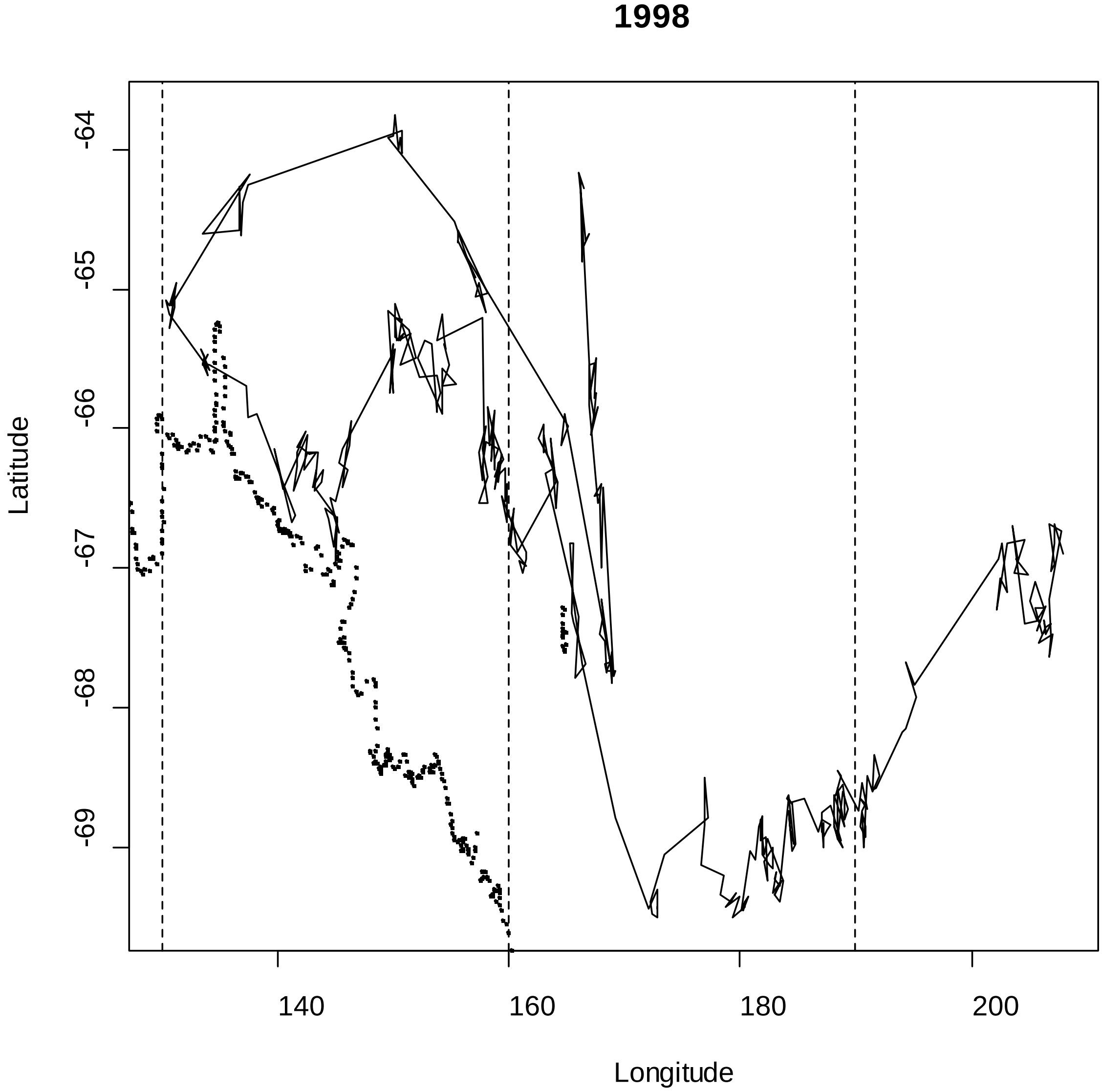
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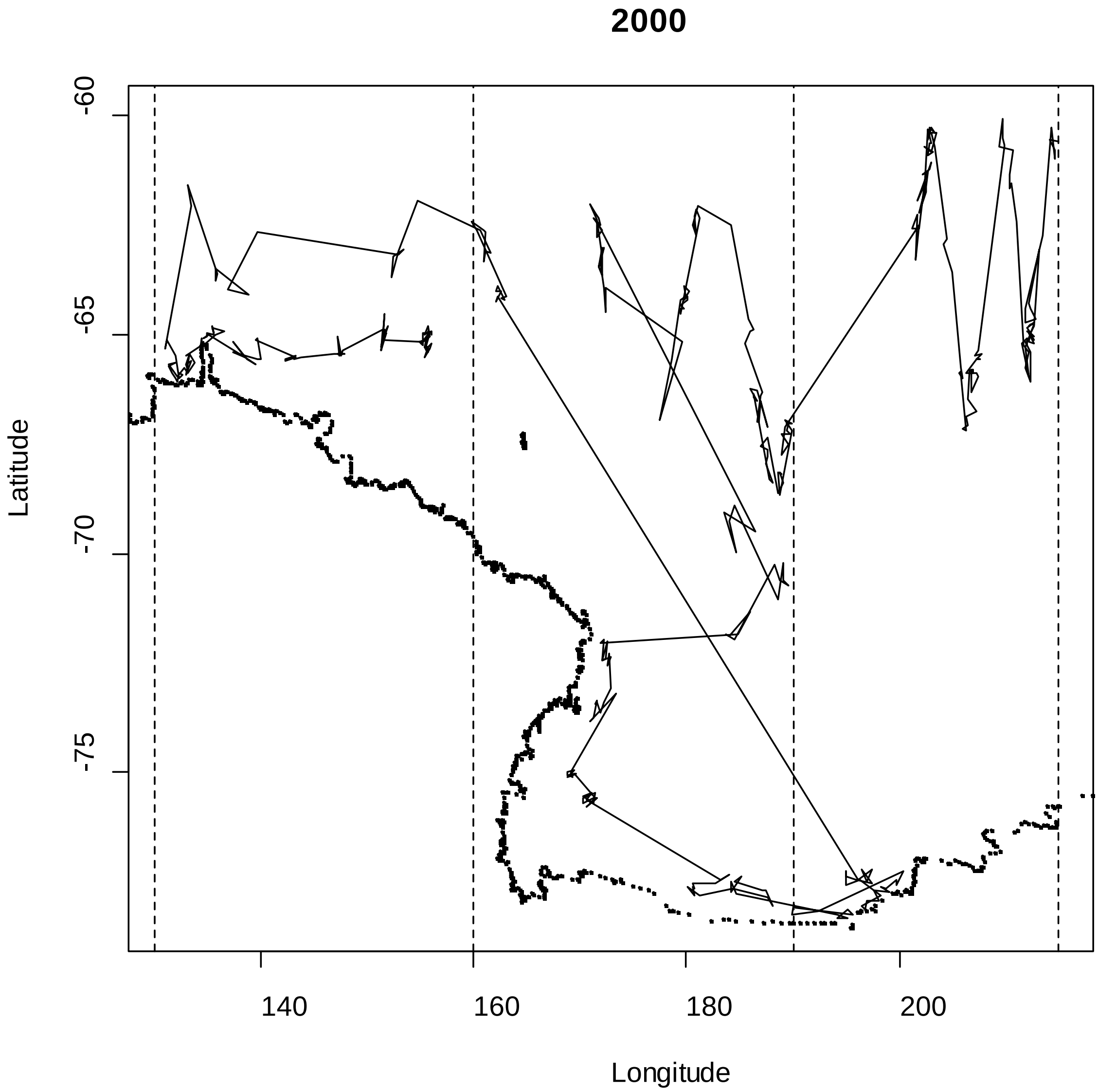
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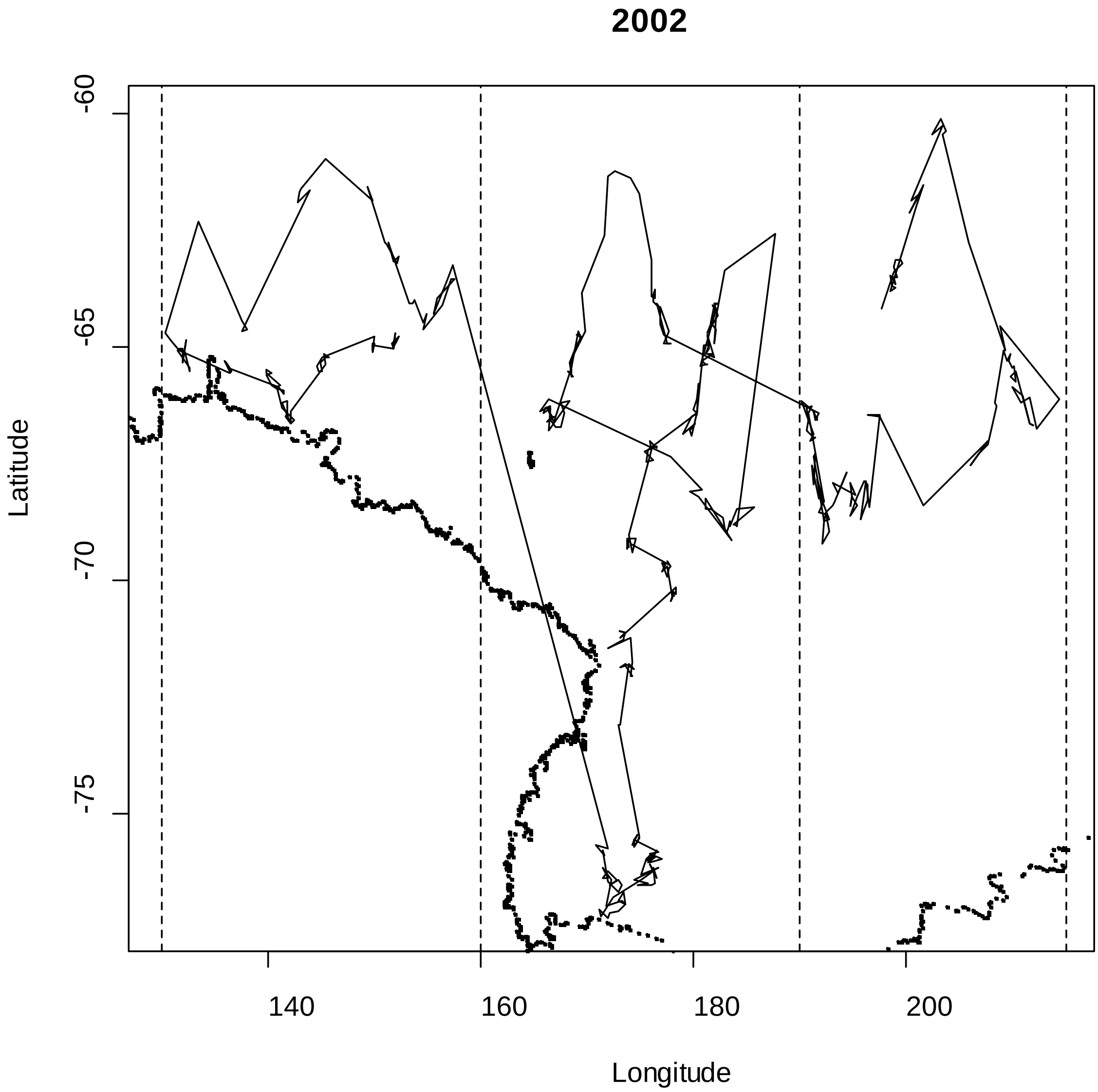
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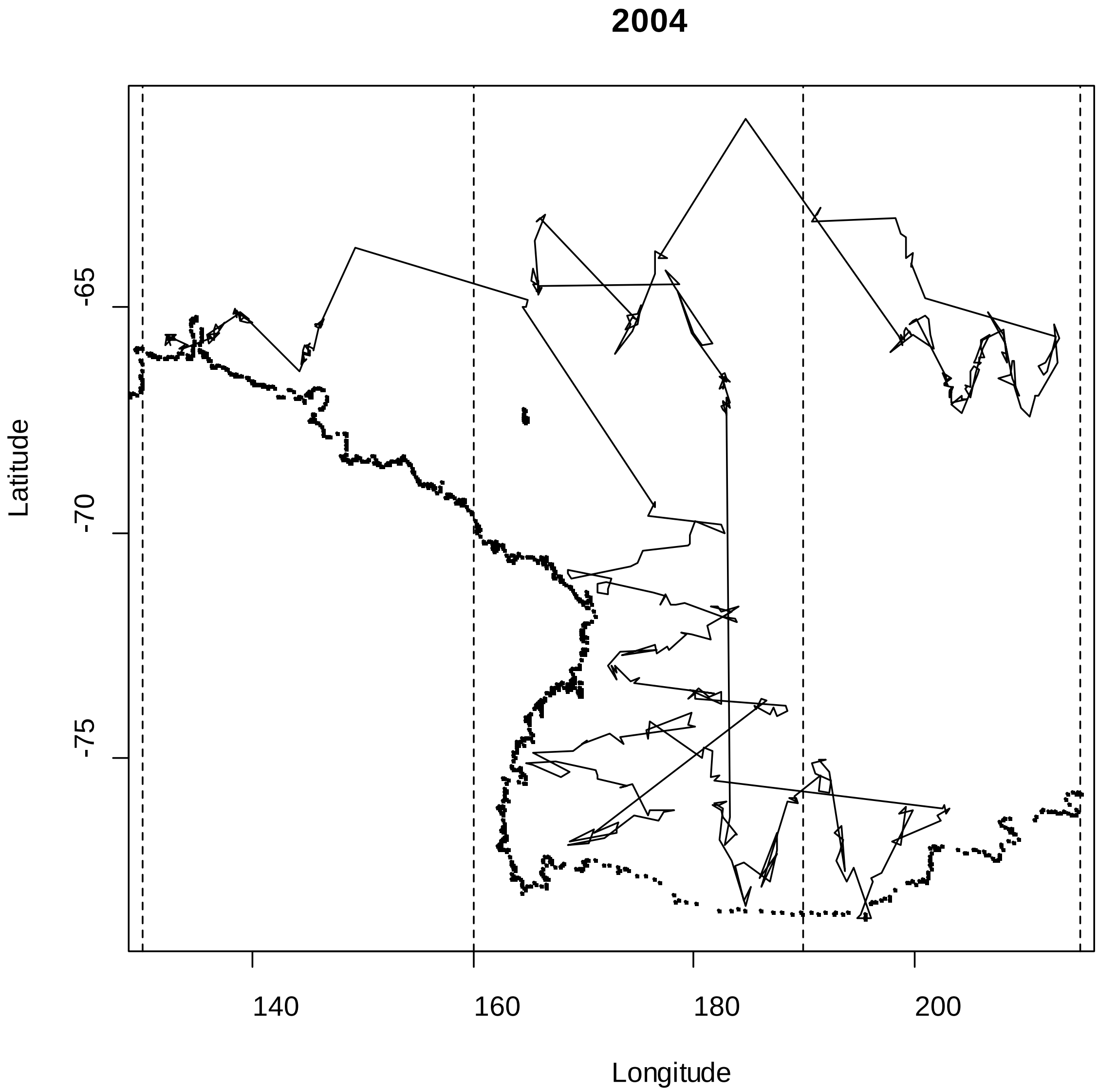
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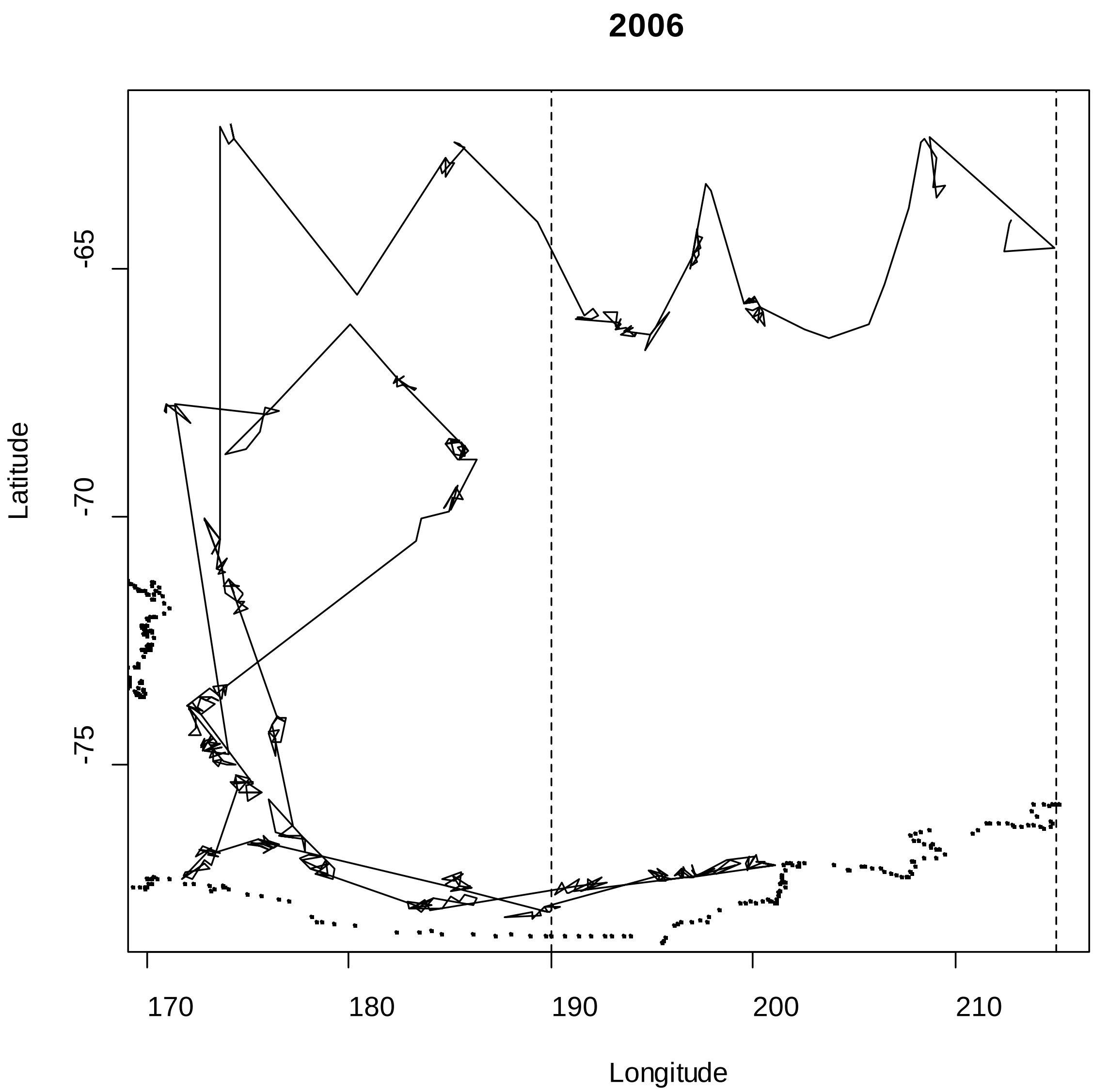
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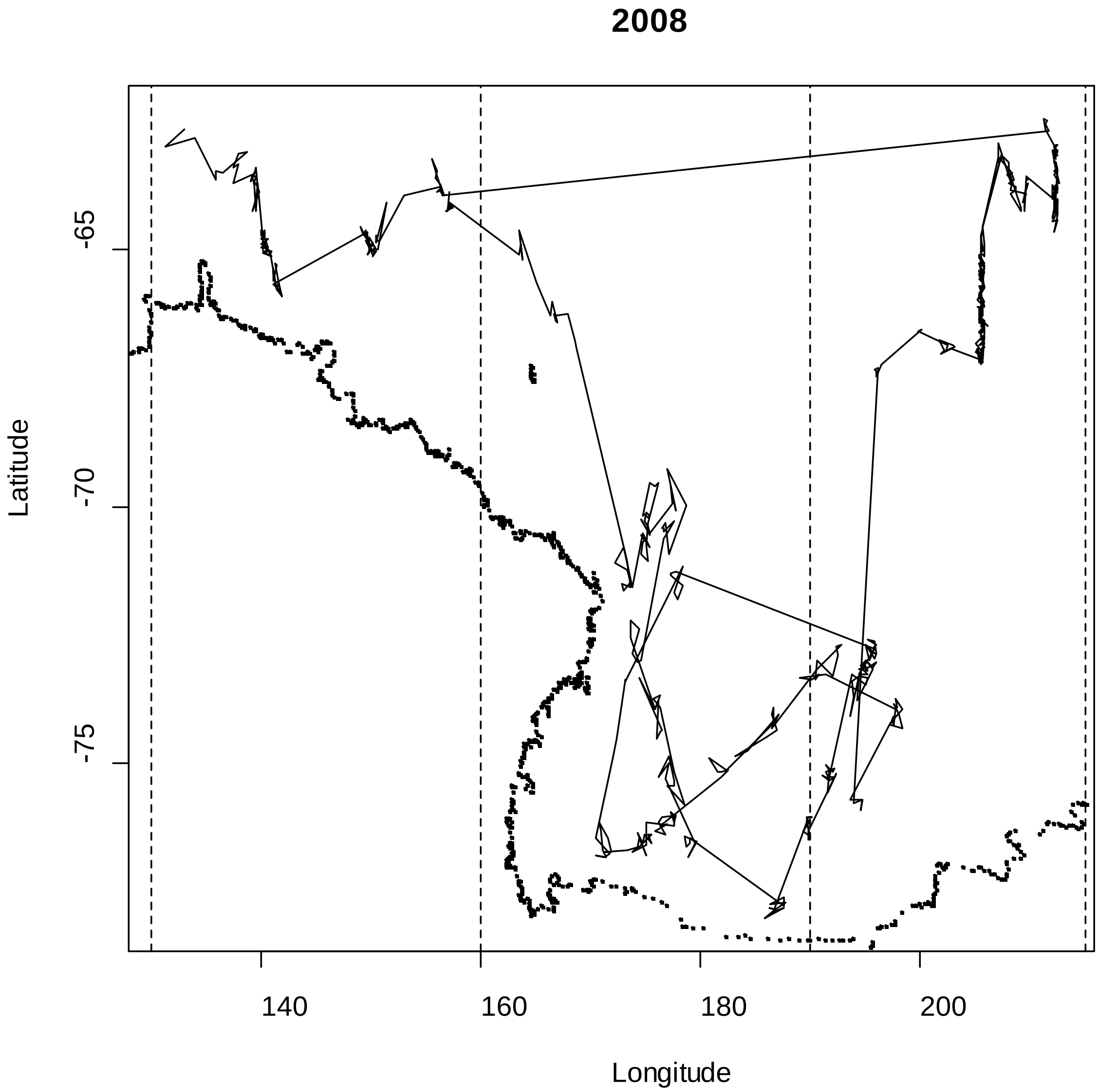
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