STATISTICAL METHODS FOR THE ANALYSIS OF LONG-TERM WADER COUNTS IN THE OOSTERSCHELDE AND WESTERSCHELDE, SW-NETHERLANDS

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Door de Dienst Getijdewateren (DGW) is een uitbesteding gedaan aan de heer J. van der Meer van het Nederlands Instituut voor Onderzoek der Zee (NIOZ) om de toepasbaarheid van statistische technieken na te gaan voor de analyse van tijdreeksen van vogeltellingen van steltlopers in de Oosterschelde en de Westerschelde. De methode moest zodanig zijn dat de effecten van de variabelen gebied, jaar en seizoen op de vogeltellingen te bepalen zijn.

De uitbesteding is gedaan in het kader van het project Duurzaam[1]. Dit projekt staat een tweetal doelen voor, te weten :

a) het opstellen van toetsingscriteria voor duurzame ontwikkeling van mariene ecosystemen
b) verkenning van beheersmaatregelen voor herstel en bescherming van mariene ecosystemen, voor de geleiding van duurzaam gebruik en voor de ontwikkeling van potenties van deze ecosystemen.

Van een drietal soorten, te weten de Scholekster, de Bonte Strandloper en de Tureluur zijn van de genoemde gebieden voor de jaren vanaf 1979 tot en met 1991 van elke maand de tijdreeksen verzameld. Alvorens tot de analyse over te gaan wordt in dit rapport eerst stilgestaan bij de overwegingen die verwerking van dergelijke gegevens met zich meebrengt :

a) welke figuren zijn nodig om een zo goed mogelijk beeld van de tellingen te krijgen?
b) hoe nauwkeurig zijn de tellingen?
c) wat is het verschil in gebruik van maandelijkse tellingen i.p.v. dagelijkse tellingen?
d) wat te doen met zogenaamde incomplete (slechts een deel van het gebied is geteld) of ontbrekende tellingen?
e) wat is het stochastisch proces van de residuen nadat de tellingen zijn geschoond van de systematische componenten als seizoen en trend?

Vervolgens wordt de keuze gemaakt om de gegevens te analyseren met een ANOVA-model, waarbij de factoren gebied, jaar en maand als een multiplicatief model zijn geformuleerd. Daar per gebied, jaar en maand slechts één waarneming aanwezig is, kan alleen de eerste-orde interactieterm meegenomen worden. Dit model bleek dermate bevredigend dat de residuen geen autocorrelatie vertoonden, waarmee wordt aangegeven dat de tijdreeksen op een voldoende manier met dit model worden beschreven. De kwantitatieve variabelen jaren en maanden zijn vervolgens geschat met respectievelijk een algebraische en een trigonometrische polynoom. Dergelijke polynomen zijn ook gebruikt om de interactietermen van deze variabelen te beschrijven. Het voordeel van een dergelijke benadering is dat men de ontbrekende gegevens zou kunnen schatten.

De kracht van de hier gepresenteerde methode ligt in zijn eenvoud en direkte interpreteerbaarheid van de resultaten. Met het hier gepresenteerde model kan een veelvoud aan gegevens worden gereduceerd tot de interessante effecten van gebied, jaar en maand. Het is de bedoeling om deze analyse toe te passen op andere soorten, zodat de brede toepasbaarheid kan worden onderzocht. De volgende stap is het koppelen van de geconstateerde effecten aan veranderingen in het watersysteem ten gevolge van natuurlijke of menselijke oorzaken.

[1] Projectplan Duurzaam, I. de Vries, 1992, DGW-Rijkswaterstaat.

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JAAP VAN DER MEER

ABSTRACT Multiplicative linear models with year, month and site main and first-order interaction effects proved to be satisfactorily as a descriptive summarizing tool of long-term wader counts from the Oosterschelde and Westerschelde, SW-Netherlands. A more parsimonious version of the model, with year described by an algebraic polynomial and month by a trigonometrical polynomial enabled the imputement of missing values. This might be helpful when other descriptions than model parameters, e.g. the total number of bird-days per year, are needed. By removing the temporal and spatial trends and seasonal effects, the model makes a time-series analysis possible. However, lack of autocorrelation as experienced in the present data takes away the need of a stochastic process model to describe the random (correlated) variation.

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INTRODUCTION

Since the mid-1970s monthly counts of waterbirds have been made in the delta of the rivers Rhine, Meuse and Scheldt. From the start of the programme it was aimed to take each month a complete census of all waterbirds present in the area. The main objective was the description of possible changes in the use of the area by migrating and wintering birds. As a next step these changes could possibly be related to environmental changes, which are either natural, e.g. the stochastic recruitment of prey species, or man-induced. The impact of man's activities in the area has been considerable. A storm-surge barrier and two secondary dams have been built in the Oosterschelde in the early 1980s. The last decades also showed an increase in tourism and fishing activities. Nevertheless, the second step could at best yield tentative answers (Hurlbert 1984, Stewart-Oaten et al. 1986, Schekkerman et al. in press).

The present report is merely of a methodological nature. It aims to examine the applicability of different statistical methods in achieving the main objective. Methods that will be considered range from the classical linear models, like regression analysis and analysis of variance, to time series analysis techniques. The data used are restricted to counts from the Oosterschelde and Westerschelde, the two most important estuarine areas in the region. The Krammer-Volkerak counts are left out, because they are rather incomplete.

Before the suitability of any data analytical method can be discussed, the questions that need to be answered have to be specified in more detail. Assuming for the moment that for each (sub)area daily counts, measured without any error, are available, what kind of analyses are useful? As at each time the censused populations coincide with the populations about which information is wanted, one might argue that there is only need for descriptive summary statistics and informative graphics. Thirteen years of daily counts in five areas would result in over 20,000 figures for each species. This large number supports the need for summary statistics in order to understand the main features of the data. Examples of such statistics are: the overall average, the trend over the years of the number of bird-days (this figure is of course equivalent to the yearly averaged number of birds present), averages per month reflecting the seasonal pattern, etc. There is no need for inferential statistics: p-values are meaningless.

Alternatively, the time series (i.e. the collection of observations made sequentially in time) itself might be regarded as a single realization of some underlying stochastic process (Chatfield 1989). It is a sample, containing only a single unit, of an unknown superpopulation of time series. A stochastic process is described by the joint distribution function of the observations. Since only a single realization is available, the estimation of this joint distribution function is generally speaking not possible. However, when it is assumed that the stochastic process is stationary (or, more precisely ergodic) the underlying model can in theory be identified and its parameters can be estimated. Stationarity means that there is no systematic change in mean (no trend), there is no systematic change in variance and there are also no strictly periodic (e.g. seasonal) variations. These systematic parts have to be removed before a time-series analysis can be conducted. Unfortunately, it is rather arbitrary how this removal can be performed. As Cressie (1986) points out: 'What is one person's nonstationarity (in mean) may be another person's random (correlated) variation'. In our view it is more informative to describe the present series in terms of temporal and spatial trends and seasonal effects, then in terms of random (correlated) variation. It should be noted that we do not aim to predict future values of the series, which is a common objective of time series analysis.

In practice, observations are only on a monthly basis, and counts are sometimes missing or incomplete. A count is incomplete when only a part of the entire area was visited. Finally, the assumption that each census is conducted without any error is

questionable. One may ask what the accuracy of counts, that are claimed to be complete censuses, actually is. The following points therefore may be distinguished:
- what kind of figures and graphics are useful to describe the census data?
- what is the effect of measurement error on these figures in terms of bias and variance?
- what is the effect of having only monthly instead of daily counts?
- how to deal with incomplete and missing counts?
- what kind of stochastic process models are able to describe the time series after removal of a systematic change in the mean and a seasonal effect?
- how can a trend and a seasonal effect be removed?

ADDITIONAL COMMENTS ON THE POINTS OF CONCERN

Descriptive methods

The usefulness of some descriptive figure strongly depends upon the data itself. Assume that the following census data (measured without any error) of the number of birds present at two sites during three days have been obtained:

	day 1	day 2	day 3	average
site 1	27	74	201	**101**
site 2	74	201	546	**274**
average	**51**	**138**	**374**	**187**

The obvious summary of these figures are the arithmetic averages over sites and over days, but what do these averages tell about the original data? In order to answer this question a model is needed. An example is the following additive model:

$$\mathbf{x_{jk}=m+day_j+site_k+(day{\cdot}site)_{jk}} \qquad (1)$$

where m is the overall mean, the day effects sum to zero, the site effects sum to zero, and the interaction effects sum to zero rowwise and columnwise. The values obtained for the overall mean (in the lower right cell), day effects (remaining part of the last row), site effects (remaining part of the last column) and interaction effects (remaining part of the table) are:

	day 1	day 2	day 3	parameter
site 1	63	23	-86	**-86**
site 2	-63	-23	86	86
parameter	**-137**	**-50**	187	**187**

The average per day simply follows from the sum of the overall mean and the day effect (e.g. for day 1: 187-137=51, taking rounding errors into account). Ignoring interaction effects, the original data can be predicted by the sum of the overall mean, the day effect and the site effect. For example, for day 1 the prediction equals 187-137-86=-36. The difference between this prediction and the true value equals 63, i.e. the interaction effect. So the summary in terms of day and site effects is not very good, because all interaction effects are quite large. The following multiplicative model performs much better:

$$\mathbf{x_{jk}=m \cdot day_j \cdot site_k \cdot (day \cdot site)_{jk}} \qquad (2)$$

which yields:

	day 1	day 2	day 3	parameter
site 1	1	1	1	**0.607**
site 2	1	1	1	1/0.607
parameter	**0.368**	1	1/0.368	**122**

where all multiplicative interaction effects equal one. Note that 51/138 equals 0.368 and that 101/274 equals 0.607^2. The prediction for day 1, site 1 is now 122 times 0.368 times 0.607 which equals 27. Perfectly good. Clearly, this method is superior in summarizing the original data in terms of day and site effects. Undoubtedly, this approach has disadvantages too. As people are accustomed to arithmetic (additive) scales, the use of geometric (multiplicative) scales might be confusing. Particularly, when emphasis is on comparisons with figures, like the arithmetic mean, from other datasets. Finally, note that no probability model was postponed yet.

The accuracy of a census

The problem of the accuracy of a single census has been examined by Matthews (1960), Prater (1979), Kersten et al. (1981), and Rappoldt et al. (1985). Rappoldt et al. (1985) showed that the standard deviation of the random error is proportional to the mean. For large-scale shorebird counts this error was assessed to be approximately 5 to 10 percent. As already pointed out by Underhill (1989) Rappoldt et al. (1985) failed to address the serious problem of flocks being overlooked completely. Undetected flocks will cause a negative bias. If this bias is consistent, i.e. always 10 percent, it is not a serious problem concerning within dataset comparisons on a multiplicative scale. If it is not consistent, an extra random variance concerning differences among counts will be introduced.

Monthly counts

Matthews (1960) investigated the effect of having only monthly counts instead of having daily counts. He counted several species of waterfowl on different days within a single month. He found a deviation of the daily counts from the monthly mean between 25% and 50%. The accuracy of each daily census is of course also reflected in this estimate. Again, not much can be said. However, if, for example, the total number of bird days have to be calculated, assumptions concerning the number of birds on days in between the counts must be made. Such assumptions can be operationalized by the use of models or smoothing methods. For example, Schekkerman et al. (in press) use the product of the monthly count and the number of days in a month as the number of bird-days. This means that they used the bin-smoother (Hastie & Tibshirani 1989). Besides, the implicit assumption was made that counts always were conducted in the same period of the month

Incomplete and missing counts

The problem of incomplete and missing counts is dealt with by Underhill (1989). He used a multiplicative model, in which the expected count is the product of a year effect, a month effect and a time effect. The counts were supposed to have a Poisson-like distribution. This means that the variance of the error is assumed proportional to the mean. This assumption contradicts with Rappoldt et al. (1985), who found that the standard deviation is proportional to the mean. Nevertheless, the model has much appeal. Computations are straightforward and easily understood: parameter estimates can be derived from simple sums (e.g. the year effect j equals the sum over all months and areas within year j divided by the sum over all months and areas in some base year). Other models of the error structure, e.g. a multiplicative log-normally distributed error (suitable for data where the standard deviation is proportional to the mean), do not share these properties. Underhill (1989) used the EM algorithm to estimate the parameters and at the same time impute missing values. Incomplete values were only replaced when they were smaller than the imputed values. The assumption of no interaction effects, which means that relative trends and seasonal effects are assumed equal at different sites and that the seasonal pattern does not change over the years, is a strong one (see for a counter example Mitchell et al. 1988) and might be a nuisance.

Removal of the trend and the seasonal effect

For the removal of a trend one might difference the time series (including seasonal differencing). This is the procedure advocated by Box & Jenkins (1970). Alternatively, some other filter might be used. For example, one could subtract a moving average from the series or apply median based filters. Finally, some sort of model can be applied. As was said earlier, our interest merely focuses on the systematic part. The latter approach therefore is most appealing. For shorebird counts a possible candidate is the multiplicative model discussed earlier:

$$x_{ijk}=m \cdot year_i \cdot month_j \cdot site_k \quad (3)$$

The same or an almost similar model to describe fluctuations of bird populations has been used by Mountford (1982), Underhill (1989) and Moses and Rabinowitz (1990). Their approaches differ concerning the assumed error structure of the data. Moses and Rabinowitz (1990) used ordinary least squares estimation, after logarithmic transformation of the counts. This approach fits with the assumption of independent multiplicative lognormal errors. Alternatively, Underhill (1989) assumed independent Poisson-like distributed variables. The assumption of independence might be contradicted by an analysis of the autocorrelation structure of the residuals. Then, in case of lognormality an iterative generalized least squares (GLS) procedure could be helpful (Wetherill 1986 p. 288-290).

The model can be extended by the inclusion of interaction terms, although in practice this becomes a nuisance when assuming Poisson-like distributed variables.

Identifying and estimating a stochastic process model

After removal of the trend and seasonal effects an ARMA model can be fitted (Chatfield 1989). A general examination for irregularities in the residuals is worthwhile anyway. Before ARMA models can be fitted missing values have to be replaced. Since several areas are observed at a single time step one actually deals with multivariate (or vector) time series: VARMA models might be applied. In practice, however, this approach is presumably too complicated (Chatfield 1989).

RESULTS

An evident first step in analyzing long-term monthly shorebird counts is the fitting of the fixed-factor analysis of variance model:

$$y_{ijk}=m \cdot year_i \cdot month_j \cdot site_k \cdot (year \cdot month)_{ij} \cdot (year \cdot site)_{ik} \cdot (month \cdot site)_{jk} \cdot \varepsilon \quad (4)$$

It is an evident step, since (a) the standard deviation of the random counting error is proportional to the mean (Rappoldt et al. 1985) which fits with the assumption of a multiplicative lognormal error; (b) interaction effects cannot be ruled out a priori and must therefore be included (Mitchell et al. 1988). This is particularly true when the model is used as a descriptive data-summarizing tool. Because there is just a single observation per cell, there are no replicate observations for measuring error. With the eyes closed and the fingers crossed (Miller 1986), I used the second-order interaction the error term for testing the main effects and first-order interactions; (c) incomplete counts can easily be handled by including a covariate indicating the completeness of the count, like cover index or a zero-one dummy variable; (d) it reduces the problem of missing values (but not of missing cells) as parameters are fitted by simple OLS after logarithmic transformation; (e) missing values can simply be replaced by model predictions after bias correction (f) it might also serve the purpose of trend and seasonal effects removal.

Firstly, the log-transformed data (n=678) of the Oystercatcher (*Haematopus ostralegus*) are analyzed with the two-way interaction model mentioned above. Since the problem concerns a missing cell design the GENSTAT 5.0 multivariate regression procedure, which is a least squares program, was used. The analysis of variance table is given in Table 1. Assuming independent normally distributed errors all fitted terms, including the first-order interaction terms are significant. The anti-logged standard error of the estimate equals exp(√0.104)=1.38. So the precision of a model prediction is approximately ± 38%. When all interaction terms are ignored it equals exp(√ 0.17)=1.50. The estimated parameters (following GENSTAT parametrization) are given in Table 2. It follows that e.g. the number of birds present in 1989, March in the Westerschelde is predicted as 14458*0.69*0.63*1.45*0.75*0.66*1.04 which equals 4691. The actual number was 5662. The ratio 5662/4691=1.21 is indeed not far from 1.38.

Admittedly, the GENSTAT parameter table is not very informative at first glimpse. Least squares means per year-month, year-site and month-site offer a more understandable alternative. Unfortunately, the presence of missing cells is a nuisance. The problem of missing cells was tackled in three different ways:

1- drop the years 1983/1984 and 1984/1985 from the dataset and repeat the analysis;

2- leave out the first-order interaction terms;

3. fit a parameter sparse multiple regression model. For a balanced design, the year and month categorical variables (factors), with respectively 13 and 12 levels, could be replaced by an algebraic polynomials:

$$\mathbf{b_0+b_1 \cdot year+b_2 \cdot year^2+...+b_{12}year^{12}}$$

and a trigonometrical polynomial (Bliss 1970, see also Underhill et al. 1992)of the form

$$\mathbf{b_0+b_{11} \cdot sin(t)+b_{12} \cdot cos(t)+b_{21} \cdot sin(2t)+...+b_{61} \cdot sin(6t)}$$

where t equals (2*month-1)/24*2π and month runs from 1 to 12. This would reveal the same variance partitioning. In case of unbalanced missing cell designs lower order polynomials can be used.

Table 3 shows the ANOVA table of the analysis of variance without the years 1883/1984 and 1894/1985 for the Oystercatcher. The design is almost balanced. Only

12 observations were missing for the Westerschelde area. The results are in agreement with those of the full dataset analysis. Least squares means of all year·site, month·site and year·month combinations are visualized in Fig. 1. In all figures the year 1978 means the 'season' 1978/1979, etc. The central part of the Oosterschelde has become more important over the years. The opposite is true for the Eastern part. The seasonal pattern of all five sites looks more or less the same. Only the autumn values for the Westerschelde are relatively low. Particularly, the year·month interaction needs some further summarizing. Fig. 2 shows the slopes and intercepts (at both the 1978 and 1990 level) of the linear component of the interaction term. These values were obtained by regressing the least-squares means against year for each month. Deleting all non-linear terms for the year main effects and interaction effects from the original model yielded almost the same picture. The figure shows a negative trend over the years for the winter months and a positive trend for the summer months. A probability plot of the residuals showed a clear straight line, supporting the assumption of a lognormal distribution of the errors. Apparently no relationship between the residuals and the estimated values could be detected (Fig. 3). This was also true for the relation between the residuals and an 'index of completeness'. This index roughly indicates the completeness of a count (Berrevoets pers. comm.). For all sites, except the Westerschelde (r_1=0.27), no significant auto-correlation could be found (Fig. 4A). The only apparent correlation among the residuals was the cross-correlation among sites. This cross-correlation varied around a value of 0.25 (Fig. 4B). This, however, arises from the fact that even under the hypothesis of independent errors the five residuals within each year·month combination are dependent. Its expected correlation can be precisely calculated from the difference between the identity matrix and the hat matrix (Draper & Smith 1981), and will be in the order of 1/(5-1).

Table 4 and 5 and Fig. 5 to 8 give the analysis of variance results for the Dunlin *Calidris alpina* and the Redshank *Tringa totanus*. The (back-transformed) standard error of the estimate is for the Dunlin much larger than for the Oystercatcher: $\exp(\sqrt{1.013})=2.74$. The Redshank's back-transformed standard error of the estimate equals: $\exp(\sqrt{0.379})=1.85$. For the Dunlin the year·site and year·month interaction are non-significant at the five percent level. The Eastern part of the Oosterschelde reveals, apart from the Westerschelde, the highest numbers of the Dunlin in winter and spring. However, numbers from July to September are much lower compared to the other parts of the Oosterschelde. Both species showed a decrease over the years of a few percent per year. An exception are the number of Redshanks in the months September and October and May and June. Generally, for both species the residuals showed the same behaviour as was found for the Oystercatcher.

Table 6 gives the results of the parameter sparse models in terms of the residual sum of squares. The polynomial model gives quite satisfactory results (Fig. 9) and did considerably better than the main effects model. Its predictions can be used for imputing missing values. Because simple back-transformation yields biased results, the following well known approximately bias correcting back transformation has been used (Fig. 10):

imputed value=exp(estimate+residual mean square/2).

This way, arithmetic summary values can also be calculated for periods with missing values. Fig 11 shows the trend over years in the number of bird-days.

DISCUSSION AND CONCLUSIONS

The multiplicative linear model with year described by an algebraic polynomial, month by a trigonometrical polynomial and site as a categorical variable including all first-order interaction effects plus a lognormal error proved to be quite satisfactorily concerning almost all points of concern raised.

It served as a descriptive tool, taking into account the interesting (and in the present case significant) first-order interactions. This is an improvement compared to earlier approaches (Mountford 1982, Underhill 1989, Moses & Rabinowitz 1990). However, it should be noted that these studies had different objectives. The criticism of Underhill (1989) against an analysis that is based on logtransformed data is only relevant, when systematic components (e.g. a year•site interaction) are present in the data, but are not taken into account in the fitted model. When the (multiplicative) errors are purely random no serious misinterpretation of the model results have to occur.

The model enabled the imputement of missing values, which can be helpful when other descriptions than the model parameters are wanted. An example is the total number of bird-days per year in the entire area. Contrary to Moses & Rabinowitz a bias correcting backtransformation was used. More work has to be done concerning the variance of such (arithmetic) figures. The model can handle incomplete counts. This can be done by including a completeness index. This index can even be a zero-one dummy variable. The need for the inclusion of such an index was examined by inspecting the plot of the index on the residuals. Surprisingly, no relation was found between the residuals and the index of completeness. I have no explanation.

The model removed the trend and seasonal effects, making a time-series analysis possible. However, the lack of autocorrelation as experienced in the present data takes away the need of a stochastic process model. Specially as I am merely interested in long-term changes in the mean and not in short term predictions. Only the latter goal requires full insight in the high-frequency stochastics.

In practice, at the start of an analysis the degree of the polynomial should preferably be taken as large as k-1 when there are k levels. In that case the model is equivalent to the categorical analysis of variance model. If a number of cells are missing, alternatively a lower order polynomial can be used as the most appropriate way to describe the data. Subsequently, one might test whether the degree of the polynomials can be taken lower than k-1. For example, can the trend over the years be described only by a linear term? Not for the three birds of this analysis. Polynomial interpolation for longer periods without any data points should be interpreted with caution.

Whether the error mean square represents only measurement error or also includes a true second-order interaction cannot be revealed from the present dataset. For the Oystercatcher a measurement error of a factor 1.38 looks a reliable value. Whether this is also true for the considerably larger errors found for the Dunlin and the Redshank seems questionable. Future examinations on the true measurement error and on the variability within a month are needed.

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Table 1. Analysis of variance of the log-transformed Oystercatcher counts (*n=678*).

	df	SS	MS	F
main effects	27	437	16.18	
-year	12	4	0.33	2.0
-month	11	379	34.44	208.0
-site	4	49	12.33	74.5
error	650	108	0.17	
main and interaction effects	233	498	2.14	
-interaction effects	206	61	0.30	2.9
-year•month	114	29	0.26	2.5
-year•site	48	19	0.40	3.8
-month•site	44	13	0.28	2.7
error	444	46	0.104	
total	677	544	0.80	

Table 2. Analysis of variance of the log-transformed Oystercatcher counts (n=678). GENSTAT 5.0 (back-transformed) parameters. Question marks indicate missing cells.

	OC	ON	OE	W		79/80	80/81	81/82	82/83	83/84	84/85	85/86	86/87	87/88	88/89	89/90	90/91
OC					**1.57**	0.92	0.86	1.03	1.30	0.88	0.98	1.21	1.18	1.00	1.10	1.81	0.96
ON					**1.61**	0.85	0.75	1.14	1.83	1.42	2.05	1.76	1.61	1.55	1.31	2.35	1.61
OE					**2.62**	0.67	0.41	0.50	0.78	0.76	0.53	0.54	0.55	0.63	0.46	0.95	0.61
W					**1.45**	0.43	0.39	0.47	0.71	0.65	1.08	0.78	0.63	0.59	0.66	1.20	0.73
	1.57	**1.61**	**2.62**	**1.45**	**14458**	**0.88**	**1.20**	**1.25**	**0.83**	**0.85**	**0.71**	**0.71**	**0.65**	**0.72**	**0.69**	**0.48**	**0.67**
Feb	0.96	1.46	1.34	1.20	**0.72**	1.05	1.18	0.99	0.86	?	?	1.15	1.53	1.16	1.36	0.98	1.22
Mar	0.75	1.05	0.93	1.04	**0.63**	0.65	0.56	0.52	0.62	?	?	0.80	1.68	0.93	0.75	0.64	0.80
Apr	0.62	0.65	0.67	0.95	**0.34**	0.82	0.85	0.53	0.75	?	?	1.36	0.94	1.11	1.39	0.81	1.22
May	0.92	0.73	0.93	1.15	**0.16**	1.39	0.97	0.63	0.60	0.89	?	1.90	1.33	1.74	1.75	1.27	1.57
Jun	0.99	0.62	1.04	1.34	**0.14**	0.77	0.75	0.48	0.78	?	?	1.36	1.14	1.57	1.45	1.29	1.24
Jul	1.12	0.80	0.81	1.17	**0.14**	1.78	0.76	1.00	1.09	2.76	?	1.45	4.50	1.93	2.76	2.54	2.78
Aug	0.80	0.83	0.70	0.85	**0.71**	1.76	0.81	0.93	1.27	1.27	1.38	1.58	2.13	1.27	1.86	2.18	1.54
Sep	0.62	0.82	0.65	0.74	**0.76**	2.02	1.56	1.38	1.58	?	?	1.77	1.94	1.69	2.44	2.17	2.36
Oct	0.77	1.07	0.70	0.76	**0.67**	2.01	1.73	1.15	1.99	?	?	2.21	2.13	2.10	2.47	2.31	1.65
Nov	0.76	0.85	0.77	0.73	**0.88**	1.43	1.57	0.99	1.11	?	?	1.58	1.50	1.54	1.78	1.22	1.53
Dec	0.84	1.16	1.07	0.96	**0.94**	1.40	0.85	0.69	0.83	?	?	1.06	1.14	1.20	1.06	0.96	1.09

Table 3. Analysis of variance of the log-transformed Oystercatcher counts. Data without the years 1983/1984 and 1984/1985 (n=648).

	df	SS	MS	F
year	10	4	0.42	4.0
month	11	358	32.61	309.7
site	4	46	11.47	108.9
year•month	110	28	0.25	2.4
year•site	40	18	0.45	4.3
month•site	44	13	0.29	2.7
error	428	45	0.105	

Table 4. Analysis of variance of the log-transformed Dunlin counts. Data without the years 1983/1984 and 1984/1985 (n=648).

	df	SS	MS	F
year	10	29	2.89	2.9
month	11	2212	201.1	198.4
site	4	279	69.67	68.8
year•month	110	121	1.10	1.1
year•site	40	53	1.33	1.3
month•site	44	337	7.66	7.6
error	428	434	1.013	

Table 5. Analysis of variance of the log-transformed Redshank counts. Data without the years 1983/1984 and 1984/1985 (n=648).

	df	SS	MS	F
year	10	17	1.71	4.5
month	11	93	8.46	22.3
site	4	165	41.15	108.7
year•month	110	63	0.57	1.5
year•site	40	55	1.37	3.6
month•site	44	55	1.25	3.3
error	428	162	0.379	

Table 6. Analysis of variance of the log-transformed Oystercatcher counts (n=678). Results of several parameter sparse models. The polynomial applied for the year effect is a fourth order algebraic polynomial. The polynomial applied for the month effect is a third order trigonometrical polynomial. RSS means residual sum of squares, RMS residual mean square.

model	Rdf	RSS	RMS	exp(√RMS)
only main effects	650	108	0.171	1.50
year linear and month polynomial	632	95	0.150	1.47
year and month polynomial	599	80	0.133	1.44
main and first-order interaction effects	444	46	0.104	1.38

Figure 1A. Least squares means, including standard errors, for all site·year combinations.

O	Oosterschelde Northern part
>	Oosterschelde Western part
□	Oosterschelde Central part
*	Oosterschelde Eastern part
▪	Westerschelde

Figure 1B. Least squares means for all site·month combinations. Symbols as A.

Figure 1C. Least squares means for all month·year combinations. Oystercatcher, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648). The upper figure gives the months July to December, the lower figure the months January to June.

O	July	January
>	August	February
□	September	March
*	October	April
▪	November	May
Δ	December	June

Figure 2. Linear approximation of the trend (given in Fig. 1C) in the least-squares mean over the years for each month separately. The upper and lower figure respectively give the back-transformed slope and intercept (open circles at x=1978, filled squares at x=1990) of the linear regression line. Oystercatcher, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

Figure 3A. Residuals against estimate. Oystercatcher, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

Figure 3B. Residuals against index of completeness. Oystercatcher, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

Figure 4A. Auto-correlation of the residuals. Per site. Oystercatcher, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

Figure 4B. Cross-correlation of the residuals. Per site combination. Oystercatcher, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

Figure 5. As Fig. 1A and 1B. Dunlin, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

Figure 6. As Fig. 2. Dunlin, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

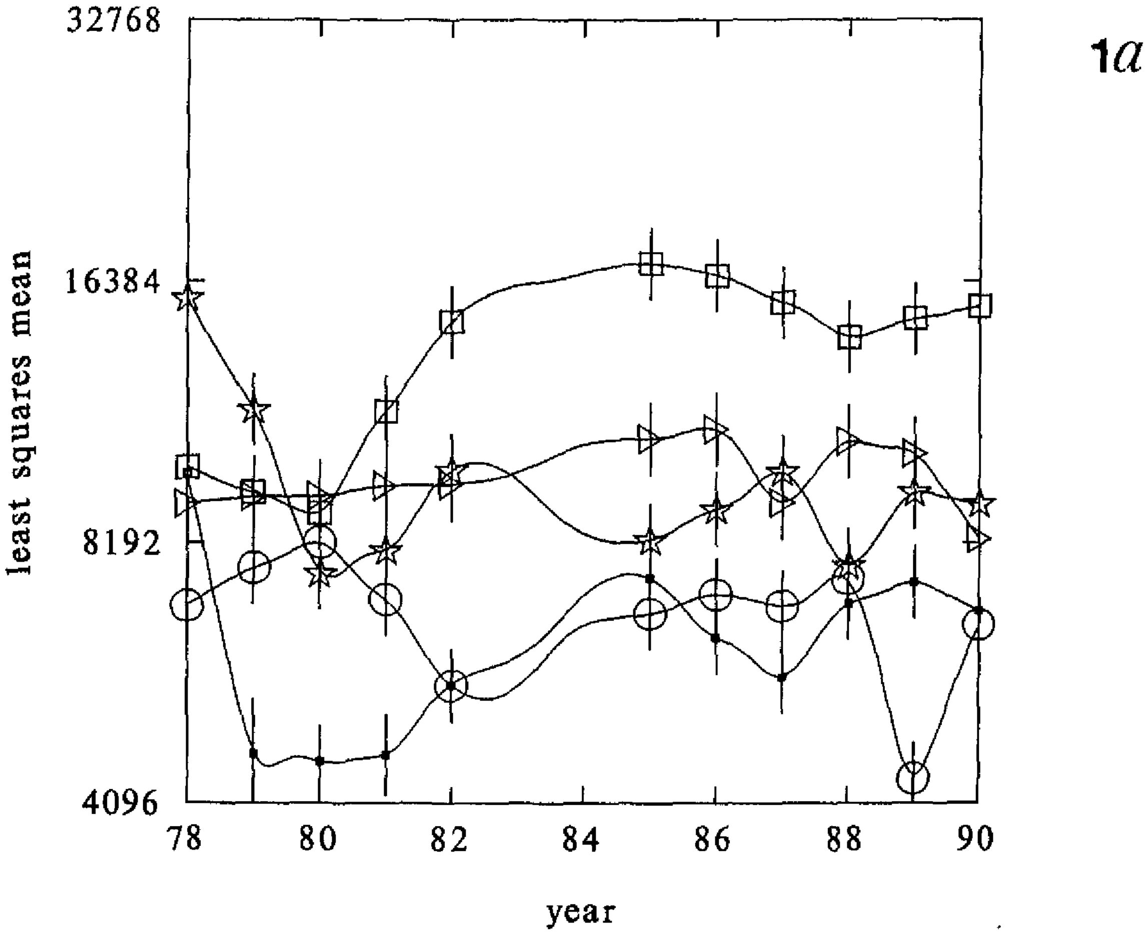
Figure 7. As Fig. 1A and 1B. Redshank, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

Figure 8. As Fig. 2. Redshank, analysis of variance model without the years 1983/1984 and 1984/1985 (n=648).

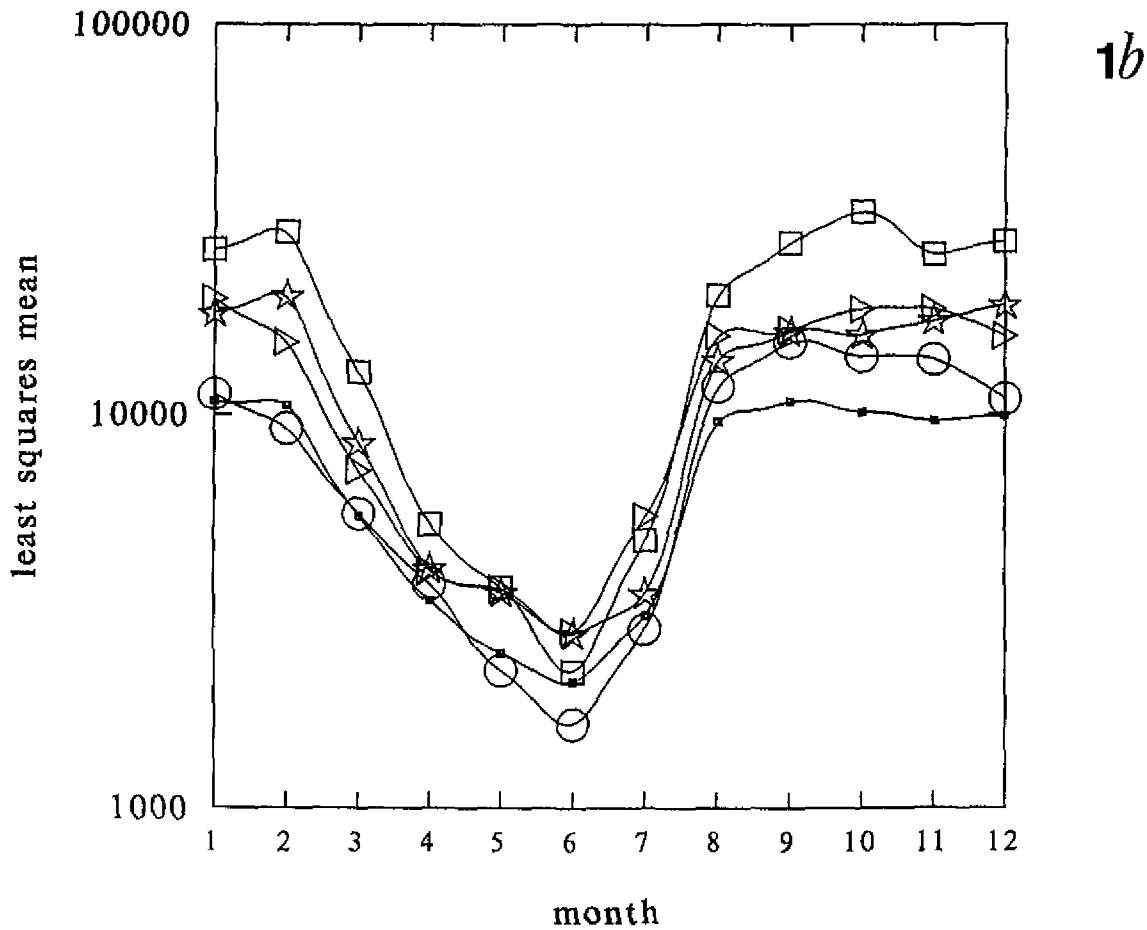
Figure 9. Oystercatcher.counts (dots) and estimates of the polynomial model (line) versus time. Per site. Symbols as Fig. 1A.

Figure 10. Estimates of the polynomial model versus Oystercatcher counts

Figure 11A. Bird-days versus time. Per site, symbols as Fig. 1A. Based upon raw data and when necessary values imputed by polynomial model. Oystercatcher.
Figure 11B. Bird-days for the entire area versus time. Based upon raw data and when necessary values imputed by polynomial model. Oystercatcher.

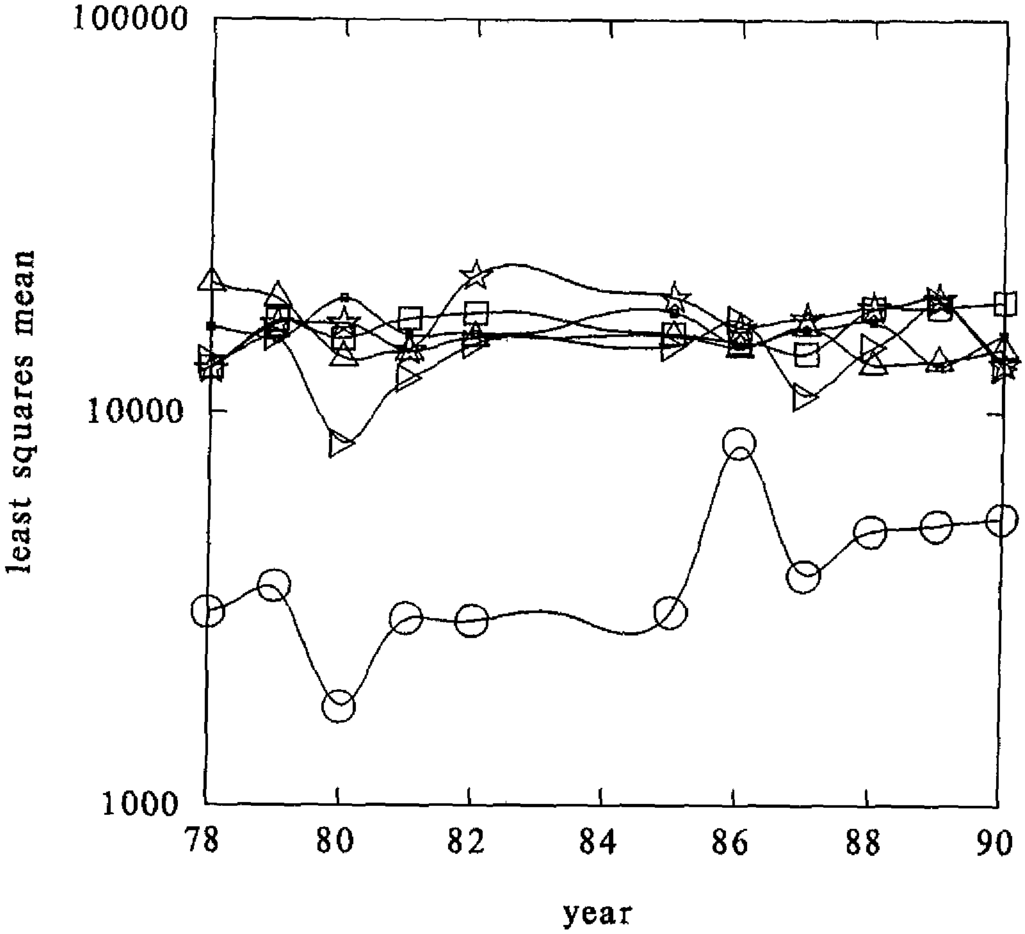


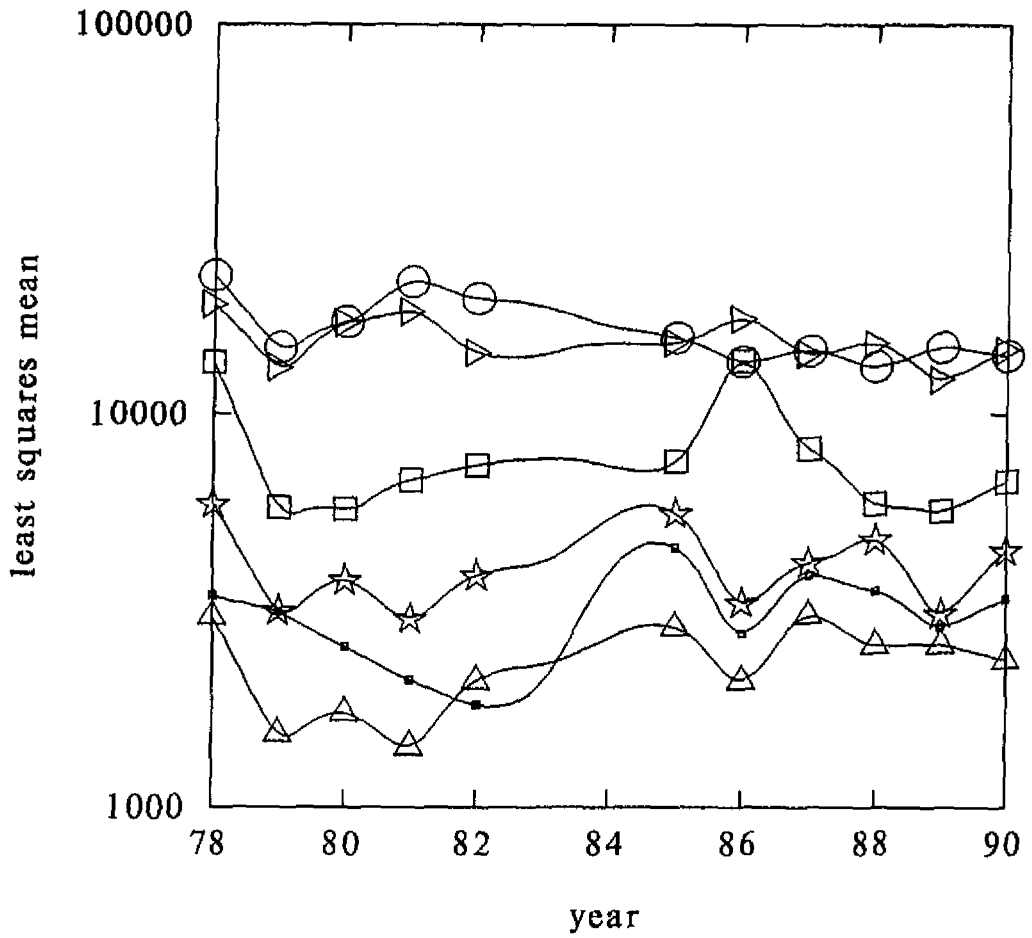
1a
32768
16384
8192
4096
least squares mean
78
80
82
84
86
88
90
year



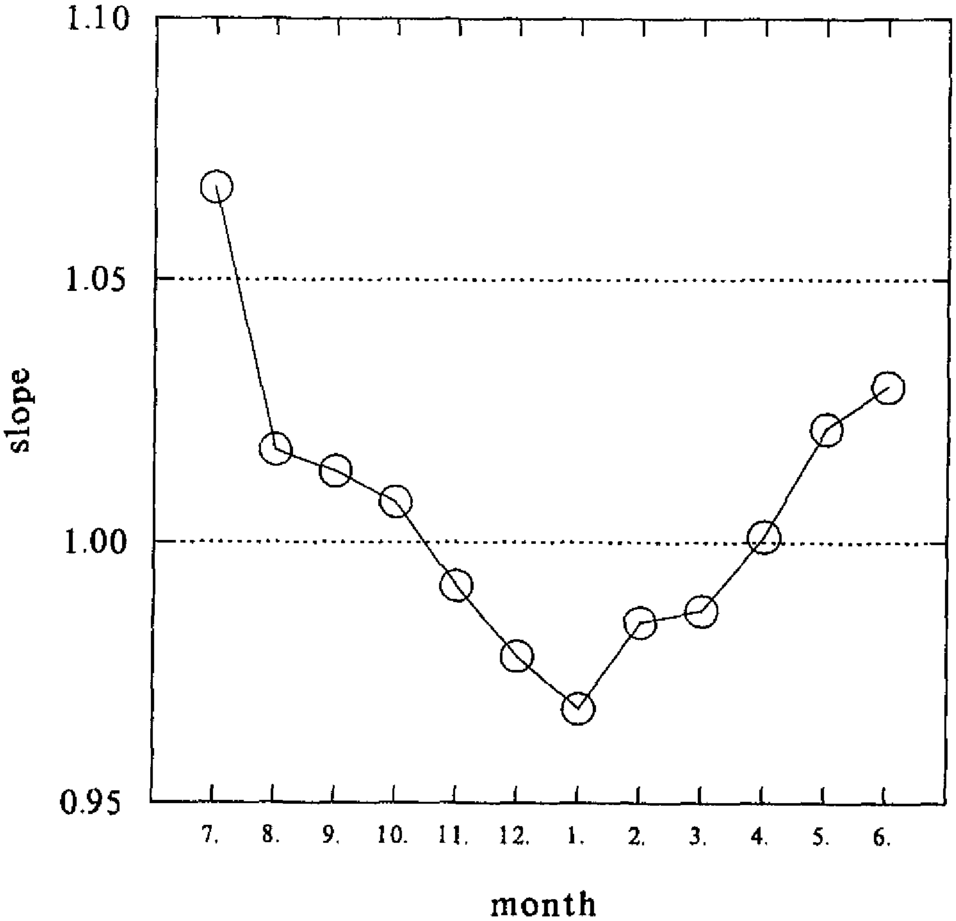
1b
100000
10000
1000
least squares mean
1
2
3
4
5
6
7
8
9
10
11
12
month

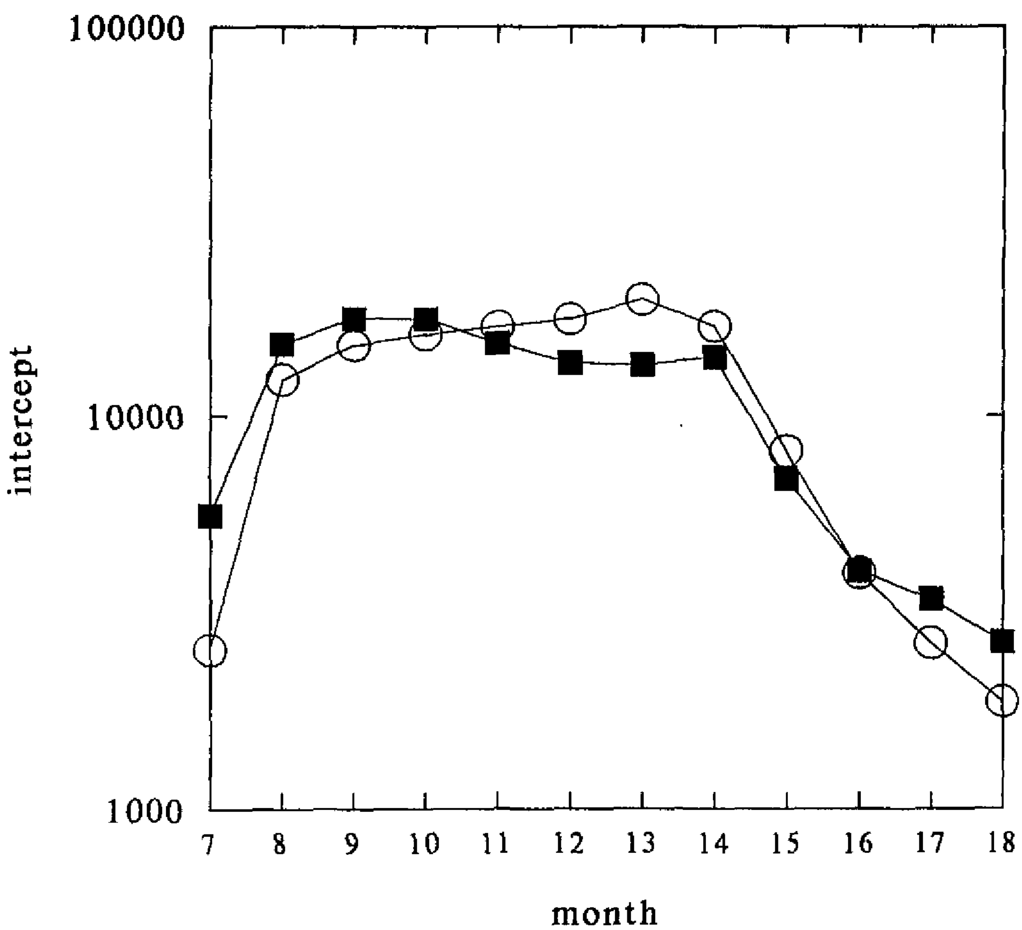
1C

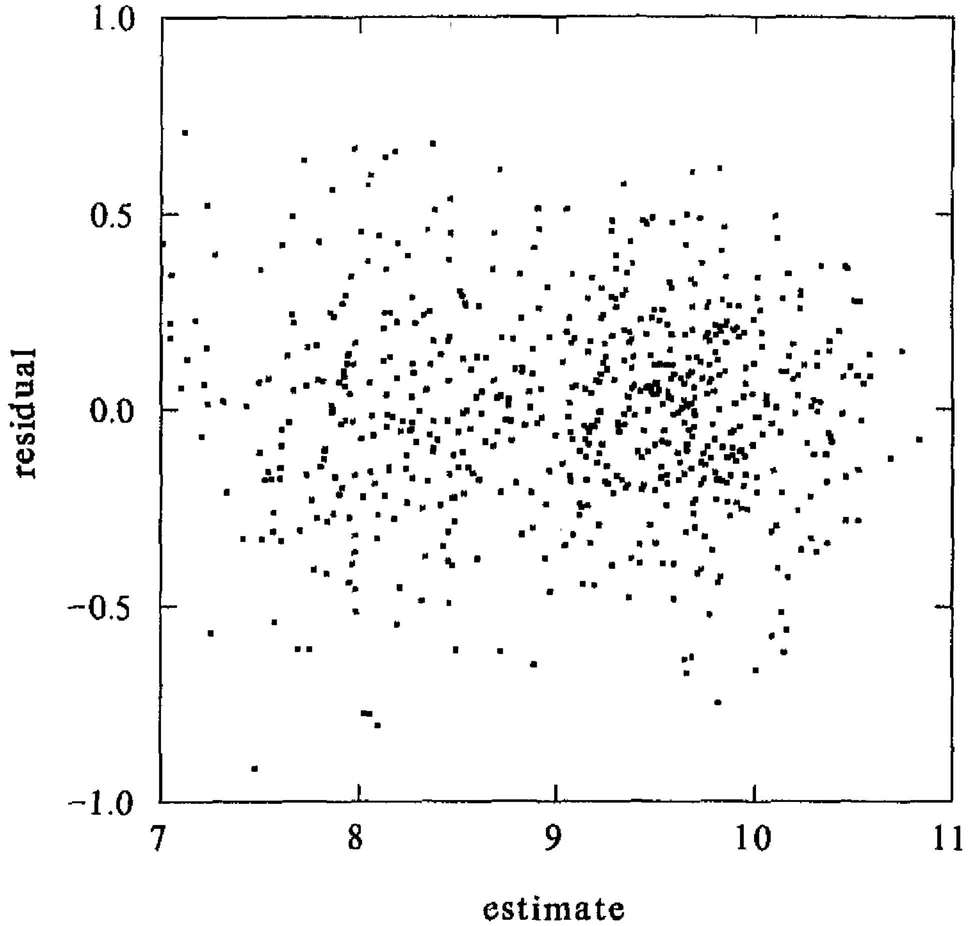

100000
10000
1000
least squares mean
78
80
82
84
86
88
90
year


100000
10000
1000
least squares mean
78
80
82
84
86
88
90
year

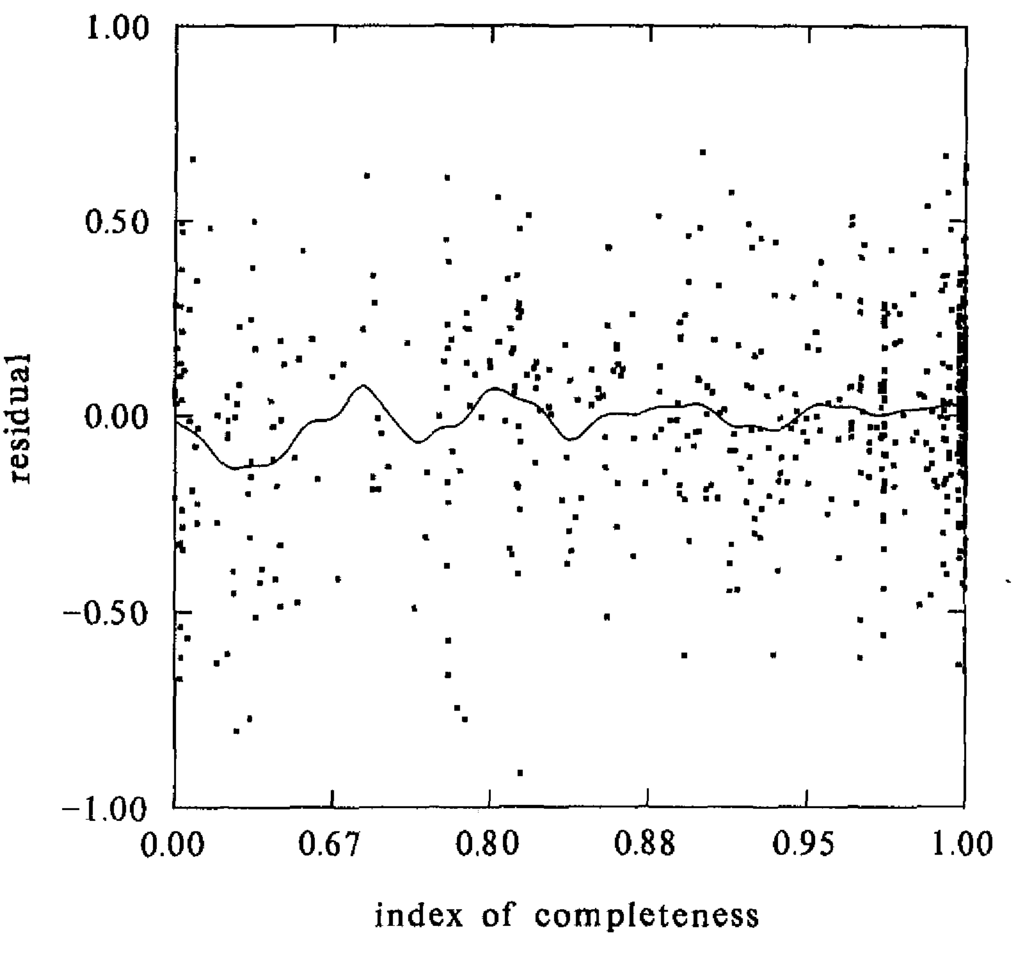
2


1.10
1.05
1.00
0.95
slope
7. 8. 9. 10. 11. 12. 1. 2. 3. 4. 5. 6.
month

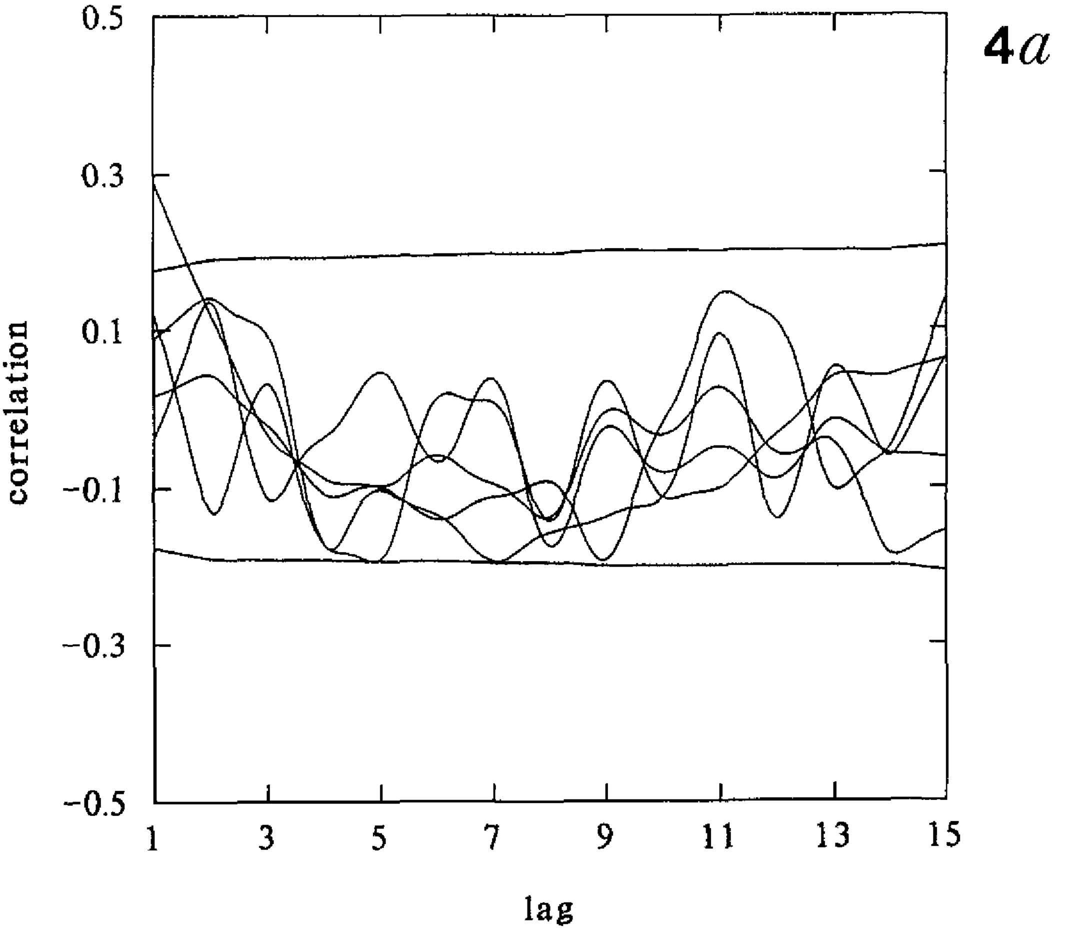

100000
10000
1000
intercept
7 8 9 10 11 12 13 14 15 16 17 18
month

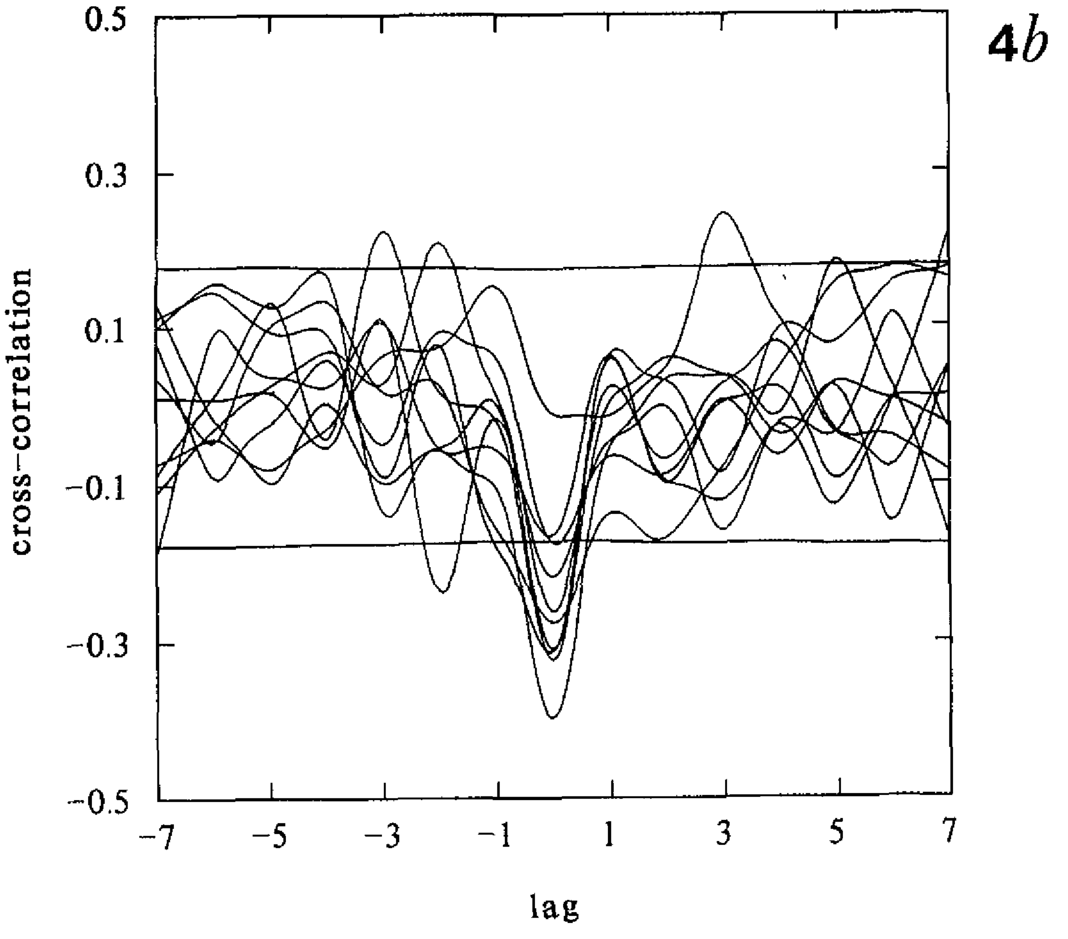

1.0
0.5
0.0
−0.5
−1.0
residual
7
8
9
10
11
estimate

3*a*

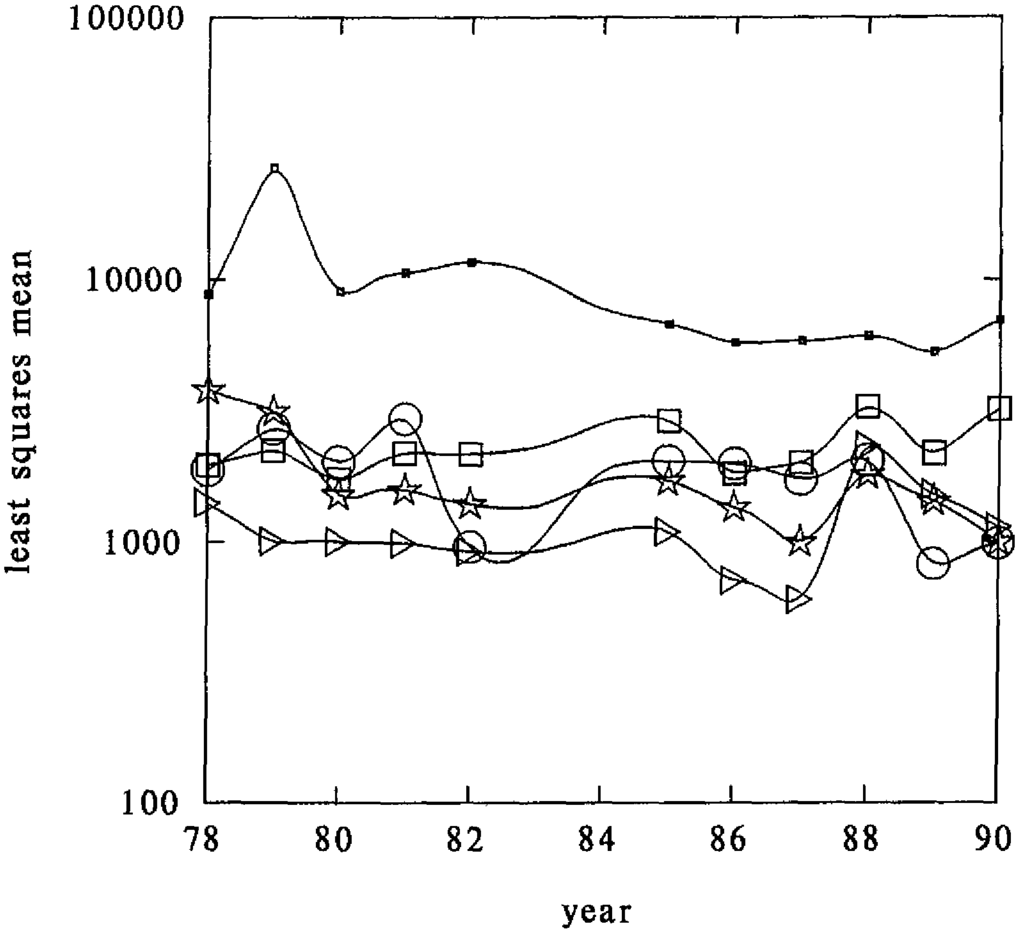

1.00
0.50
0.00
−0.50
−1.00
residual
0.00
0.67
0.80
0.88
0.95
1.00
index of completeness

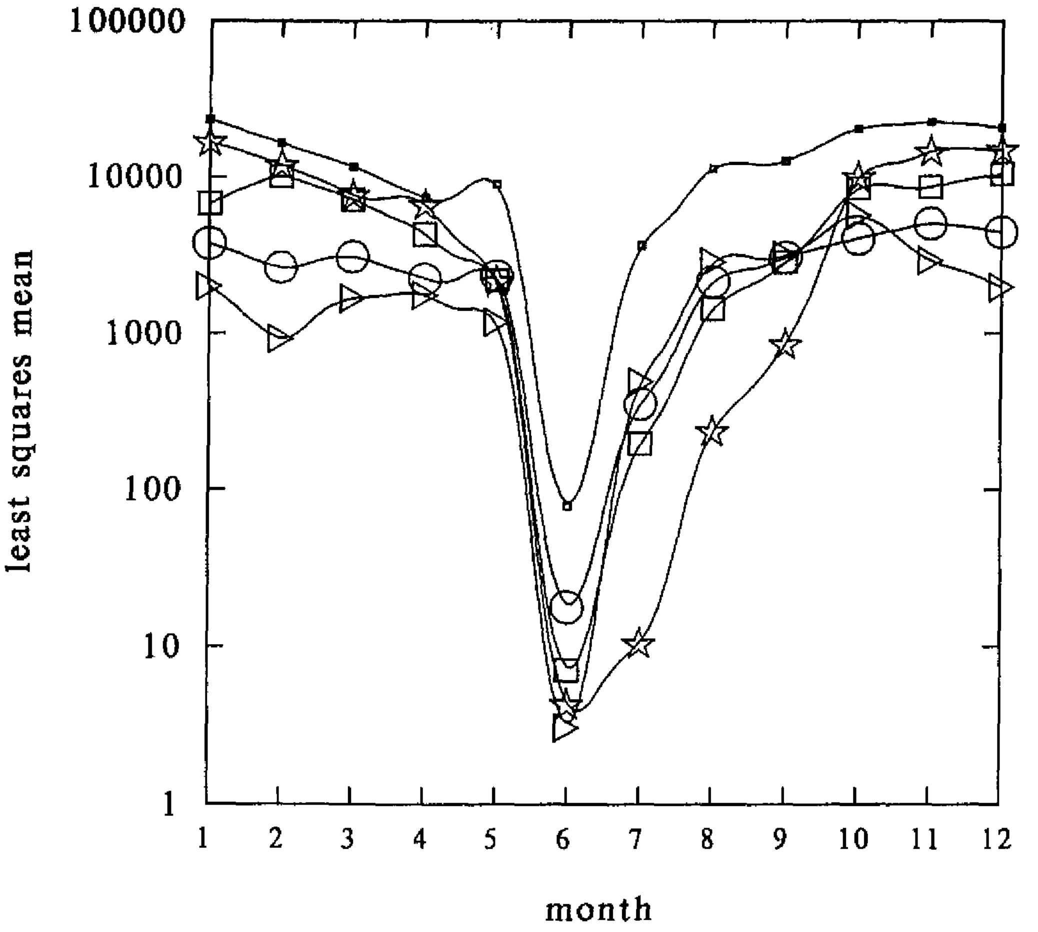
3*b*


4a
0.5
0.3
0.1
−0.1
−0.3
−0.5
correlation
1
3
5
7
9
11
13
15
lag

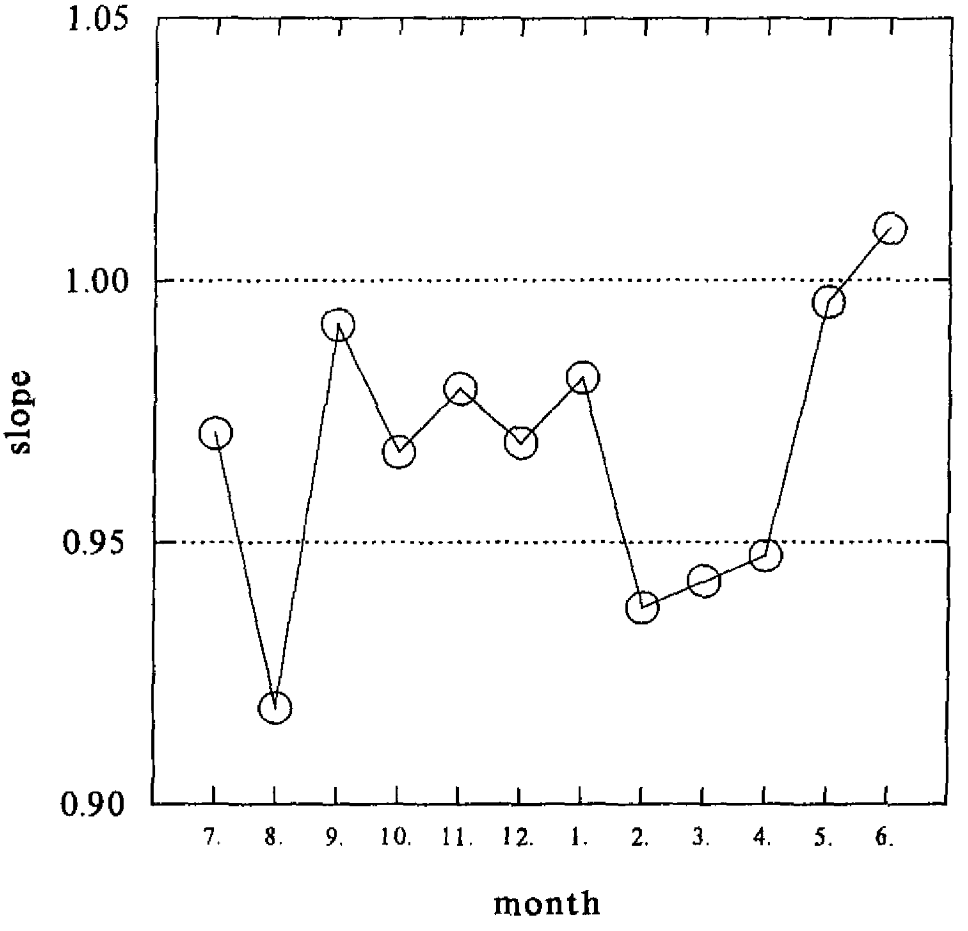

4b
0.5
0.3
0.1
−0.1
−0.3
−0.5
cross-correlation
−7
−5
−3
−1
1
3
5
7
lag

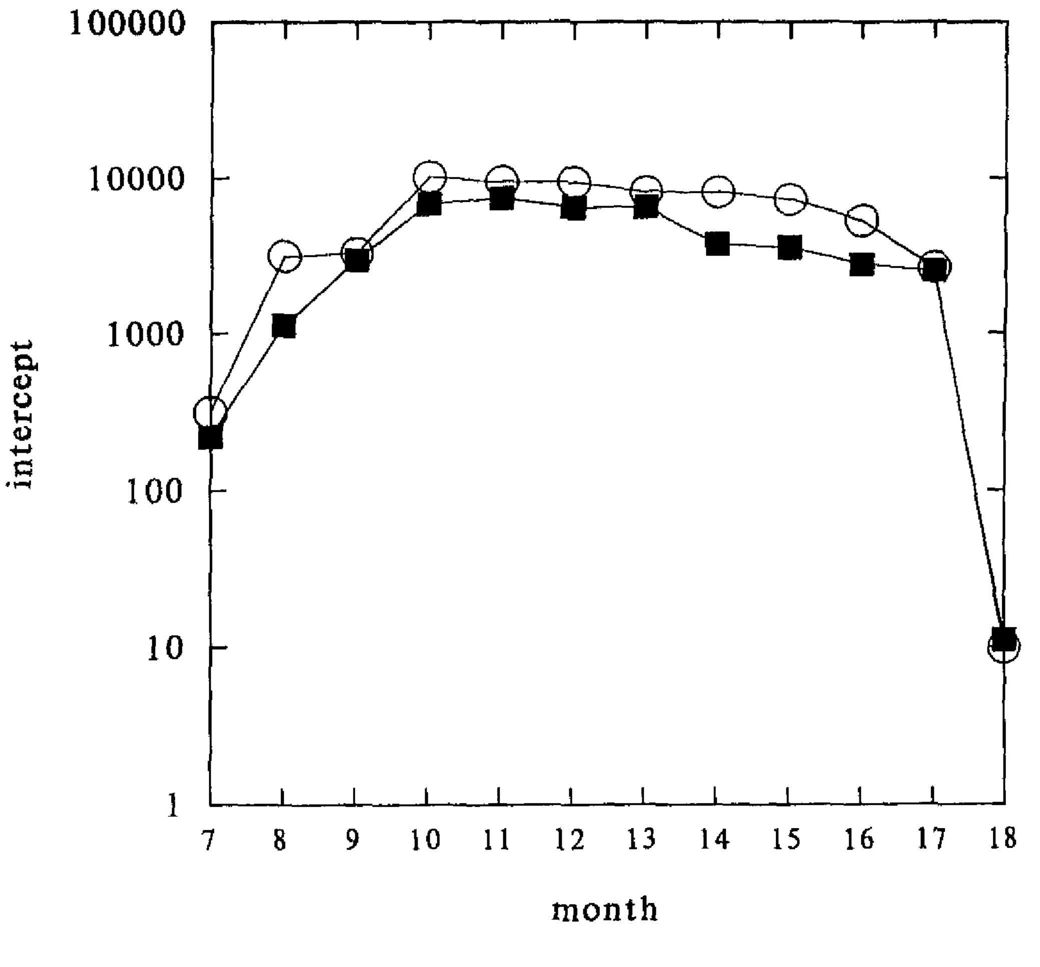
5


100000
10000
1000
100
least squares mean
78
80
82
84
86
88
90
year

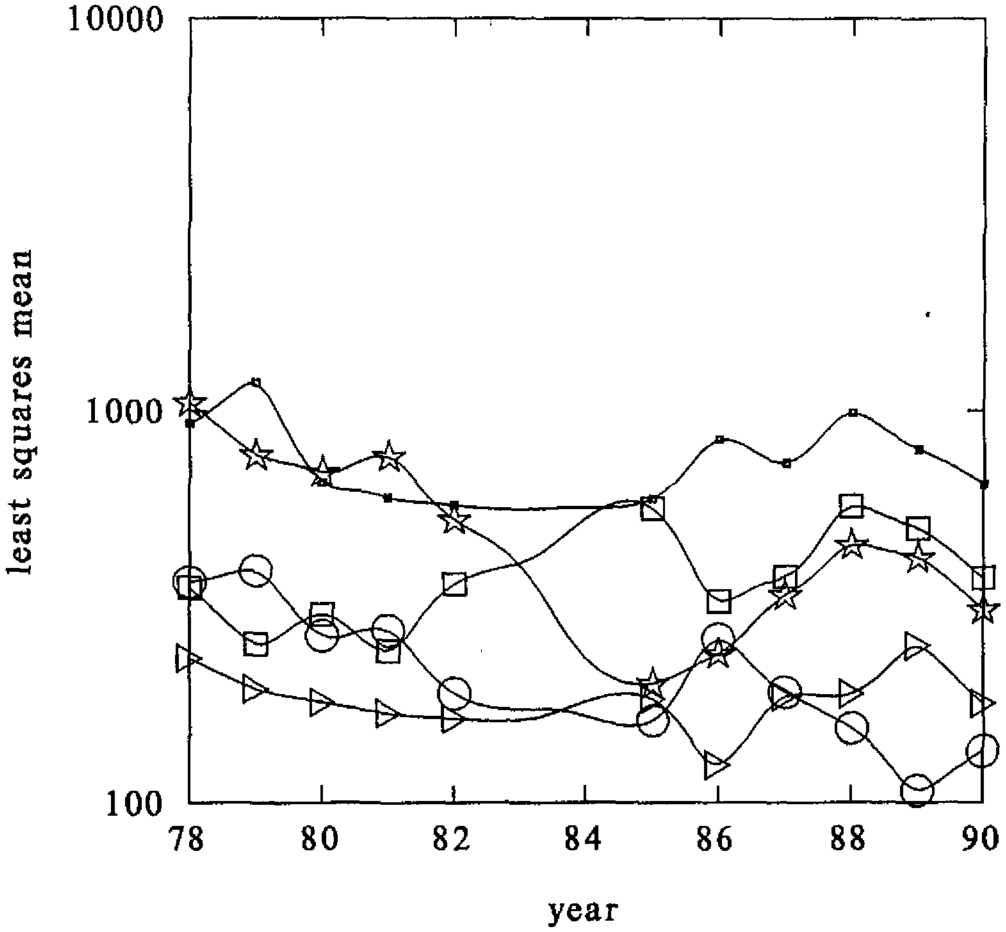

100000
10000
1000
100
10
1
least squares mean
1
2
3
4
5
6
7
8
9
10
11
12
month

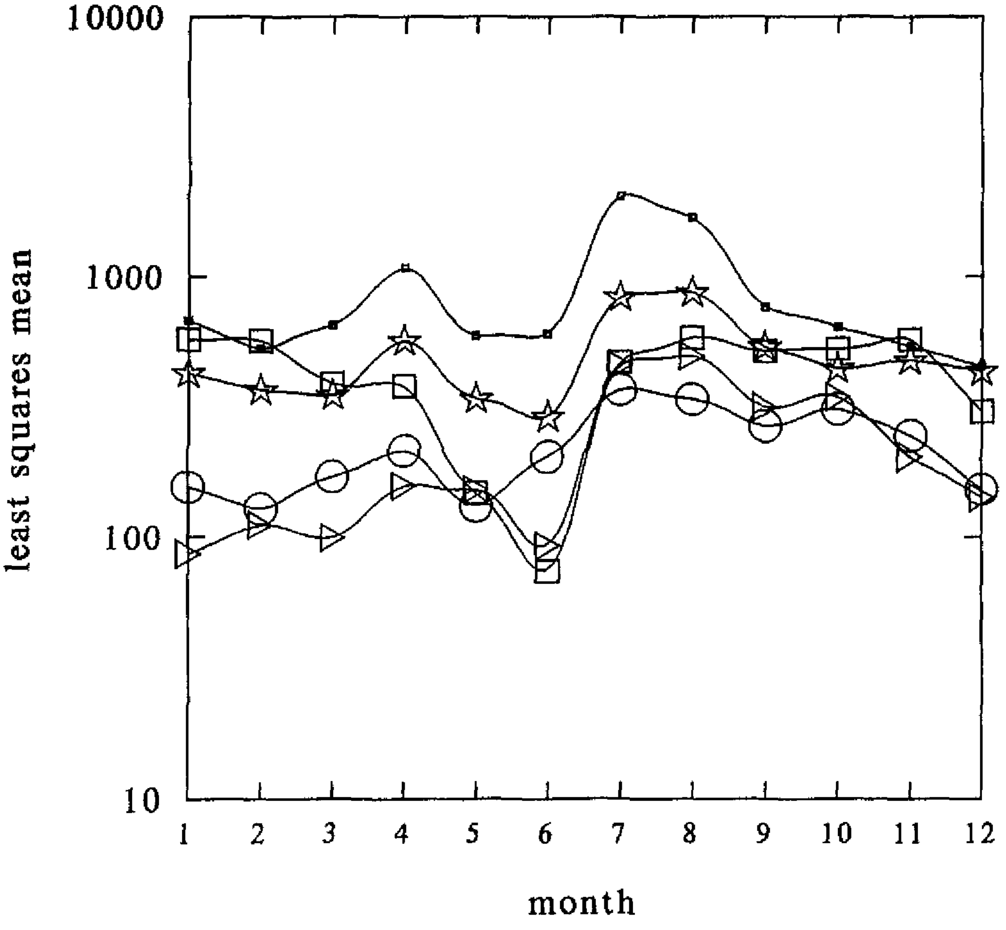
6


1.05
1.00
0.95
0.90
slope
7.
8.
9.
10.
11.
12.
1.
2.
3.
4.
5.
6.
month

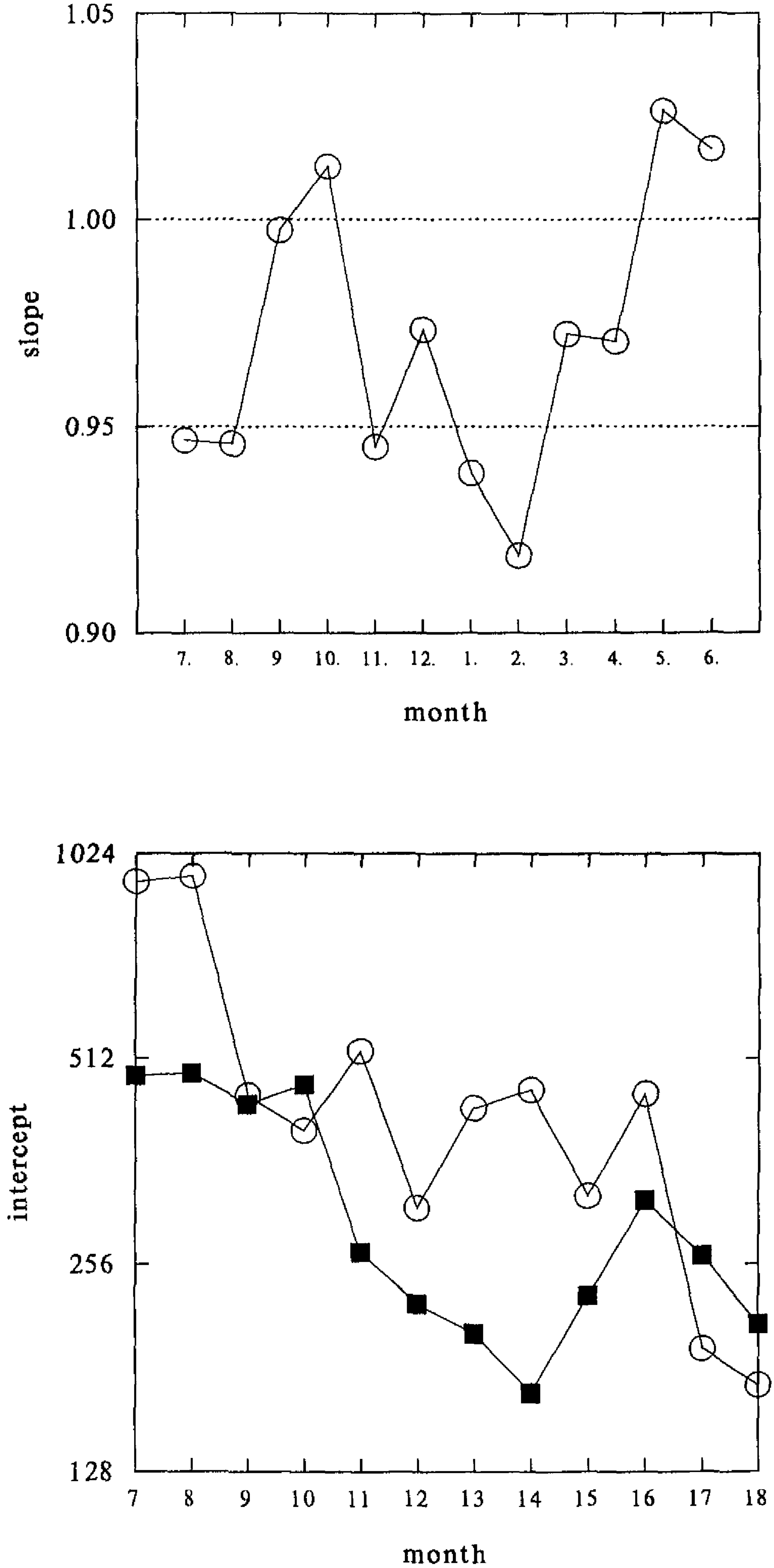

100000
10000
1000
100
10
1
intercept
7
8
9
10
11
12
13
14
15
16
17
18
month

7

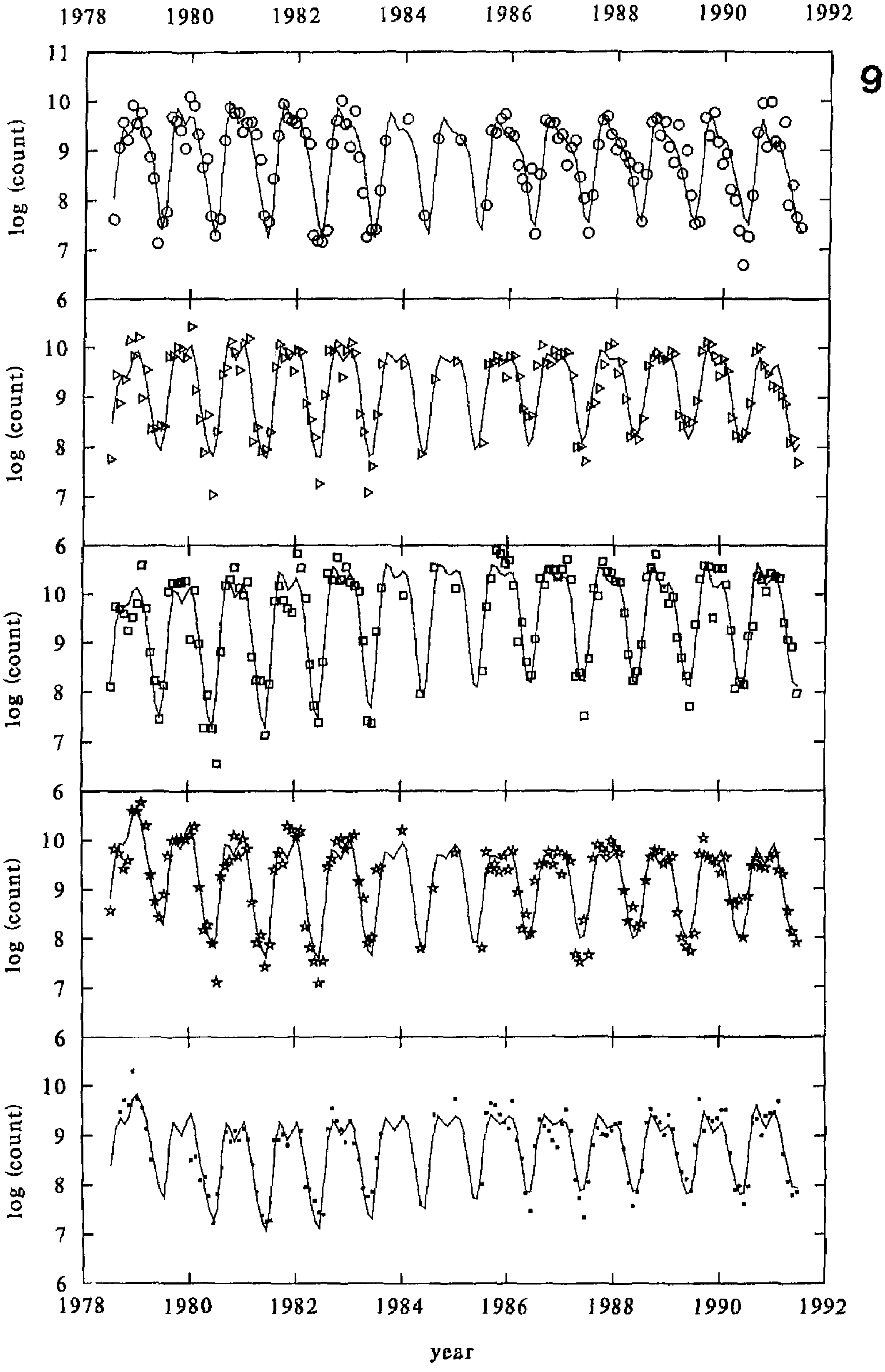

10000
1000
100
least squares mean
78
80
82
84
86
88
90
year


10000
1000
100
10
least squares mean
1
2
3
4
5
6
7
8
9
10
11
12
month

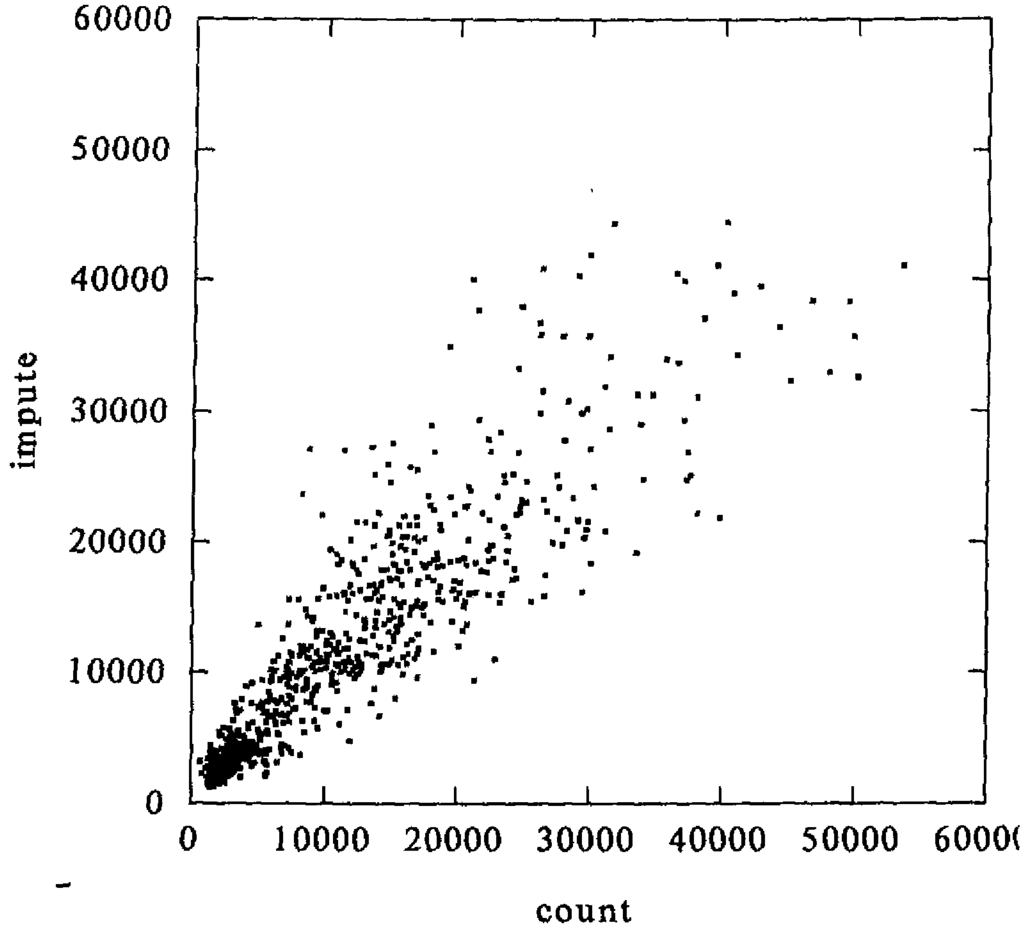
8



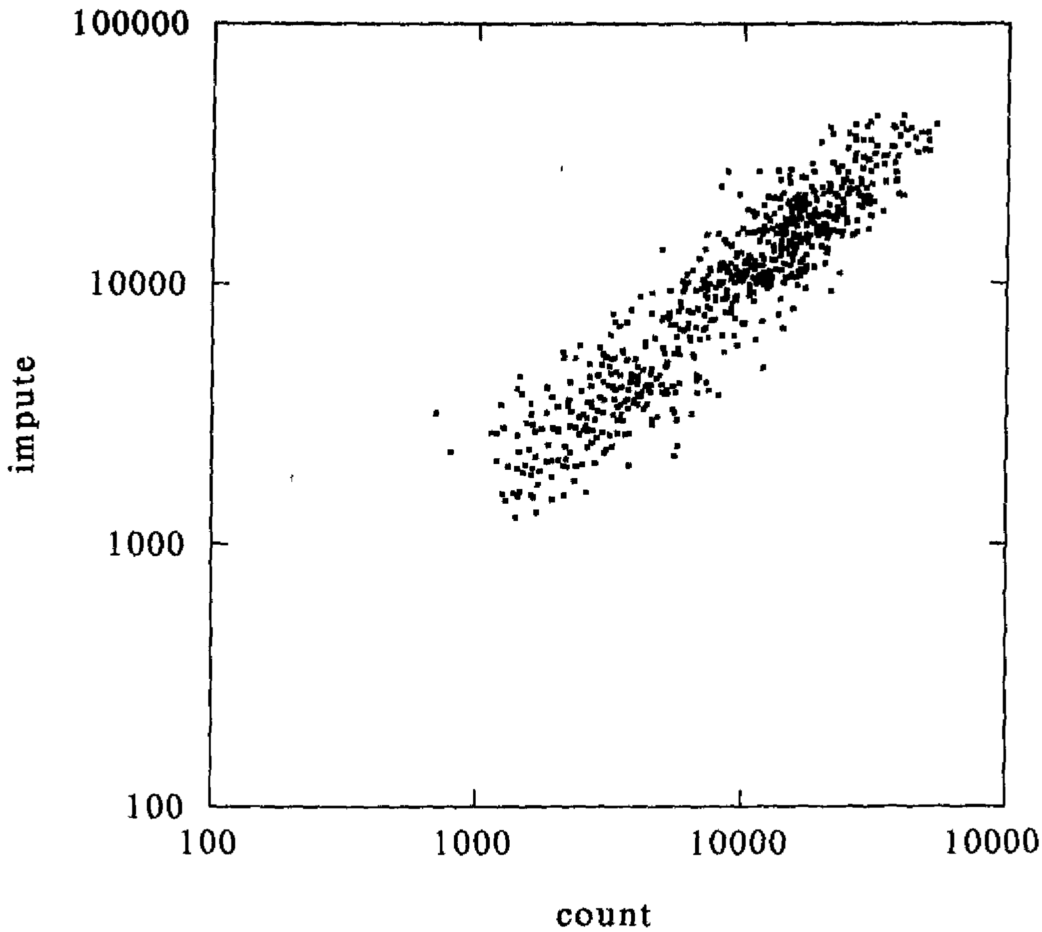
1.05
1.00
0.95
0.90
slope
7.
8.
9
10.
11.
12.
1.
2.
3.
4.
5.
6.
month
1024
512
256
128
intercept
7
8
9
10
11
12
13
14
15
16
17
18
month


1978
1980
1982
1984
1986
1988
1990
1992
9
log (count)
year

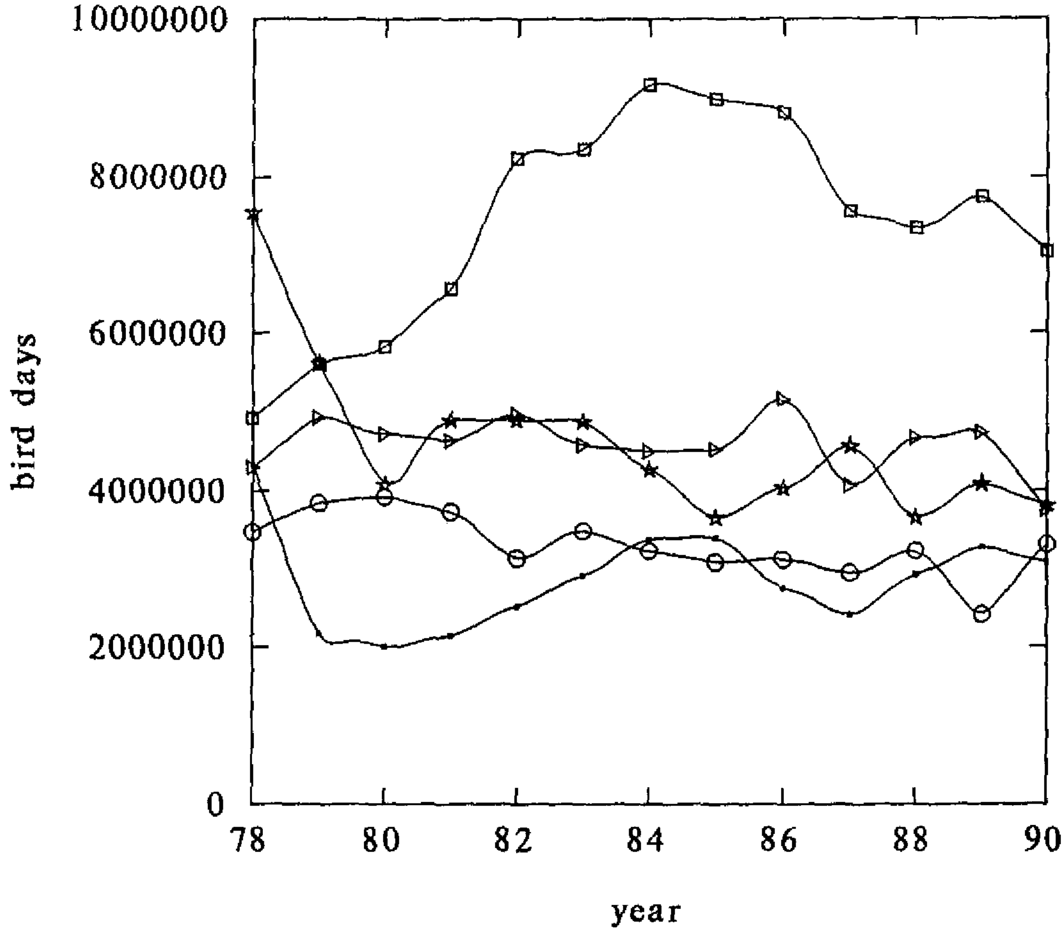
10



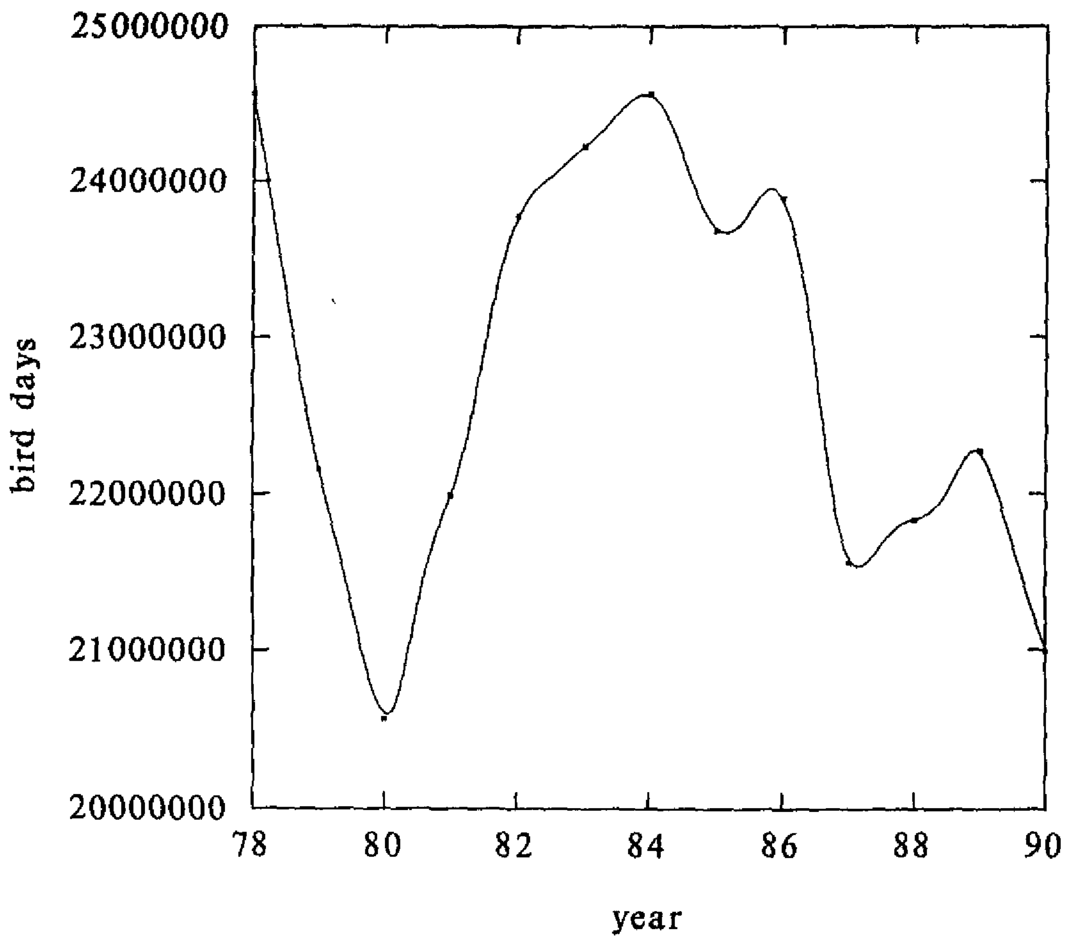
60000
50000
40000
30000
20000
10000
0
impute
0
10000
20000
30000
40000
50000
6000(
count



100000
10000
1000
100
impute
100
1000
10000
10000
count


10000000
8000000
6000000
4000000
2000000
0
bird days
78
80
82
84
86
88
90
year

11*a*


25000000
24000000
23000000
22000000
21000000
20000000
bird days
78
80
82
84
86
88
90
year

11*b*