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PREDICTION OF PACIFIC OYSTER SET INTENSITY IN DABOB BAY

by

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INTRODUCTION

The purpose of predicting the setting intensity of Pacific oysters (*Crassostrea gigas*) in Dabob Bay is to advise the industry on the likelihood of achieving an adequate set of spat on commercial shell strings. If the strings have been placed in the bay and an inadequate set of less than 10 spat per shell occurs, then the industry suffers an economic loss. Missing a set by not having placed cultch in time can mean an even larger loss of potential profits. Thus, a heavy dependence is placed by the industry on the Washington State Department of Fisheries' forecast of oyster larvae set intensity.

Dabob Bay is a deep, fiord-like arm of Hood Canal. It is protected from severe tidal currents by an underwater sill near the Hood Canal toll bridge, which allows a stratified body of warm water to develop during the summer months. The warm water layer becomes the rearing medium for the free-swimming oyster larvae, which cannot survive below 63°F. Once the larvae reach a size of 300μm, they attach to a suitable substrate, such as a clean oyster shell, and begin their sedentary life. Oyster shells are the most common cultch used; once the spat have attached to the shells they can be transported to any suitable growing area. Dabob Bay, Willapa Harbor, and Pendrell Sound in British Columbia are the only places on the West Coast where larvae survive well enough for commercial cultching operations. Oyster growers must either collect the spat themselves or import high-priced cultch from Japan. Once the seed is planted it grows very well in Puget Sound, but the profits for the industry are clearly reduced if the Japanese cultch has to be used.

The purpose of this report is to develop a prediction model for set intensity in Dabob Bay, and to estimate reliability parameters for the predictions. As the oyster industry increases, a heavier demand will be placed on domestically produced seed. Larval sets which might have been considered marginally profitable in past years will become more valuable to the industry. Accurately predicting the intensity of a set in the range from 3 to 15 spat per shell is very difficult by the current methods used. This report analyzes the prediction procedures as the data are collected now, and gives suggestions for future work into spat forecasting.

METHODS AND MATERIALS

Larval density counts are made from plankton samples taken with a multiple-depth running pipe sampler (Westley 1954). The sampler is towed behind a boat, forcing water up the pipes into a surge box. The water drains from this box through a 35μm mesh net. At the end of a sampling run the contents of the net are washed into a cup and a few drops of formalin are added. The formalin kills the oyster larvae and because they have a shell they sink to the bottom of the cup. The samples are decanted at the laboratory. This procedure drains off the algae and reduces the volume of water containing the larvae to a very small amount. The samples are then counted under a binocular microscope at approximately 3x magnification. Identification of the straight-hinge stage is difficult, but later stages are readily discernible from other bivalve larvae. The presence of large numbers of clam larvae and various crustaceans sometimes makes counting difficult. The total counts for each sample are computed to the number of larvae per 20 gallons.

Several environmental measurements are made for each sample. They include a bathythermograph drop, which gives temperature at various depths. The depth of the warm water layer, surface temperature, cloud cover, wind speed and direction, air temperature, and time of day are all recorded. The duration of the towing time for each sample is also recorded because the sampling transects are not all the same.

Once a week during the larval growing period the Washington State Department of Fisheries (WDF) issues an oyster bulletin to inform the industry of the prevailing conditions in relation to spat collection. Although no formal prediction is made, indications of the relative intensity of larval set are given.

Shell samples are taken during the period of setting to get a relative number of spat per shell. The samples are taken in the same areas that commercial cultching operations use. The only consistent sampling station over the years has been the Broadspit site, which is near the head of Dabob Bay. This site also produces the best cultching area.

Pacific oyster larvae data have been collected since 1950, but only the data from 1966-1975 were used in the model because of gaps in the earlier data. The early years (1950-1958) had incomplete records on hydrographic data. The middle years (1959-1965) were not sampled by WDF. Some samples were taken during these years but they were too limited for present use. Regular sampling has taken place since 1966.

The most important and most difficult variable to summarize was the larval counts. The difficulty arose in trying to separate the counts into distinct groups which could be followed from spawning to setting. Most spawnings occurred over a relatively short time period and were separated by enough time to be able to identify each spawning group easily. There are several exceptions, especially in years of high abundance when as many as three spawning groups were present in each plankton sample. The counts for each sample are divided into five size categories ranging from straight-hinge larvae of about 65μm to setting size larvae of about 300μm. Individual spawning groups generally do not fall within more than two size categories. Peaks of abundance and spaces between the peaks relating to the size categories were the methods used in categorizing larvae of each sample as to spawning group. Although somewhat subjective, this size frequency method was felt to be satisfactory for determining abundance of each spawning group within each sample.

The daily estimate of total abundance for a spawning group was the average of all the samples taken that day. Each day four to 10 plankton samples are taken, but counts from only the first five stations were used for the present analysis. Samples past station 5 and the samples taken before daylight or after dark were omitted in analysis because of their relative infrequency.

Larval count data were summarized as follows. First, the spawning date of each individual spawning group was determined from the weekly shell string counts and the plankton counts. The week in which a particular spawning group began setting was easily determined from the shell string counts. The particular day within this week that setting began was determined by noting significant losses of setting size larvae between two sampling days. Working backwards from the date of spawning for each group, the larvae counts were divided into those occurring 0-4 days, 4-8 days, and 8-12 days preceding the set. For those groups that could be detected in the samples more than 12 days before spawning, 12- to 16-day and 16- to 20-day periods preceding sets were also treated. Some groups apparently developed so fast due to warm temperature that the time between the first detection of a spawning group and setting was as short as 12 days.

The bathythermograph data were summarized by plotting temperature versus depth and then computing the area of each graph above 60° F. In most cases 60° F. was near the thermocline depth, so the number computed was a reflection of both temperature and depth of the warm-water layer, or, in effect, a measure of the total heat available. The surface temperature measurement at the beginning of each sample was also used in various prediction models attempted. Tide, time of day, and cloud cover were coded as "dummy" variables, receiving 0 or 1 values. Tides below +2.0 feet, samples taken after 12 noon, and days with 95 percent or greater cloud cover were coded 1; tides greater than +2.0 feet, samples before 12 noon, and days with less than 95 percent cloud cover were coded 0.

The set strength statistic was computed from spat counts on clean shell strings placed out each week, allowed to accumulate spat for 1 week, and then pulled. No two spawning groups had significant setting within the same week; however, some spawning groups set over 2 (or occasionally more) consecutive weeks. In the latter cases, the weekly counts were summed for the measure of set strength.

A multiple regression model using the six variables described above as the "independent" variables was used to predict the total number of spat per shell (dependent variable) for a spawning group. Larval numbers, surface temperature, and the bathythermograph statistic were thought to be likely candidates for predictive, or explanatory, variables. The three "dummy" variables were included for the purpose of reducing the sampling variance associated with these potential sources of error; they are not predictive variables in themselves. The regression coefficients and associated statistics were computed using the SPSS (Statistical Package for the

Social Sciences) regression subprogram with the University of Washington's CDC 6400 computer. Regressions were run for each of the time periods preceding setting (0-4 days, etc.) using various combinations of variables, transformations and data splits. The transformations used on the larval count and set variables were ln (X + 1) and ln (ln (X + 1) + 1) (ln = natural logarithm). The regressions attempted included untransformed counts, ln counts, ln-ln counts, and various combinations of these. The spawning groups were split into those early in the season and those late. Separate regressions were run predicting set intensity from the larval densities at the various 4-day time intervals preceding set. Other ways that the data were split included clear versus cloudy days, and sets less than 22 spat per shell versus sets greater than 22. The results of these regressions are summarized in Appendix A, Tables 5-9.

To indicate the predictive precision of certain of the relationships, 80 percent confidence intervals for spat numbers were calculated for several example circumstances. Standard formulas (*see* below) were used. However, because of the computational difficulty of calculating confidence intervals for multiple regression models with more than two independent variables, we restricted our computed 80 percent limits to regression models wherein only two (of the potential six) independent variables, ln-count and surface temperature, were included. In cases where more than two independent variables are significant, confidence limits as we computed them would be somewhat too wide. However, even where additional variables beyond the first two were statistically significant, they did not usually reduce the unexplained variation in spat numbers very greatly, from a practical standpoint. The prediction equations themselves in most cases will include a different set of the independent variables than larval count and surface temperature. Thus, our confidence limits are intended to offer a rough, conservative indication of expected precision.

The confidence interval estimation following Zar (1974) used the form:

$$\hat{Y} \pm t_{\alpha,d.f.} \; S_{\hat{Y}}$$

$\hat{Y}$ = estimated set from regression

$t_{\alpha,d.f.}$ = student's t-statistic

$S_{\hat{Y}}$ = standard error of Y-estimate

the formula used for computing $S_{\hat{Y}}$ value is:

$$S_{\hat{Y}} = \sqrt{S^2_{Y\cdot 1,2}\ (1 + 1/n + \sum_{j=1}^{m} \sum_{k=1}^{m} C_{jk}\ \chi^*_j\ \chi^*_k)}$$

$S^2_{Y\cdot 1,2}$ = residual mean square

C_{jk} = element of the inverted corrected sum of squares and cross products correlation matrix

$$\chi^*_j = X_j - \overline{X}_j$$

$$\chi^*_k = X_k - \overline{X}_k$$

$$C_{jk} = \frac{d_{jk}}{\sqrt{\Sigma\chi_j{}^2\ \ \Sigma\chi_j{}^2}}$$

d_{jk} = element of the inverted correlation matrix

$$\Sigma\chi_j{}^2 = \Sigma X_j{}^2 - (\Sigma X_j)^2\ /n$$

$$\Sigma\chi_k{}^2 = \Sigma X_k{}^2 - (\Sigma X_k)^2\ /n$$

j subscript = transformed larval counts

k subscript = surface temperature

RESULTS AND DISCUSSION

The basic design of the prediction models is a multiple linear regression of the form:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon$$

Y = set in spat/shell

X_1 = larval count in no./20 gals.

X_2 = bathythermograph statistic °F ft.

X_3 = surface temperature °C

X_4 = tide (0, 1)

X_5 = time of day (0, 1)

X_6 = cloud cover (0, 1)

ε = error

The SPSS program enters the variables into the regression equations by a forward stepwise inclusion method. At each step the program enters the variable which best describes the remaining unexplained variance in the dependent variable and computes the corresponding β and R^2 values.

The means and variances among counts for each time period within a spawning group were computed (Table 1). Figure 1 is a sample of the data points of Table 1, selected to show the distinct increase of sample variance with the sample mean. Table 2 and Figure 2 show that the variance of the log-transformed counts does not increase with the mean.

Figure 3 shows the relationship between the transformed 0-4 days larval counts and the intensities of the sets. A monotonically increasing curve, which was also found (but not graphed) for the 4-8 days and 8-12 days relationships, is clearly evident. For this reason a transformation was also taken on the set variable.

These transformations still left a higher degree of variance than might be expected from normal sampling randomness under a tightly controlled sampling design. The most perplexing problem is the high variance of larval counts between adjacent or nearly adjacent sampling days. There are many examples of high counts one day, low counts the next, high counts the third day, and so on. It appears that the high variance is due to substantial vertical movement of the larvae in response to light intensity. Work done at Pendrell Sound has shown that Pacific oyster larvae do have vertical movement patterns which are affected by light intensity and tides (Quayle 1974). This work has also shown that the larvae tend to be deeper during the day and at low water or very low tide cycles. (The phototaxic effect suggested by such research may explain the good correlation we found between the occurrence of relatively high morning counts and overcast days which resulted in significantly high F-values for the cloud cover "dummy" variable.) Since the running sampler reaches a depth of only 5 feet, the variability created by a substantial vertical shift of larvae is clear.

It is believed that the larvae have a clumped distribution pattern in the bay, so some of the variance between adjacent daily counts would be explained by sampling randomness. Because much of the variance may be due to factors which were recorded, such as cloud cover, tide, and time of day, the potential existed for sorting out such causes of variance and thereby improving prediction models through the "dummy" variable technique.

The estimate for set intensity is made from the count of 10 shells per week taken from Broadspit, a narrow point of land near the head of Dabob Bay. Most commercial cultching operations take place here because it is easy to anchor the cultch rafts, and the best sets have historically taken place near the head of the bay. In the past few years additional shell counts have been made at Point Whitney and Quilcene Bay, but the data were too limited for application to the model. The accuracy with which the Broadspit estimate reflects the industry average spat fall has not been determined. The spat counts were all in the correct range of industry set intensity, although there is substantial variability. In some years, the seasonal cultch string counts are much higher than the sum of the weekly string counts. Seasonal shell strings are of course left in the saltwater much longer than the weekly strings, and become fouled with algae. Fouled shells do not allow as heavy a set as clean shells, so it is inconsistent that seasonal strings would have a much higher count than weekly strings. Substantial differences are evident between the Point Whitney and Broadspit counts, also. Wind and tidal currents can move the bulk of the larvae up and down the bay several times before setting occurs so there is no guarantee that the best cultching area will always be at Broadspit. Differences in set intensity also occur between shells that are covered and not covered, and between shells on the beach and those on floats. Application of the prediction model assumes that the dependent variable (industry expected spatfall) is measured with zero variance by the Broadspit counts, which is clearly not the case. This problem may be the biggest drawback to producing an accurate prediction model from available data. It should be borne in mind when assessing our confidence limits.

Surface temperature was the second most important variable in the prediction equations following larval count. Differences in time of day sampled is a significant source of error of this variable because changes in temperature can be so rapid. Morning and afternoon temperatures on a particular day can vary by several degrees on the centigrade scale. But future sampling design should attempt to develop a standard temperature measure for prediction.

Because the winds can play such an important role in the success of a spawning group, it is unfortunate that good wind data are not available. Strong winds can mix the warm water layer with the colder water underneath and virtually wipe out a spawning group. This occurred in 1975 when a good set was expected. North winds will push the warm water to the mouth of the bay where mixing will occur with the colder water of Hood Canal. This will kill the larvae and also move them away from the main cultching area at Broadspit. Wind data are collected at the time of sampling but it does not reflect the daily patterns that cause the large mortalities of larvae. Most sampling has been done in the morning, whereas heavy winds are commonly an afternoon or evening occurrence.

Quilcene Bay is often an important factor in the success of a cultching operation. Set intensity is often higher here than in Dabob Bay. Quilcene Bay sampling has been sporadic until the last few years so we had to exclude Quilcene Bay counts from our analysis. A separate prediction model should be developed for this body of water when sufficient data have been collected.

The major purpose of our effort has been to produce the best possible relationships to predict expected set intensity given the data to date. These relationships are summarized in Table 3. For example, if one were attempting to predict a set from an early season spawning (prior to August 7) for which the larvae had reached a stage wherein set was expected within 4-8 days, each sample would provide input to the following equation:

$$Y = -5.4003 + .6011\ (\ln \text{count}) + .4048\ (\text{temperature } ^{\circ}\text{C}) - .3486\ (\text{tide}) - 1.0818\ (\text{cloud}).$$

Tide and cloud cover would be given 0 or 1 values as appropriate. The Y values of the several samples would be averaged, with the antilog of the mean of these then being the estimated set intensity.

Confidence intervals for set intensity can be estimated by using the equations in Table 4.

As mentioned previously, the data were regressed in many combinations to determine the best predictive relationship. Tables 5 through 9 show some of the combinations tried. From Table 5 it can be seen that the natural logarithm transformation yielded the best predictions. The ln-ln transformation did not significantly increase the R^2 values. The next three tables show the results of splitting the data. The early versus late sets entered the surface temperature variable first or second in five of the six regression equations. Why temperature correlated better with the data split like this is not clear. Possibly the relationship between temperature and set is not linear, and therefore splitting the data in this manner put the particular spawnings together in a linear fashion. The late sets used for the model were either very poor or very good. When a regression is run through the extreme ends of a curvilinear relationship, there is good fit to a linear model because there are no intermediate points to increase the error around the line. Hence, the addition of intermediate early sets may have diffused the temperature-set relationship. At any rate, since there is biological plausibility in a set-temperature relationship, it is probably useful for predictive purposes to split the data as such and make set intensity predictions from separate equations; one for early season and one for late.

Although all the spawnings usually take at least 15 days from the first appearance of straight-hinge larvae to the beginning of setting, during some years spawnings were not detected this early. In 1972 on both spawnings and in 1974, straight-hinge larvae appeared in very small numbers. However, samples taken several days later at the early-umbo stage showed that the spawnings were actually quite substantial. The water was then so warm during both years that it took only 12-13 more days until the onset of setting. If the sampling had been more intensive in these 2 years, the heavy concentrations of the straight-hinge larvae could possibly have been found; however, 12 days prior indication of a good set is still useful because it takes the industry about 7 to 10 days to lay out their cultch. Future sampling with more plankton tows should prove useful in detecting spawnings as early as possible.

A 12-16 days' prediction should be useful, but the 16-20 days', probably not, except as only a general indicator for years where weather indications are for cool temperatures. It would be unwise to formally predict an excellent set so far in advance even if the data looked good. Mortality rates are much higher and growth rates slower in cool weather. Wind mixing of the stratified layer is also much more likely to occur during cool weather because the warm layer is not as stable.

Determining the number of days until the beginning of setting is important so as to apply the correct prediction equation. This is not easy because the time from first appearance of straight-hinge larvae until setting ranges from 15 to 23 days and is dependent on temperature. Temperature cannot be accurately predicted for some weeks in advance, although current trends and extended weather forecasts given by the Weather Service provide a fair basis for predicting set timing within plus or minus 2 days.

A regression was run of the number of days between first appearance of a spawning group and setting, versus the average daily surface temperature over the remaining larval period (Figure 4). The average daily temperature was computed using the average of the recordings taken with the samples. On days when no samples were taken the previous sampling day's average was used. Such interpolation, combined with the fluctuation in surface temperature sampling previously discussed, make this relationship suspect, although the slope was negative, as biologically predicted, and the correlation was statistically significant ($P \leq 0.05$). A better correlation could possibly be developed by using the thermograph data from Point Whitney.

The confidence intervals (Table 4) increase in width as the mean set intensity increases. This is due to the fact that variance in set increases with mean larval abundance--the factor which caused us initially to use logarithms of both count and set data in analysis. The confidence intervals are quite wide for practical application to a prediction, and indicate the prevailing degree of uncertainty in predicting spatfall.

No attempt was made to develop a prediction model for the magnitude or timing of a spawning before it occurs. The phenomenon appears to be related to a number of factors for which there are very limited data. Bathythermograph data collected by the U.S. Navy in Dabob Bay and air temperatures from the Quilcene fish hatchery showed no clear correlations.

The need for this type of advance predicting is not as valuable as developing a prediction model once a spawning has occurred. However, it would certainly help the industry to prepare for a certain date if such a relationship could be developed.

CONCLUSIONS

The ability to predict oyster setting in Dabob Bay is hindered by sampling variance in both larval counts and measures of set intensity. Even with the high variances a definite relationship is evident between the strength of a set and the larval counts. The variance of the larval counts can be reduced by appropriate sampling design which considers time, tide, depth, and light intensity factors. Such a design would improve the accuracy of the predictions. The limiting factor for improving the sampling scheme is the funds available. There is already a fair amount of time and money expended on this project each year, and any substantial increase in the budget would certainly have to be weighed by the potential benefits. The goal of future work should then be to study the relationships using the existing funds available. The following discussion gives some suggestions.

The most important component of variance to minimize is that among the larval counts from individual spawnings. If this high variance is due to substantial vertical migrations, then the conditions that result in the highest concentration of larvae in the upper 5 feet must be determined. The work done by Quayle (1974) and his associates should apply directly to this problem. The Pendrell Sound system differs from Dabob Bay in that Pendrell Sound has a low salinity surface layer. This factor may make the comparison between the two systems not entirely parallel. To determine patterns of vertical migration, a series of 24-hour samples taken at various depths is planned for this summer. The samples will be taken with a pump at a station where there have typically been high concentrations of larvae. The 24-hour series will be repeated for various stages of larval development to determine if any differences in migration patterns exist among the stages. When the vertical movements are better understood, samples using the multiple-depth running sampler can be taken under the appropriate conditions to hopefully give more reliable estimates of larval abundance than in the past. Such counts, however, will not be applicable to the prediction models discussed in this paper. Relationships will have to be changed to incorporate the higher counts. Because of this, both the present sampling system and the new one will have to be taken simultaneously for a few years until the new relationship is understood. To prevent doubling of the budget required for this project, it is suggested that the different sampling procedures be used on alternate days. The regular morning samples could be taken Monday, Wednesday, and Friday, while the evening samples could be taken Tuesday, Thursday, and Saturday. Once the new relationship is determined the present system can be discontinued.

To get a more reliable estimate of set intensity more shells from different stations will have to be counted. Shell counts can be quite time-consuming so care should be taken not to expand this part of the project too much. One recommendation is that two more stations be set up in Dabob Bay at possible commercial cultching sites and counts made twice a week instead of once. Furthermore, attaching shell strings to different commercial floats would help.

If a good prediction of the average set for all of Dabob Bay could be made, then the relative set anywhere in the bay could be made by weighting the average setting time at that particular part of the bay. Setting intensity seems to be dependent on larval density of the surrounding water (Heritage et al. 1976). If such a relationship could be developed, commercial operations could be directed to cultch in the areas of the bay where the highest set was expected. This kind of advice is given in the present forecasting system, but no estimate of the intensity of a set can be made because of the limited shell sampling stations.

A continuous wind recording device would be valuable. Strong winds, especially from the north, are usually the factor which most influences the success or failure of a spawning. Although there is no way to predict the occurrence of such events, the probable effect of a wind storm would be more predictable with on-the-spot data on intensity and direction of the wind.

The method of taking surface temperature recordings should be standardized. The recordings should be taken at the same time every day, if possible.

Once a good predictive relationship can be developed with future work, it is hoped that accurate forecasts can be made with fewer samples. WDF should try to provide the service of spat forecasting as accurately as possible because of the investment involved, but at the same time should try to reduce the funds necessary for this service to the lowest possible level.

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Table 1. Mean of counts, variances, and sample sizes

Date of set	Spat/ shell	0-4/var (n)	4-8/var (n)	8-12/var (n)	12-16/var (n)	16-20/var (n)
8-20-66	641.5	68.5 3,804.6(5)	466.2 227,340(2)	696.5 337,020(2)	1,648.3 1,250,910(3)	927.0 583,200(2)
8-14-67	194.9	43.6 1,163.9(19)	1 .8 633.8(26)	129.7 6814.3(6)	74.4 32,263.3(9)	
8-28-67	3718.0	490.0 122,355(5)	3,996.4 3,810,329(7)	1072.4 2,463,983(5)	758.9 1,244,910(10)	
7-31-68	3.9	0.69 0.494(9)	0.83 0.229(4)	0.08 0.02(4)	0.50 0.333(4)	1.71 2.571(7)
8-22-68	10.3	39.3 4,270.0(18)	23.4 175.5(10)	63.9 972.5(15)	24.9 378.9(17)	484.4 241,659(5)
9-3-68	1.1	0.92 0.277(5)	0.40 0.489(10)	6.70 139.1(10)	24.6 1,608.9(10)	
8-18-69	3.9	1.16 0.346(7)	2.28 9.13(11)	2.85 1.18(12)	3.18 10.13(8)	10.25 30.73(16)
8-5-70	2.8	11.8 300.6(11)	15.0 122.0(15)	21.5 173.7(4)	39.4 694.8(7)	56.7 1,825.9(6)
8-17-70	1.6	0.24 0.178(9)	0.65 0.409(10)	8.46 42.95(8)	25.91 2,019.5(11)	18.00 172.0(3)
9-4-70	1.0	1.65 4.77(13)	5.48 8.76(8)	21.63 402.6(8)	22.75 1025.1(8)	33.82 2,317.0(11)
8-10-71	25536	781.2 693,901(11)	6,860.6 25,986,055(9)	5060.9 18,211,768(10)	2137.1 2,287,317(11)	3014.8 1,761,527(8)
8-27-71	2017	615.0 61,075(3)	136.0 1,756.0(3)	811.5 1,015,313(2)	1415.7 1,495,996(6)	5803.8 17,285,603( )
8-4-72	39.8	21.3 377.5(21)	14.6 330.7(9)	33.3 605.6(9)		
8-17-72	317.1	479.6 236,338(16)	1912.5 1,910,021(8)	1357.7 1,615,453(8)		
8-16-73	21.5	144.7 22,639(17)	147.3 22,113(13)	142.0 9,336(14)	131.5 21,380(8)	
8-31-73	0.9	10.63 277.3(15)	12.65 148.9(15)	10.5 116.6(20)	429.8 180,996(10)	1097.3 2,418,646(16)
8-16-74	152.1	340.8 108,379(11)	334.1 80,471(15)	383.7 167,560(19)		
8-26-74	334.0	225.0 2644(15)	72.3 3,228(14)	391.8 87,002(14)	1513.5 2,198,705(2)	
8-20-75	2.2	8.4 47.5(20)	22.2 489.3(23)	14.2 910.5(2)	77.1 11,715.3(12)	105.9 1325.1(11)
8-26-75	0	0 0(2)	33.4 538.7(6)		134.1 16,667(12)	1110.2 1,790,190(1)

Table 2. Mean and variances of transformed counts

Date of set	Ln set intensity	0-4/var	4-8/var	8-12/var	12-16/var	16-20/var
8-20-66	6.465	3.31 4.360	5.78 1.661	6.33 0.912	7.13 1.102	6.63 0.885
8-14-67	5.278	3.43 0.973	2.29 1.704	3.44 3.206	3.10 5.509	
8-28-67	8.221	5.90 0.978	8.21 0.190	5.76 3.442	5.48 3.179	
7-31-68	1.589	0.44 0.190	0.58 0.071	0.066 0.017	0.347 0.160	0.867 0.301
8-22-68	2.425	3.01 1.307	3.06 0.309	3.98 0.620	2.86 1.125	5.61 1.699
9-3-68	0.742	0.626 0.624	0.248 0.172	1.241 1.544	1.695 3.876	
8-18-69	1.589	0.737 0.074	0.849 0.716	1.330 0.094	1.181 0.577	2.313 0.223
8-5-70	1.335	1.79 1.547	2.43 0.764	2.96 0.440	3.54 0.380	3.79 0.699
8-17-70	0.956	0.180 0.076	0.435 0.144	2.06 0.422	2.18 2.191	2.70 0.923
9-4-70	0.693	0.786 0.342	1.77 0.226	2.73 1.011	2.22 2.547	2.75 2.560
8-10-71	10.148	6.26 0.881	8.56 0.652	8.27 0.573	7.38 0.749	7.91 0.273
8-27-71	7.609	6.37 0.139	4.88 0.112	5.97 3.71	6.91 0.880	8.23 1.493
8-4-72	3.709	2.79 0.742	2.11 1.488	3.28 0.620		
8-17-72	5.762	5.38 1.420	7.40 0.320	6.44 2.774		
8-16-73	3.114	4.52 1.013	4.46 1.431	4.67 0.809	3.98 3.142	
8-31-73	0.642	1.73 1.426	2.08 1.309	1.88 1.383	5.59 1.131	6.26 1.700
8-16-74	5.031	5.41 0.905	5.44 0.865	5.33 1.538		
8-26-74	5.814	3.95 0.707	3.99 0.766	5.58 0.849	7.00 1.456	
8-20-75	1.163	1.92 0.792	2.59 1.355	1.47 1.865	3.06 3.090	3.97 1.750
8-16-75	0	0	3.36 0.429		3.72 4.535	5.89 3.742

Table 3. Regression coefficients for recommended prediction equations

Regression	Constant α	Ln count $\beta1$	Btg $\beta2$	Temp $\beta3$	Tide $\beta4$	Time $\beta5$	Cloud $\beta6$
0-4 Early	-6.1072	0.5521	0.0089	0.4171	0	0	-1.1963
4-8 Early	-5.4003	0.6011	0	0.4048	0	-0.3846	-1.0818
8-12 Early	-17.7653	0.0003	0	1.1172	0.6923	0	0
0-4 Late	-8.6847	0.6596	0	0.6490	-1.4404	0	-0.9362
4-8 Late	0	0.9559	-0.0111	0	-1.6878	-3.9949	0
8-12 Late	-16.9501	0.3024	-0.0098	1.0184	1.2532	1.7957	0
0-4 Comb.	-3.3949	0.8034	0	0.2912	0	0	-1.1845
4-8 Comb.	-1.1648	0.8365	0	0	-0.6221	1.2478	-1.0000
8-12 Comb.	-15.0128	0.0003	0	0.9731	0.7481	0	-0.6408
12-16 Comb.	-20.1817	0.2307	0	1.2208	0	-1.3512	0
16-20 Comb.	-20.4816	0.0776	0.0102	1.1096	0	0.7456	0

Table 4. Confidence interval coefficients and examples of 80 percent limits for set intensity at various levels

$$Y \pm t_{(2)\ \text{d.f.}}\ s_Y$$

$$s_Y = \sqrt{s^2_{Y.1,2}\ (1 + 1/n + \sum_{j=1}^{m} \sum_{k=1}^{m} c_{jk}\ \chi^*_j\ \chi^*_k}$$

Note: See text for explanation of terms.

Regression	$s_{Y.1,2}$	$c_{11},\ c_{22}$	$c_{12},\ c_{21}$
0-4 Early	2.2617	0.00471	-0.00326
4-8 Early	2.4222	0.00396	-0.00281
8-12 Early	1.7204	0.00674	-0.00523
0-4 Late	1.8258	0.01010	-0.00783
4-8 Late	3.3116	0.00494	-0.00312
8-12 Late	1.9234	0.00904	-0.00718

Table 4. Confidence interval coefficients and examples of 80 percent limits for set intensity at various levels - Continued

Year	Regression	Actual Y Value (spat/shell)	Predicted Y Value (spat/shell)	Confidence interval (spat/shell)
1970	0-4 Early	3	2.62	$P(-0.21 \leq Y \leq 17.55) \geq .8$
	4-8 Early	3	6.53	$P(0.56 \leq Y \leq 16.44) \geq .8$
	8-12 Early	3	2.73	$P(-0.32 \leq Y \leq 20.17) \geq .8$
1972	0-4 Early	40	56.12	$P(7.10 \leq Y \leq 401.87) \geq .8$
	4-8 Early	40	24.93	$P(4.40 \leq Y \leq 123.47) \geq .8$
	8-12 Early	40	18.55	$P(2.56 \leq Y \leq 106.40) \geq .8$
1968	0-4 Late	1	2.57	$P(-0.40 \leq Y \leq 20.17) \geq .8$
	4-8 Late	1	0.05	$P(-0.91 \leq Y \leq 10.65) \geq .8$
	8-12 Late	1	0.52	$P(-0.75 \leq Y \leq 8.39) \geq .8$
1974	0-4 Late	334	133.66	$P(22.02 \leq Y \leq 786.93) \geq .8$
	4-8 Late	334	44.59	$P(3.23 \leq Y \leq 490.39) \geq .8$
	8-12 Late	334	41.83	$P(5.73 \leq Y \leq 271.75) \geq .8$

Table 5. Regression statistics for data from all spawnings and surveys

	0-4 days			4-8 days			8-12 days		
	Var.	F to enter	Multiple R	Var.	F to enter	Multiple R	Var.	F to enter	Multiple R
Dependent	Count	76.4*	0.526	Count	260.5*	0.748	Count	196.3*	0.733
variable	Btg	25.0*	0.598	Time	30.9*	0.786	Temp.	7.1*	0.746
SET	Time	11.5*	0.627	Btg	2.7	0.789	Time	3.7	0.752
	Cloud	9.5*	0.648	Tide	2.1	0.792	Tide	3.2	0.757
	Tide	4.8	0.659	Cloud	1.3	0.793	Btg	2.3	0.761
	-	-	-	-	-	-	Cloud	0.2	0.762
Dependent	LCNT	337.7*	0.792	LCNT	241.8*	0.737	Temp.	408.6*	0.841
variable	Cloud	41.2*	0.832	Cloud	29.6*	0.776	LCNT	20.8*	0.860
LSET	Temp.	13.1*	0.843	Time	13.8*	0.792	Tide	12.5*	0.871
	Tide	2.9	0.846	Tide	7.0	0.800	Cloud	9.6*	0.878
	Time	3.5	0.849	Temp.	2.9	0.803	Time	5.0*	0.882
	Btg	2.9	0.851	Btg	12.5*	0.816	Btg	0.0	0.882
Dependent	LLCT	361.3*	0.802	Temp.	108.9*	0.590	Temp.	477.2*	0.859
variable	Temp.	46.4*	0.843	LLCT	42.6*	0.678	LLCT	24.0*	0.878
LLST	Cloud	20.4*	0.859	Tide	11.0*	0.698	Tide	34.7*	0.900
	Tide	7.2*	0.864	Btg	9.0*	0.714	Cloud	29.5*	0.916
	Time	3.1	0.867	Cloud	2.0	0.717	Time	4.5	0.918
	Btg	1.5	0.868	Time	0.3	0.718	Btg	0.4	0.919

*Significant reduction in residual variance at the probability level of 5 percent or less.

Table 6. Regression statistics for data split between clear and cloudy larval sampling days

	0-4 days			4-8 days			8-12 days		
	Var.	F to enter	Multiple R	Var.	F to enter	Multiple R	Var.	F to enter	Multiple R
Dependent	LCNT	65.0*	0.823	LCNT	56.9	0.725	LCNT	65.1*	0.813
variable	Tide	4.8	0.823	Tide	3.2	0.725	Tide	19.3*	0.849
LSET,	Time	6.2*	0.826	Time	4.6	0.778	Time	1.2	0.849
clear	Btg	2.8	0.846	Btg	7.3	0.779	Btg	2.0	0.855
days	Temp.	3.7	0.852	Temp.	11.1	0.801	Temp.	2.7	0.860
Dependent	LCNT	87.9*	0.778	LCNT	97.7*	0.835	LCNT	13.1*	0.841
variable	Time	0.0	0.781	Time	6.4*	0.839	Time	1.1	0.845
LSET,	Tide	6.5*	0.798	Tide	14.1*	0.862	Tide	3.4*	0.854
cloudy	Btg	0.7	0.803	Btg	2.2	0.867	Btg	0.9	0.858
days	Temp.	0.0	0.803	Temp.	0.2	0.868	Temp.	23.5*	0.896

Note: Regression method for these combinations was not a forward, stepwise, inclusion process.

* Significant reduction in residual variance at the probability level of 5 percent or less.

Table 7. Regression statistics for data split between early and late sets. (Date of split was Aug. 7)

	0-4 days			4-8 days			8-12 days		
	Var.	F to enter	Multiple R	Var.	F to enter	Multiple R	Var.	F to enter	Multiple R
Dependent	LCNT	153.2*	0.744	Temp.	145.2*	0.726	Temp.	251.3*	0.843
variable	Temp.	32.0*	0.804	LCNT	21.9*	0.772	LCNT	16.5*	0.868
LSET,	Cloud	16.8*	0.831	Cloud	24.4*	0.813	Tide	7.2*	0.877
early	Btg	8.1*	0.842	Time	15.3*	0.835	Cloud	3.5	0.881
sets	Time	3.0	0.847	Tide	2.5	0.839	Btg	1.4	0.883
	Tide	1.4	0.849	Btg	1.9	0.841	-	-	-
Dependent	LCNT	200.1*	0.853	LCNT	134.0*	0.805	Temp.	135.8*	0.822
variable	Temp.	19.6*	0.886	Tide	9.0*	0.829	Time	36.7*	0.891
LSET.	Tide	12.2*	0.903	Time	13.5*	0.858	Tide	9.8*	0.906
late	Cloud	11.6*	0.917	Btg	4.3	0.867	Btg	4.0	0.912
sets	Btg	0.5	0.918	Cloud	0.4	0.868	LCNT	6.8*	0.921
	Time	0.4	0.918	-	-	-	Cloud	2.3	0.924

* Significant reduction in residual variance at the probability level of 5 percent or less.

Table 8. Regression statistics for data split between sets with less than 22 spat and sets with greater than 22

	0-4 days			4-8 days			8-12 days		
	Var.	F to enter	Multiple R	Var.	F to enter	Multiple R	Var.	F to enter	Multiple R
Dependent variable LSET, sets LT 22	LCNT	156.1*	0.784	Temp.	96.3*	0.680	Temp.	200.6*	0.817
	Btg	27.0*	0.836	LCNT	15.3*	0.726	LCNT	12.8*	0.839
	Temp.	5.9*	0.846	Time	8.9*	0.750	Tide	7.0*	0.851
	Time	0.9	0.848	Btg	4.2	0.761	Time	1.7	0.854
	Cloud	0.2	0.848	Cloud	1.7	0.765	Btg	1.4	0.856
	Tide	0.0	0.848	Tide	0.1	0.766	Cloud	0.0	0.857
Dependent variable LSET, sets GT 22	LCNT	38.3*	0.526	LCNT	91.4*	0.708	LCNT	54.8*	0.671
	Cloud	8.0*	0.575	Time	29.5*	0.790	Temp.	10.7*	0.726
	Time	6.8*	0.612	Btg	11.9*	0.818	Btg	15.7*	0.786
	Btg	1.2	0.618	Tide	4.0	9.827	Time	1.1	0.791
	Tide	0.4	0.620	Temp.	0.9	0.828	Cloud	1.6	0.797
	Temp.	0.1	0.621	Cloud	0.0	0.829	Tide	1.4	0.802

*Significant reduction in the residual variance at the probability level of 5 percent or less.

Table 9. Regression statistics for combined data

	12-16 days			16-20 days		
	Var.	F to enter	Multiple R	Var	F to enter	Multiple R
Dependent variable LSET	Temp.	345.6*	0.841	Temp.	130.4*	0.749
	Time	9.4*	0.852	Btg	3.3	0.758
	LCNT	5.3*	0.858	Time	1.9	0.763
	Cloud	2.8	0.860	LCNT	0.5	0.765
	Tide	0.4	0.861	-	-	-
	Btg	0.1	0.861	-	-	-

*Significant reduction in the residual variance at the probability level of 5 percent or less.

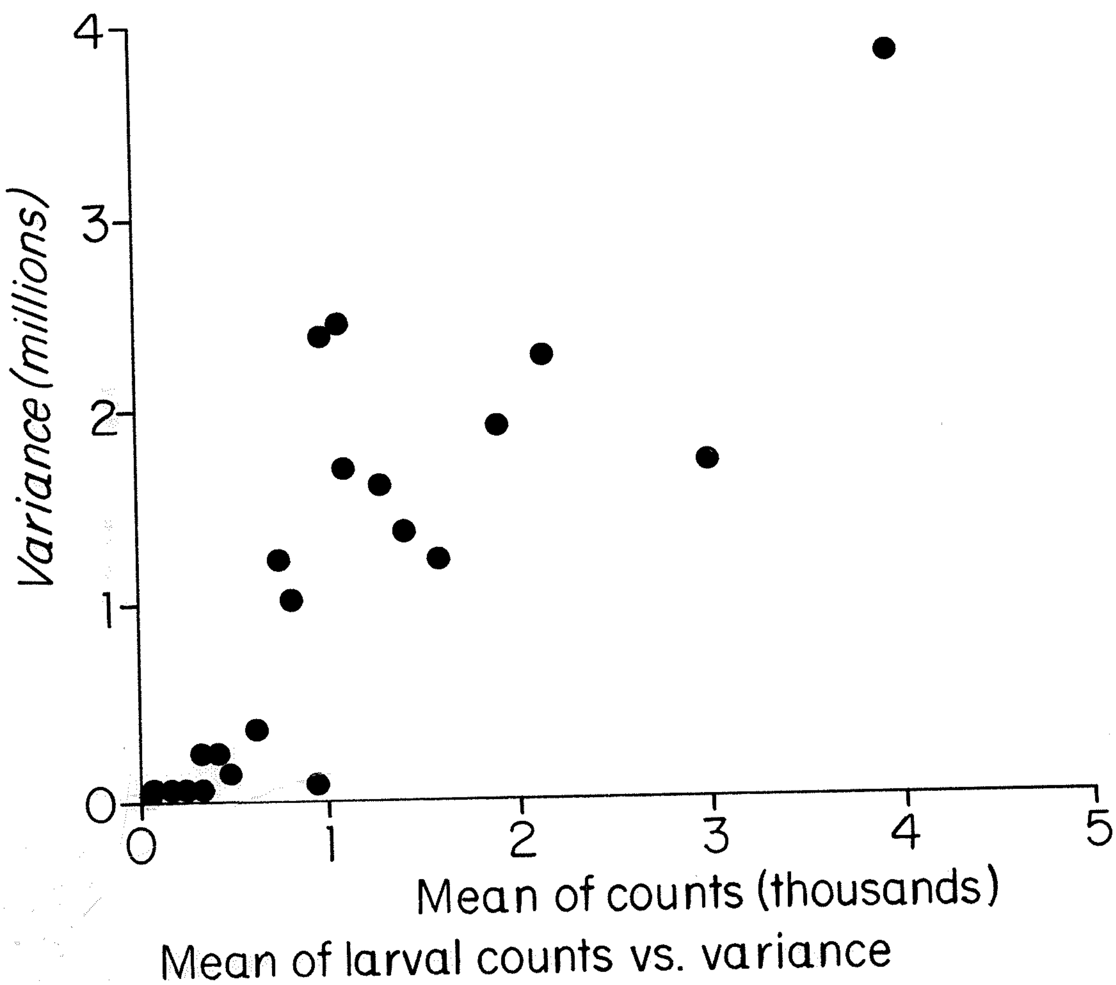


Fig. 1. Mean of larval counts vs. variance.

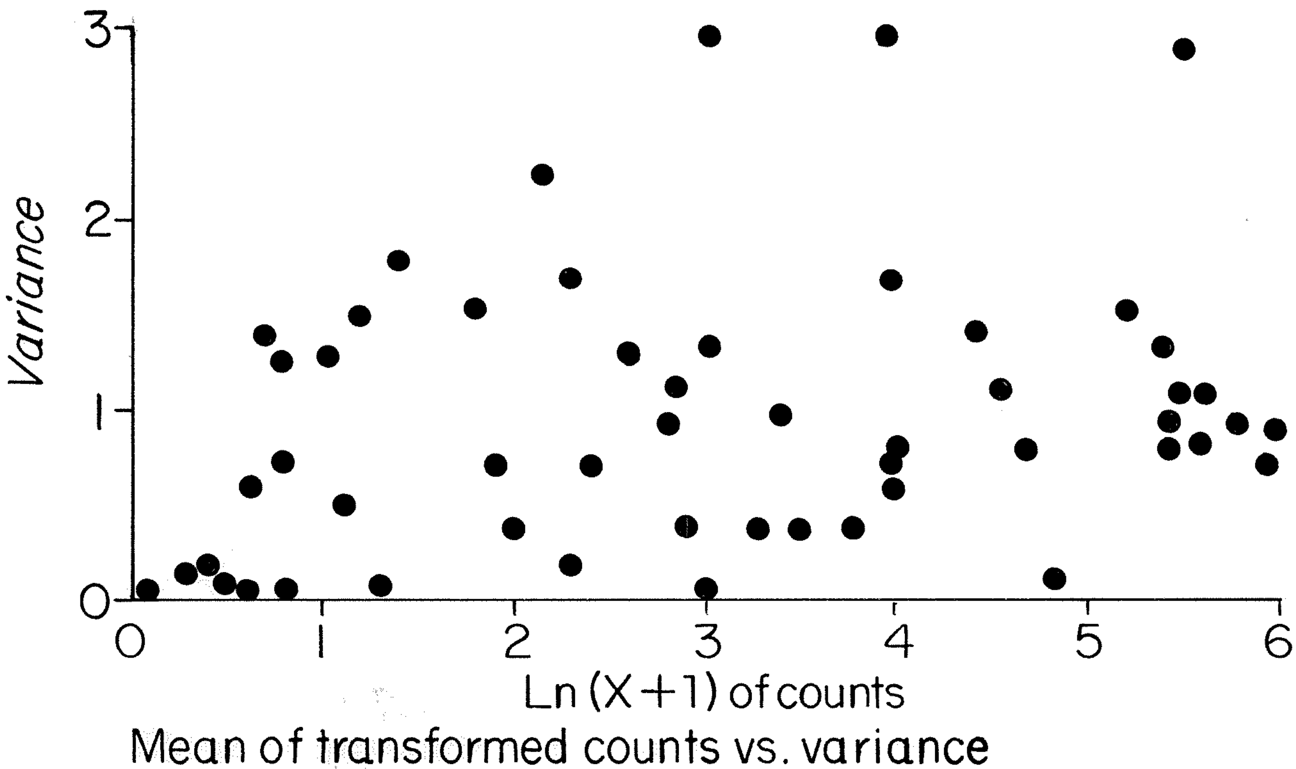


Fig. 2. Mean of transformed counts vs. variance.

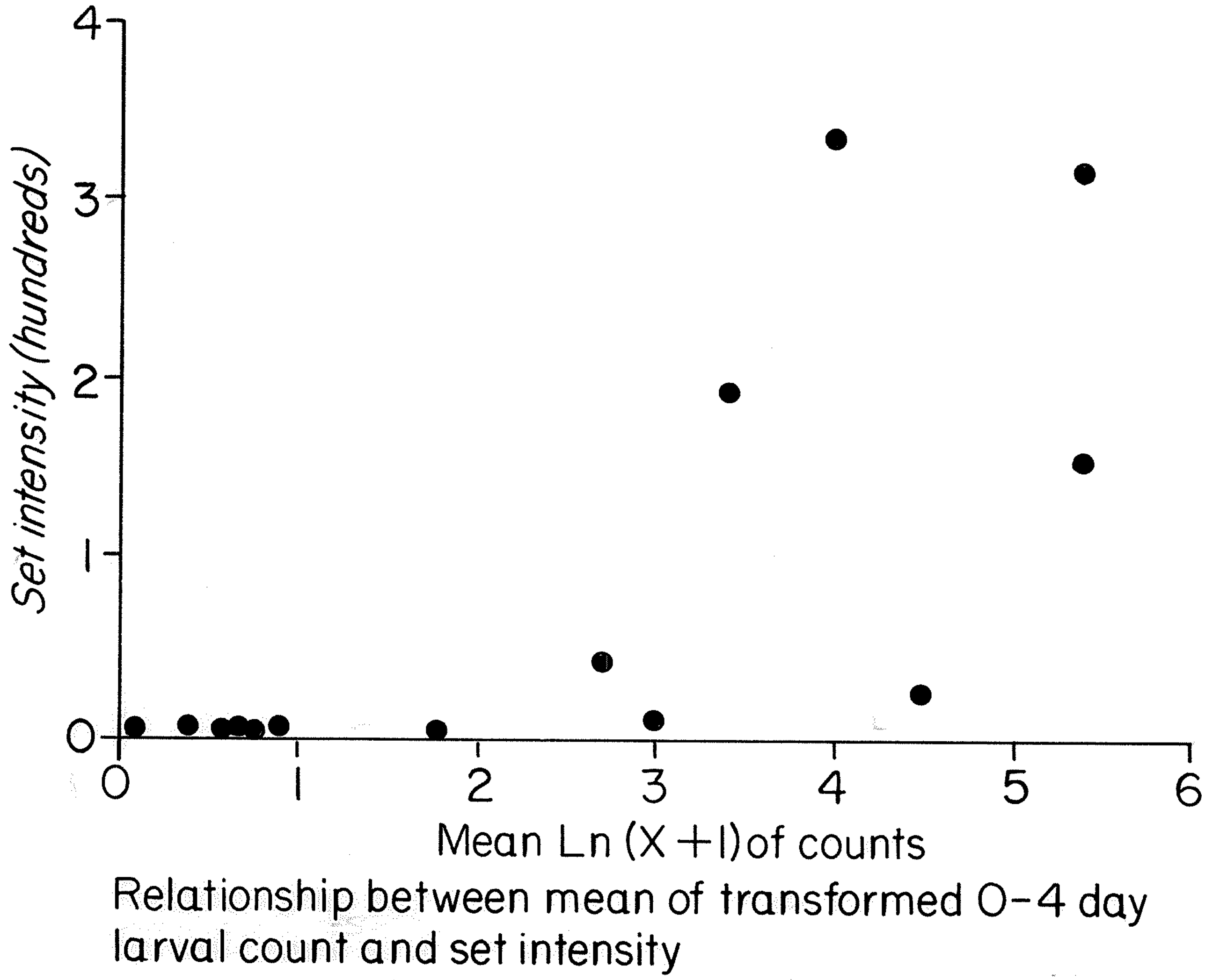


Fig. 3. Relationship between mean of transformed 0-4 larval counts and set intensity.

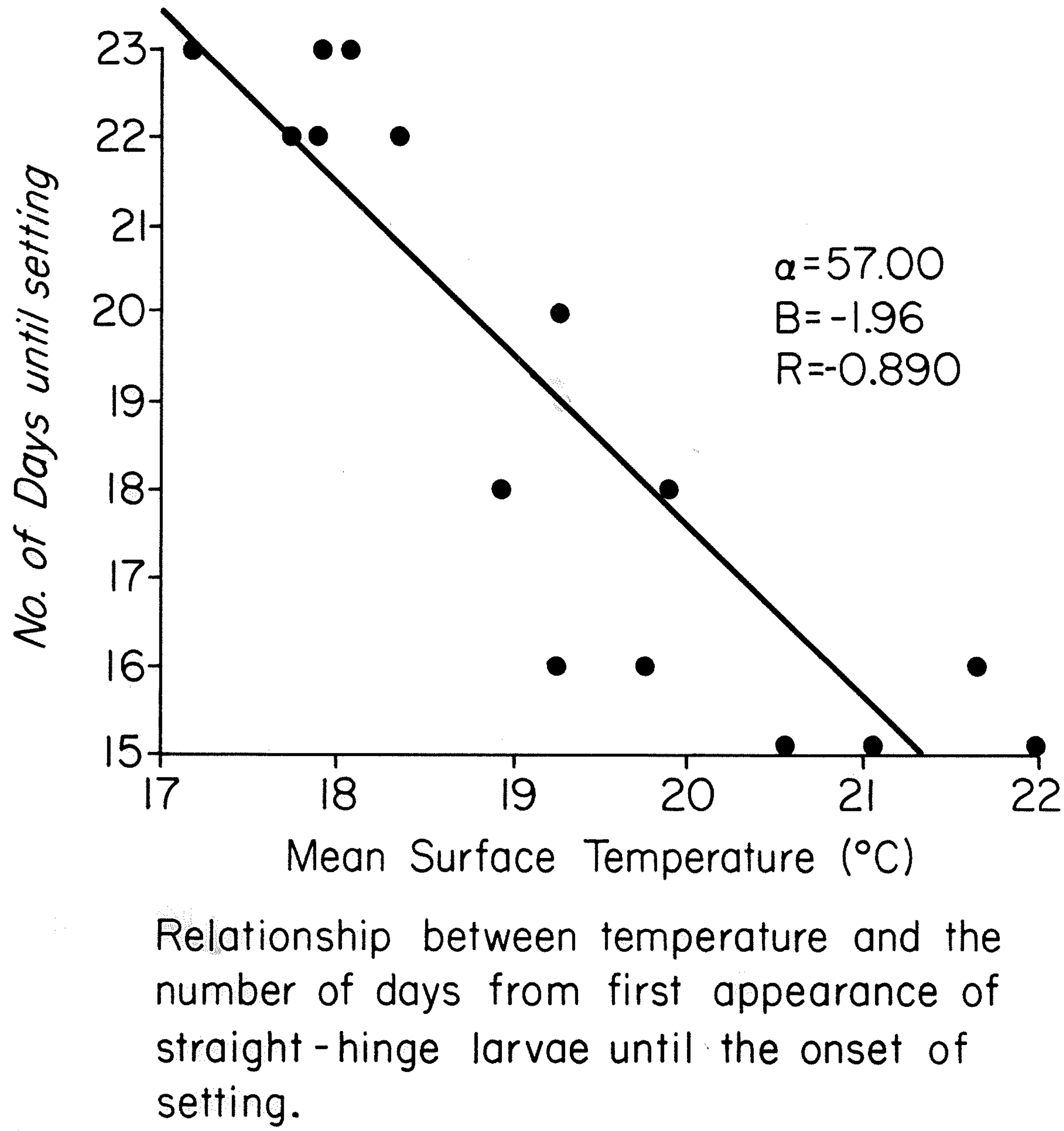
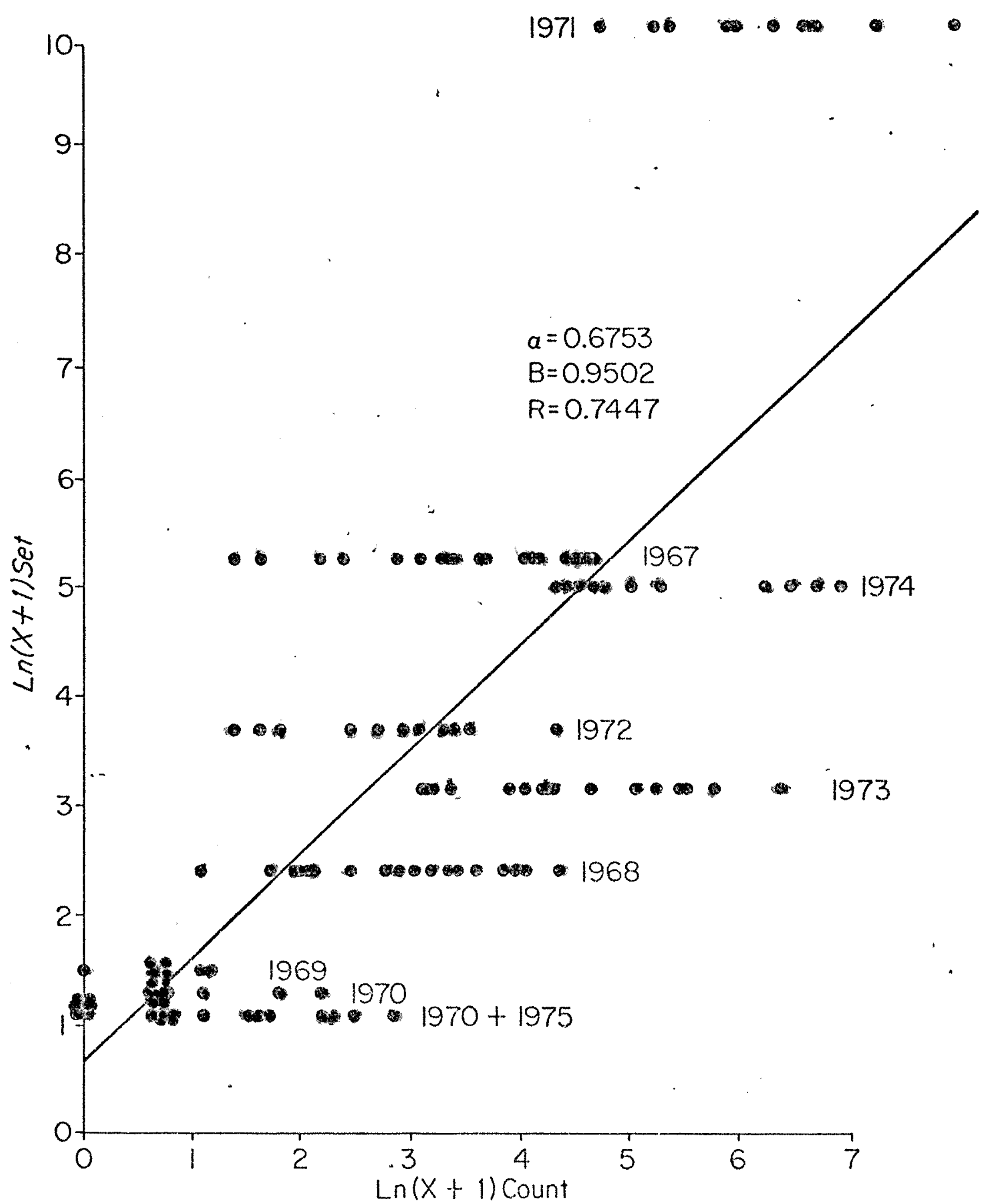
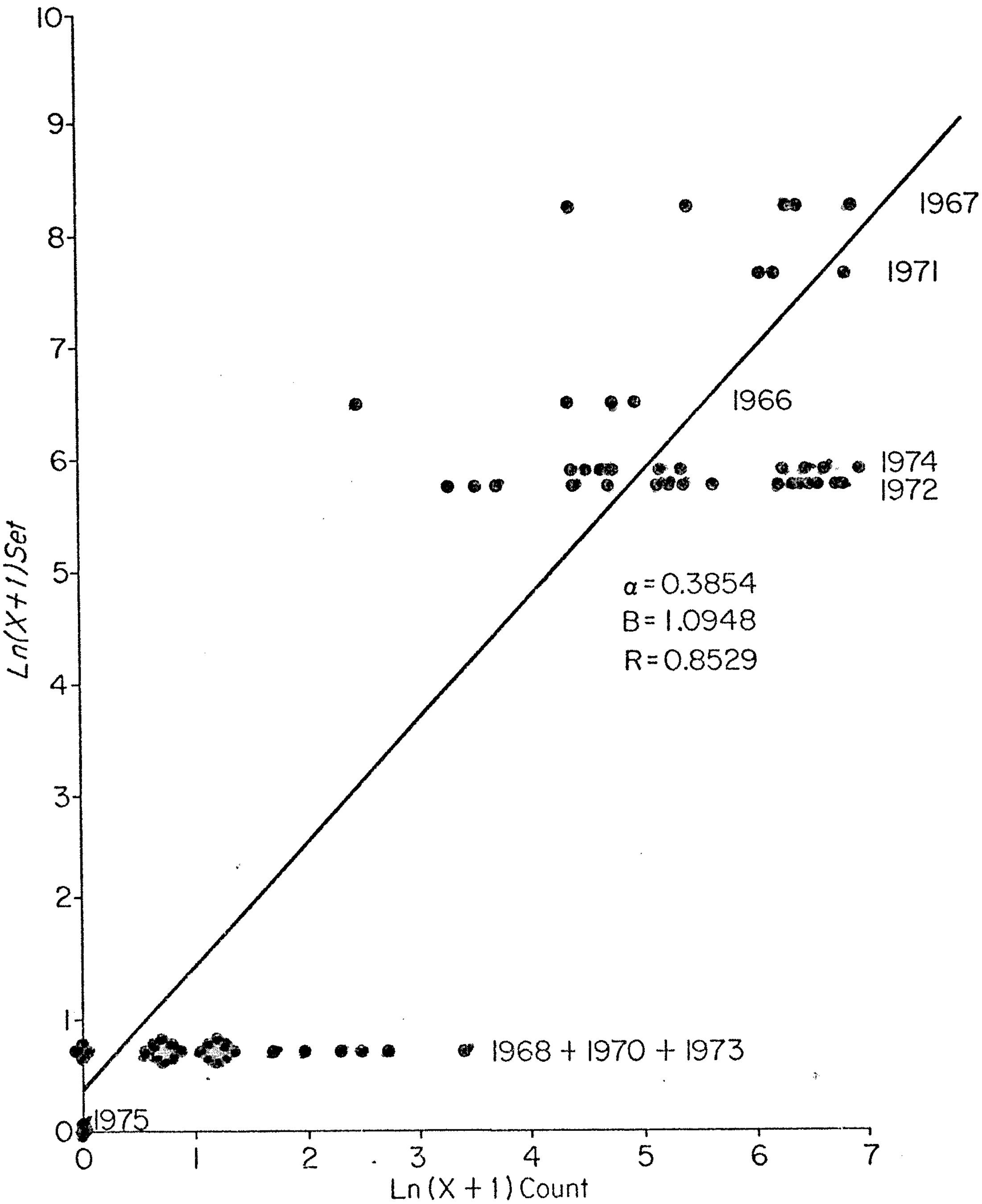


Fig. 4. Relationship between temperature and the number of days from first appearance of straight-hinge larvae until the onset of setting.

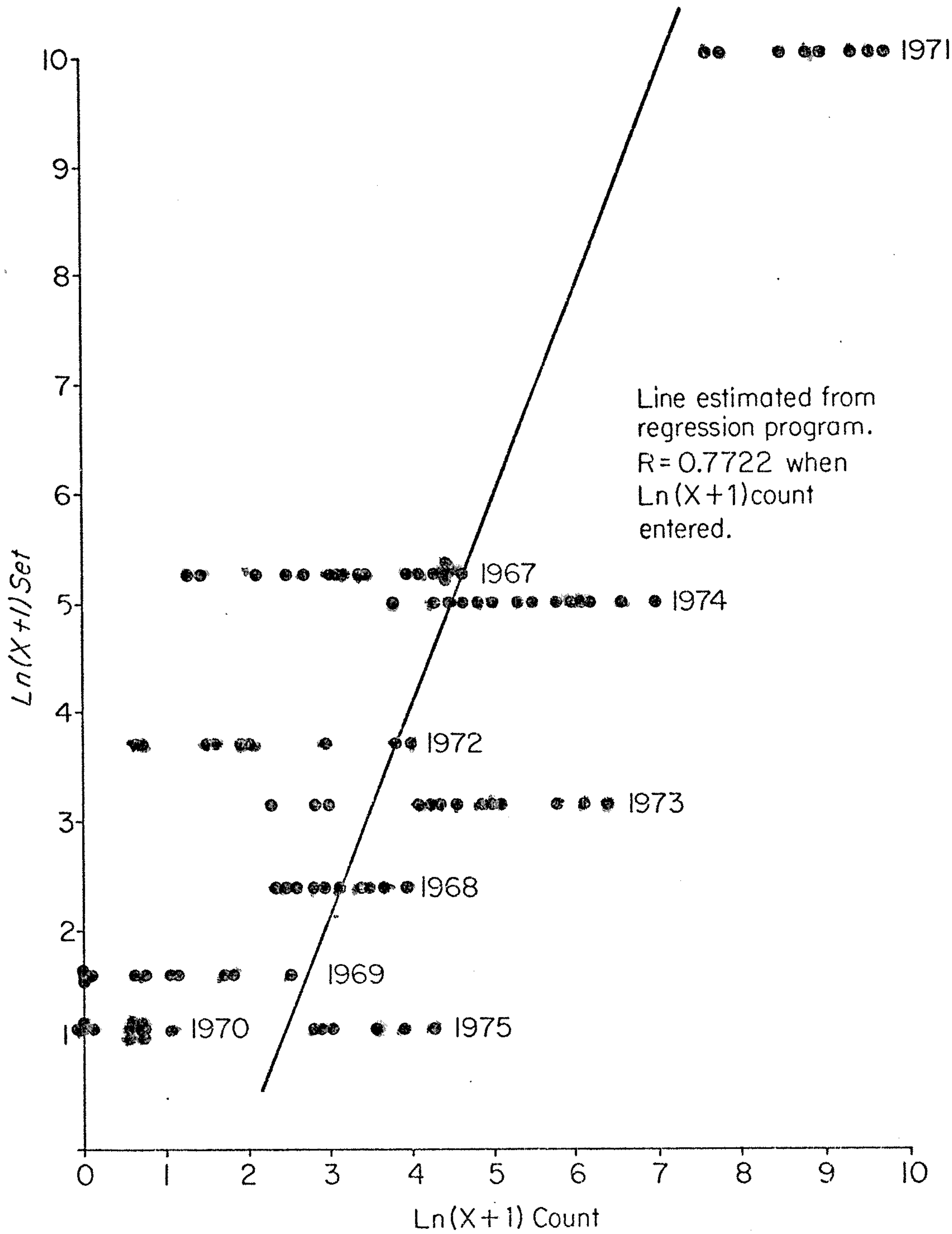
APPENDICES



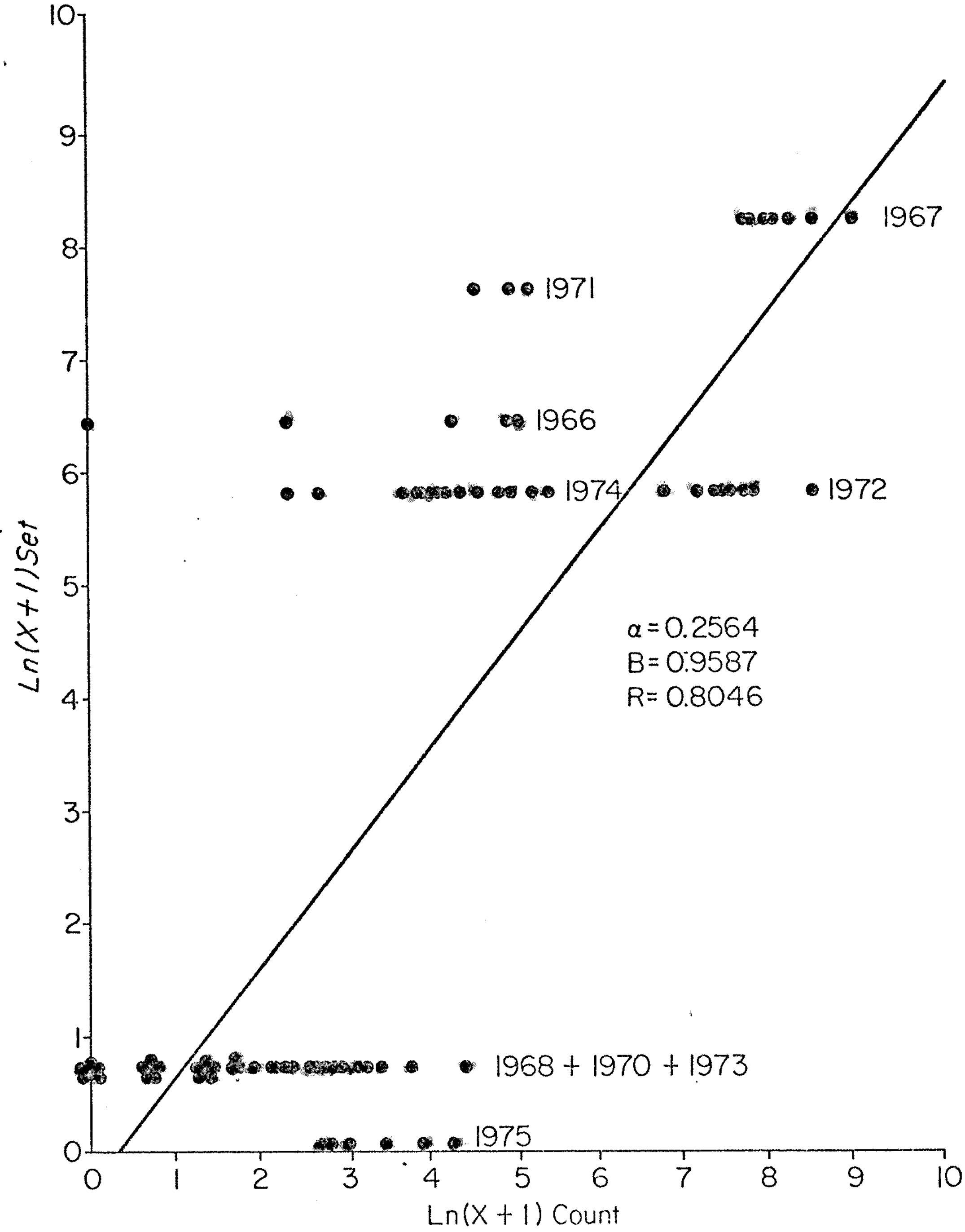
Graph 1A. Ln of count vs. Ln of set, 0-4 days, early spawnings



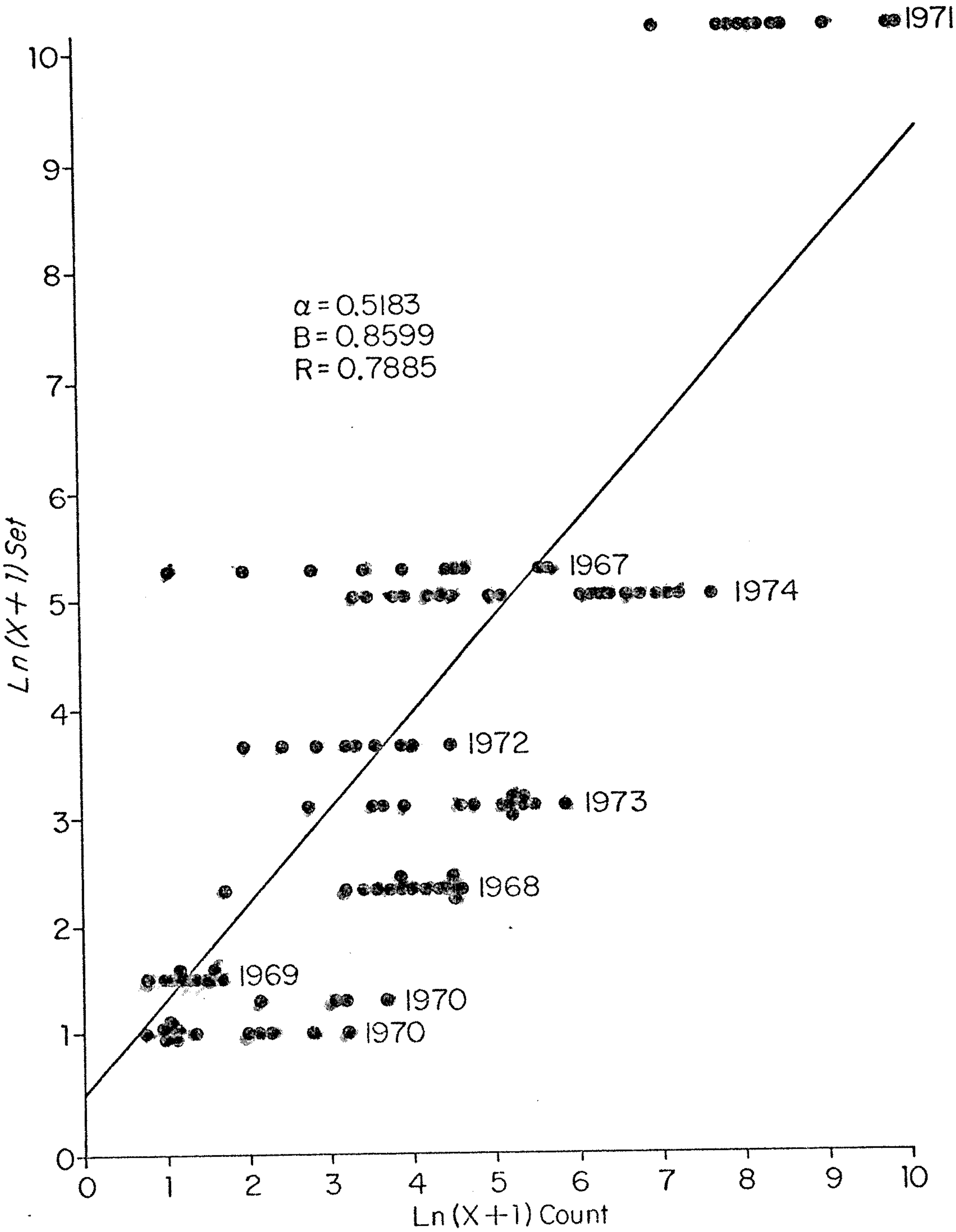
Graph 1B. Ln of count vs. Ln of set, 0-4 days, late spawnings



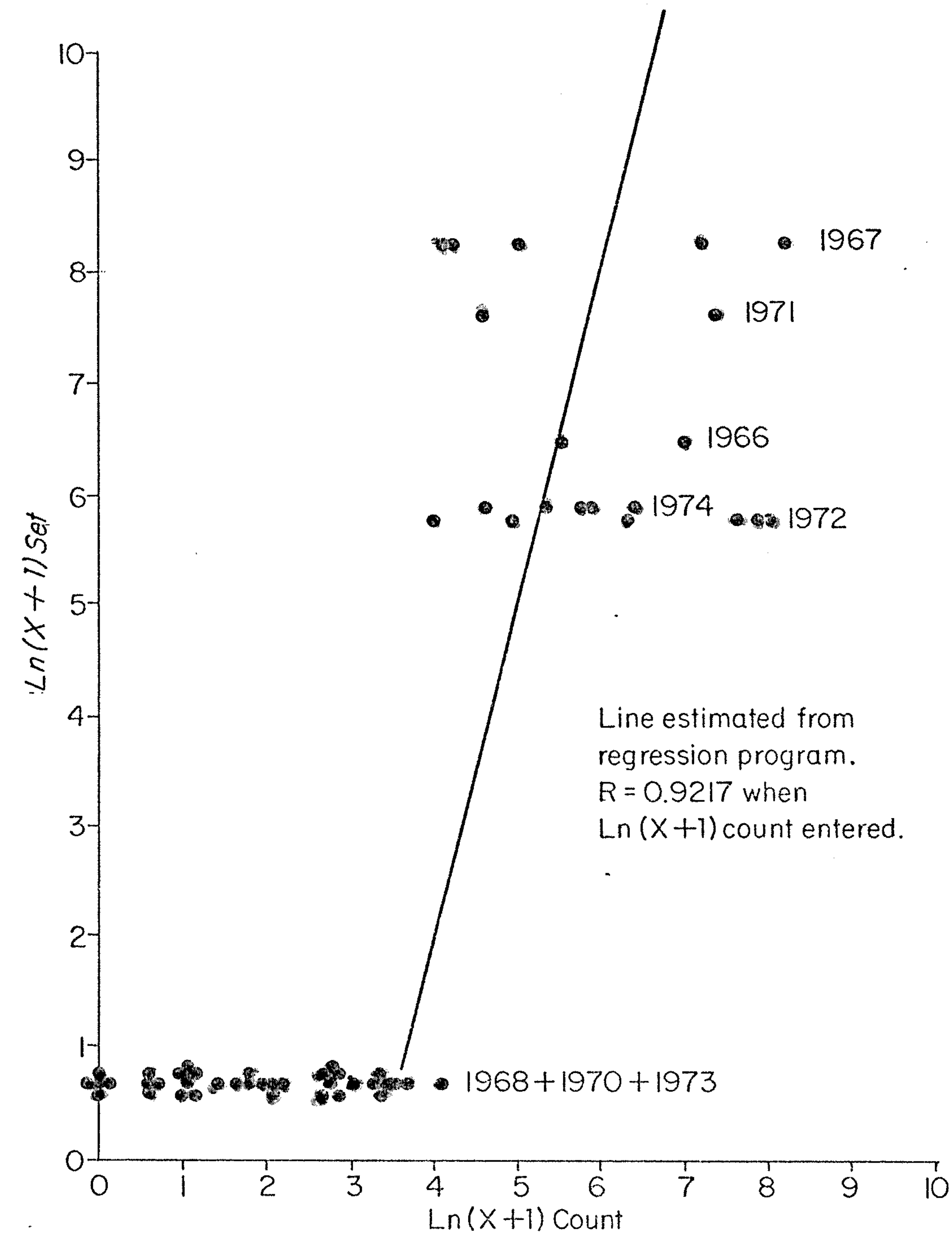
Graph 2A. Ln of count vs. Ln of set, 4-8 days, early spauwning



Graph 2B. Ln of count vs. Ln of set, 4 - 8 days, late spawnings



Graph 3A – Ln of count vs. Ln of set, 8–12 days, early spawnings



Graph 3 B - Ln of count vs. Ln of set, 8-12 days, late spawnings