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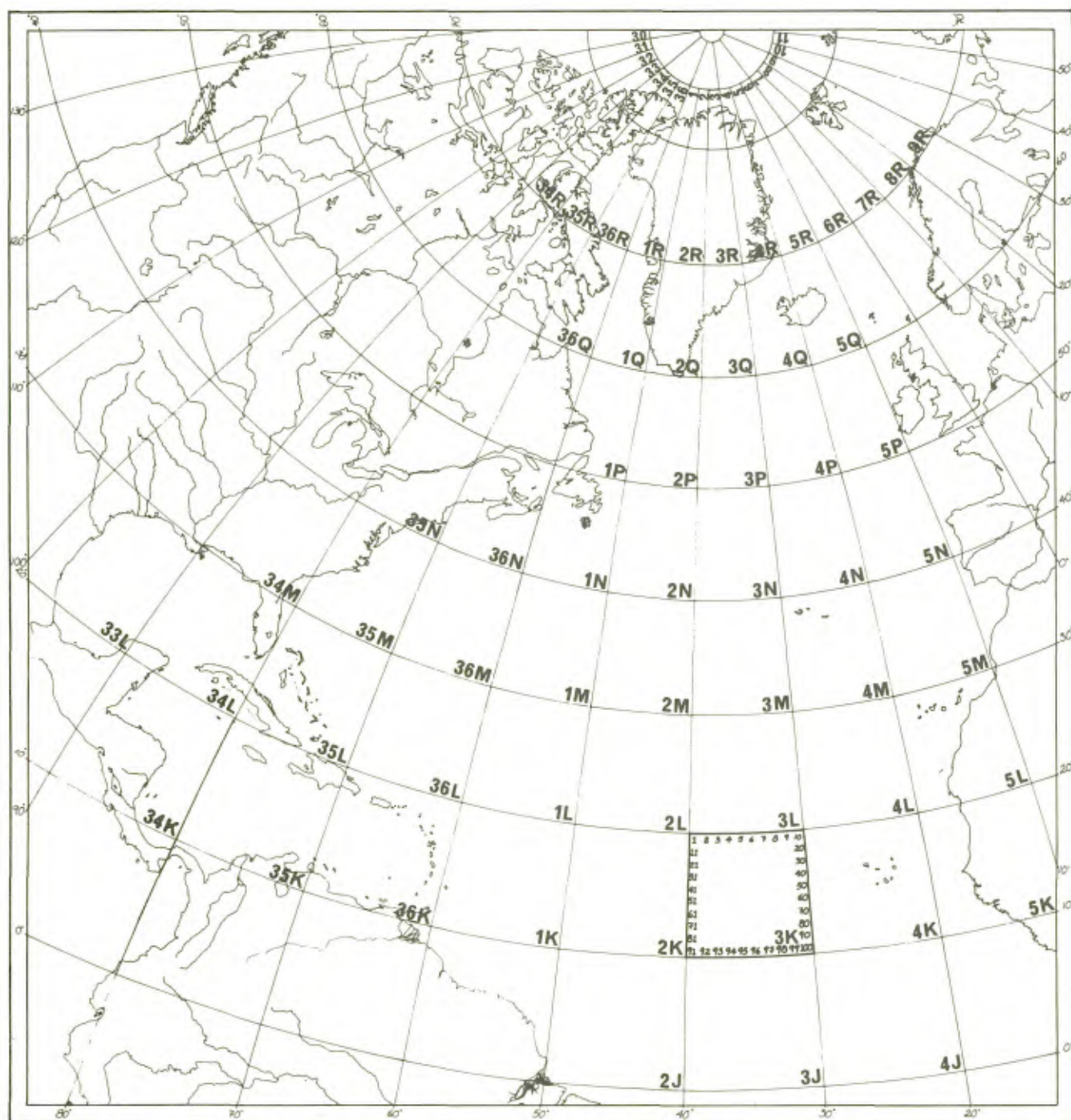
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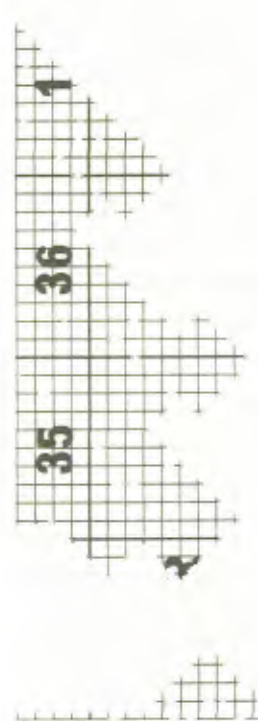
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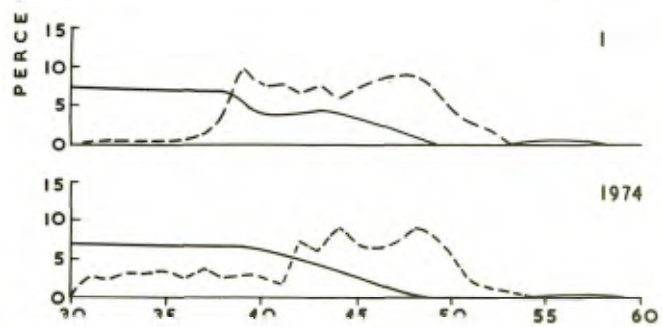


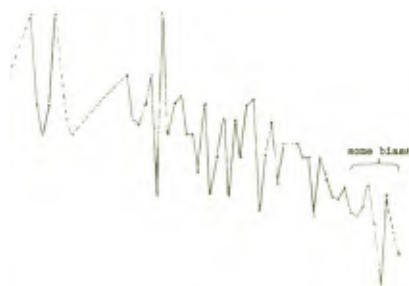


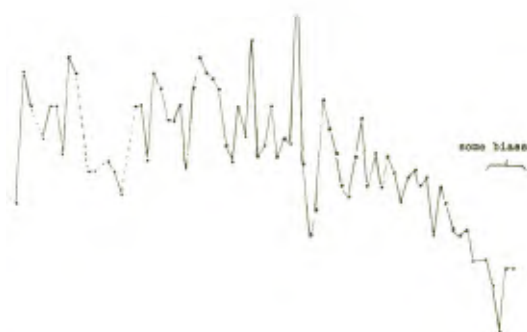




$$\left[\frac{P_{I-L}}{P_x} \right]^{n+1} R_0$$







The first part of the paper discusses the importance of understanding the underlying data-generating process in order to make valid inferences. This is particularly true in the case of time series data, where the temporal dependence between observations can lead to misleadingly small standard errors and inflated test statistics if not properly accounted for. The second part of the paper presents a new method for testing the null hypothesis of no cointegration between two time series. This method is based on the use of a bootstrap procedure to approximate the distribution of the test statistic under the null hypothesis. The third part of the paper applies this new method to a set of simulated data and compares the results to those obtained using traditional methods. The results show that the new method is more powerful than the traditional methods in detecting cointegration when the sample size is small.



Figure 1: A time series plot showing a downward trend. The solid line represents the observed data, and the dashed line represents the fitted model. The label 'some bias here' indicates a potential bias in the fit.

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Figure 2: A time series plot showing an upward trend. The solid line represents the observed data, and the dashed line represents the fitted model. The label 'some bias here' indicates a potential bias in the fit.

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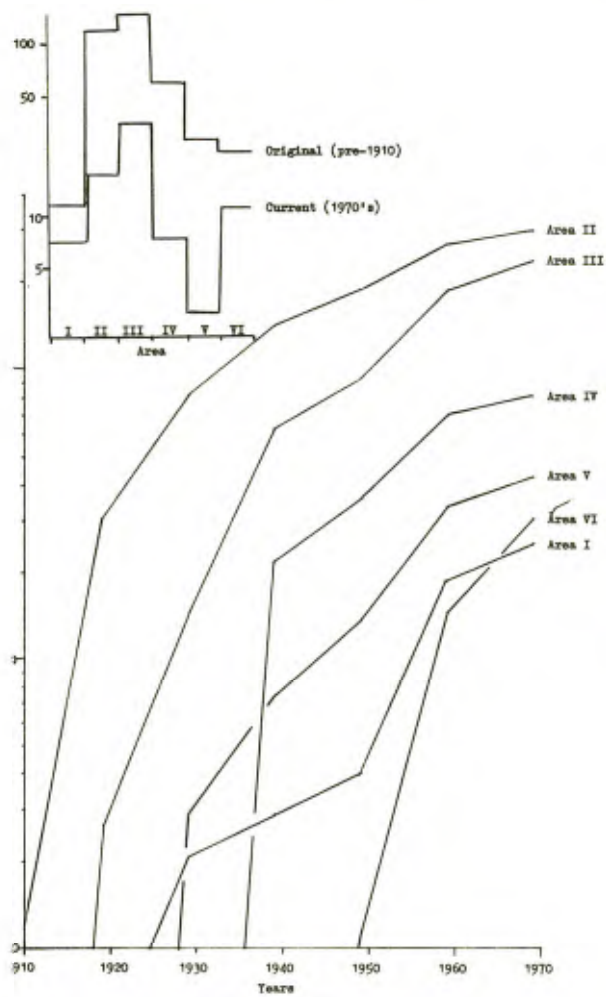


Figure 1. Distribution of the Pacific halibut in the North Pacific Ocean.

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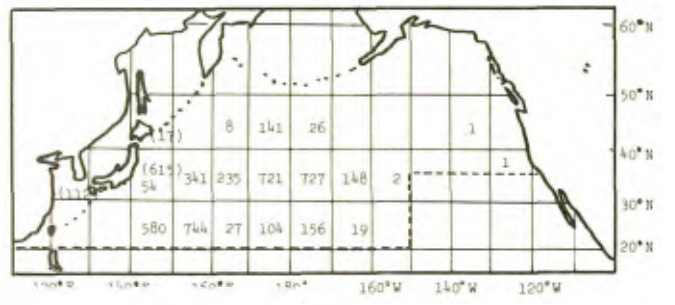
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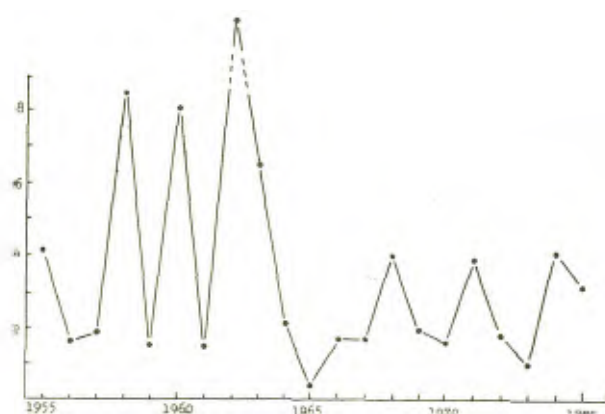
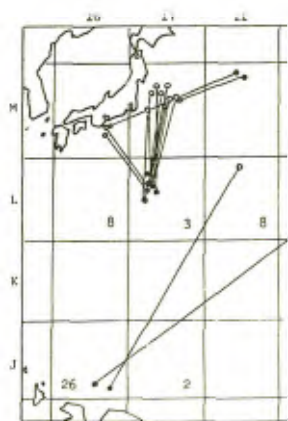
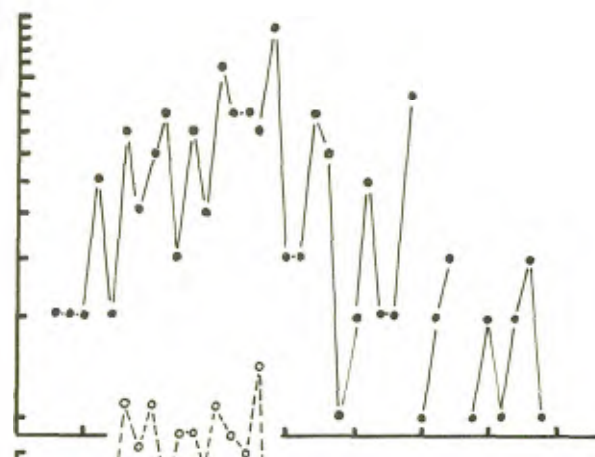
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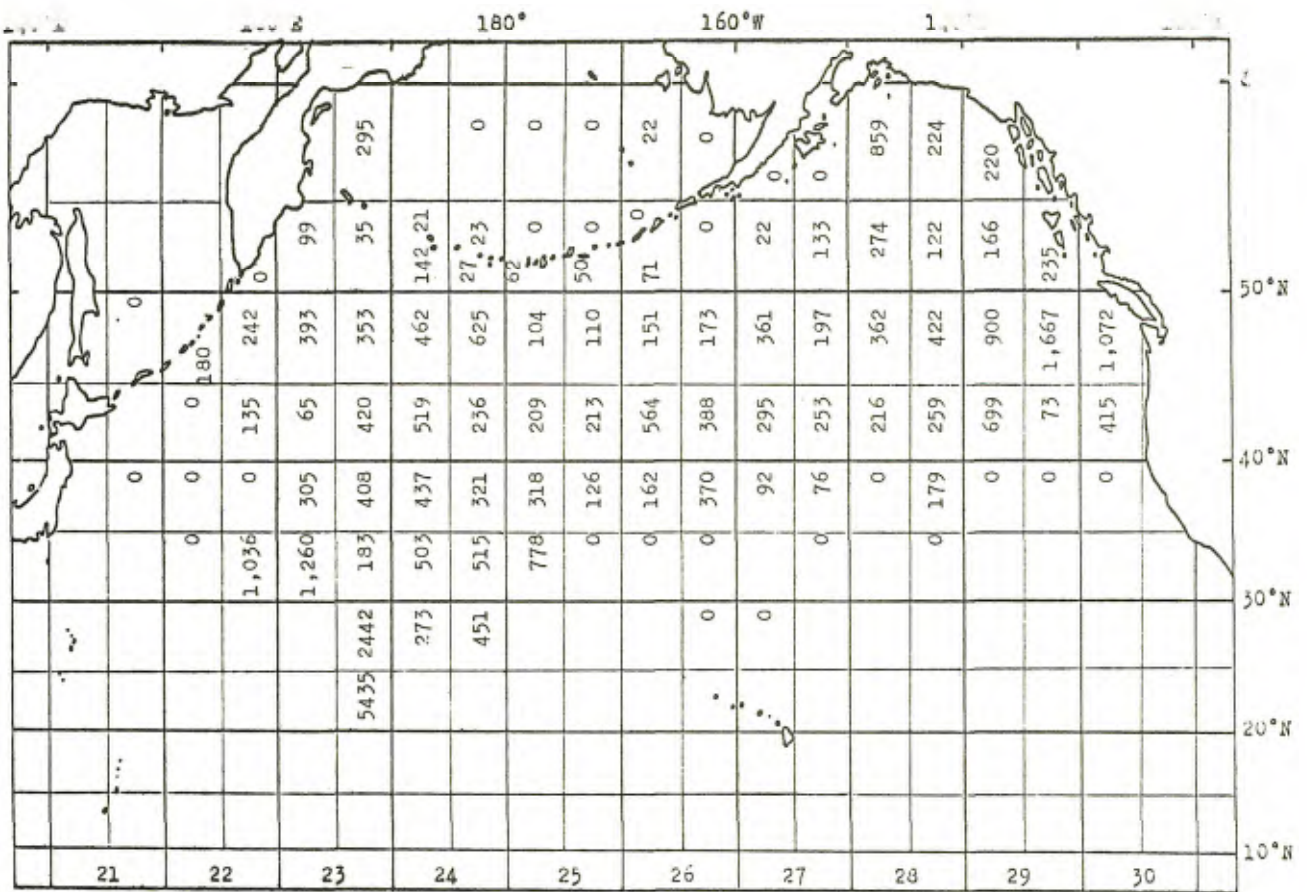
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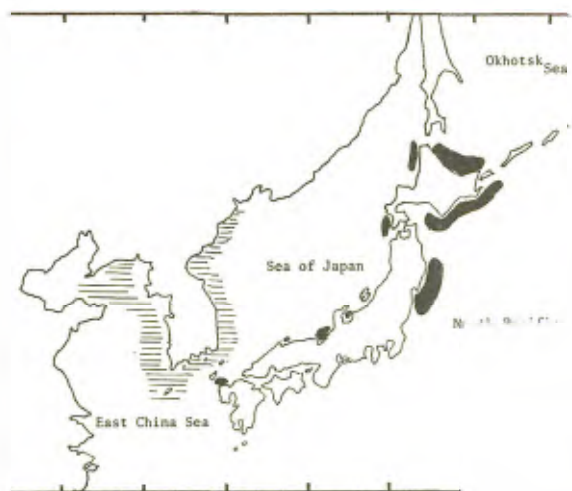
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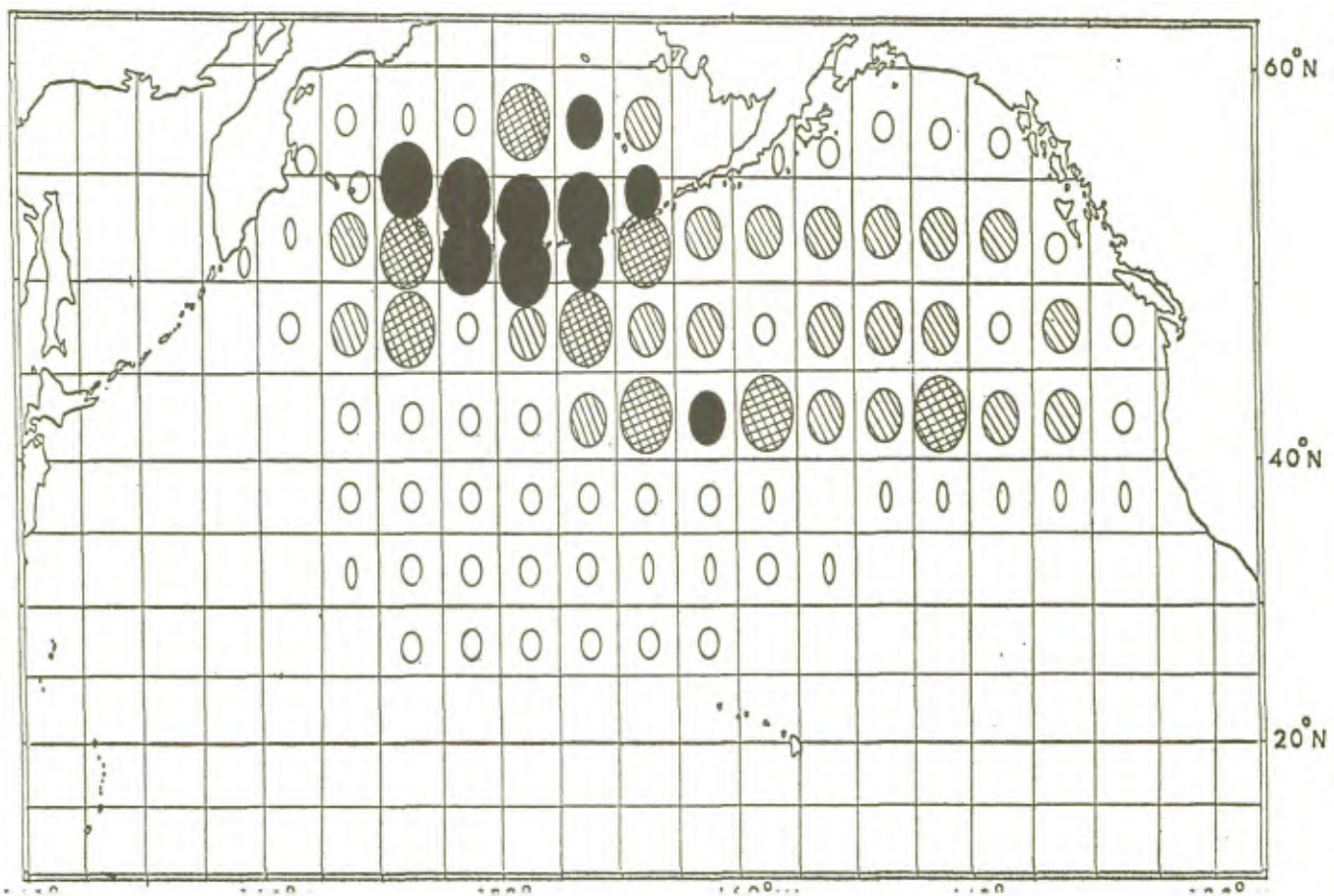
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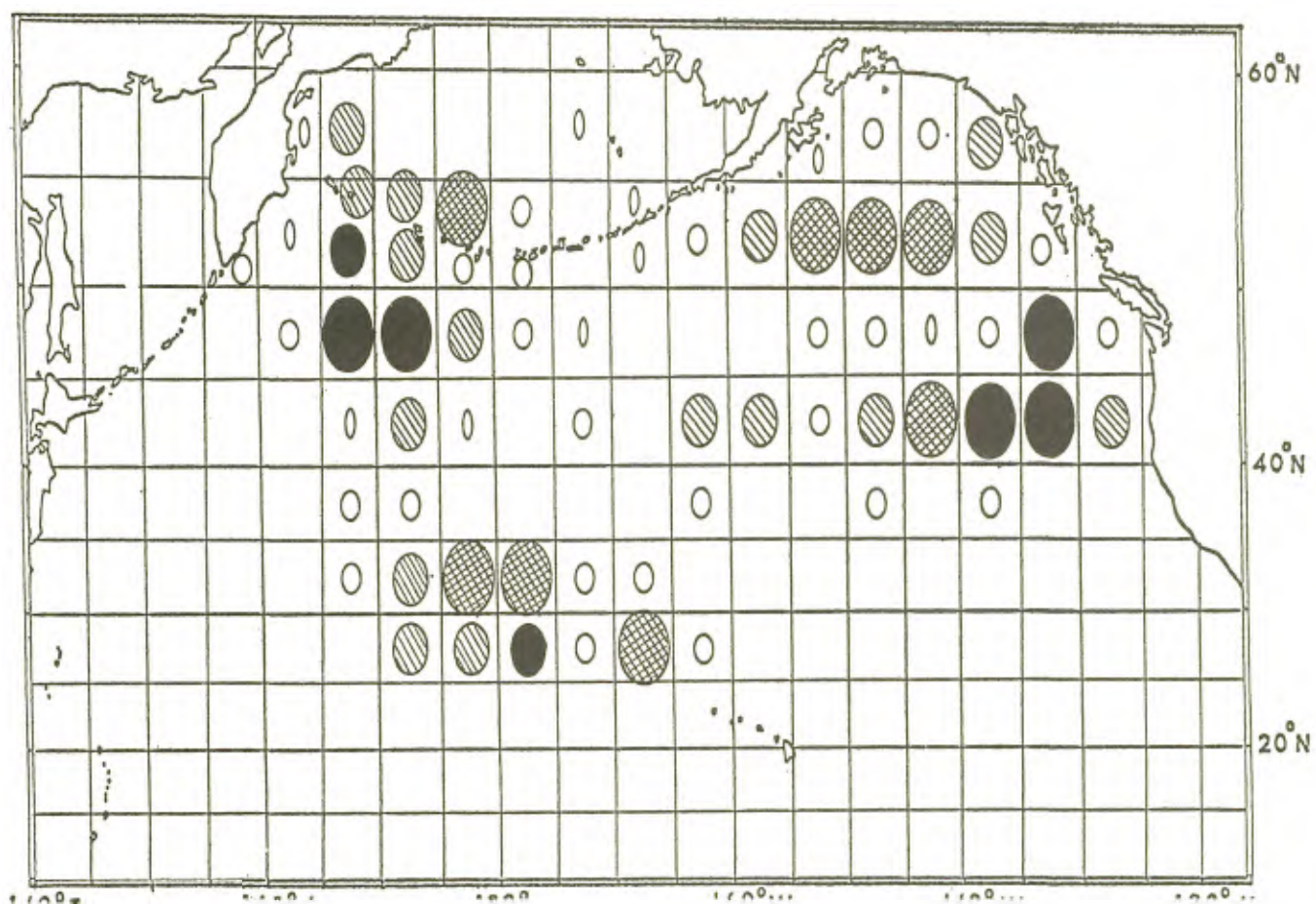


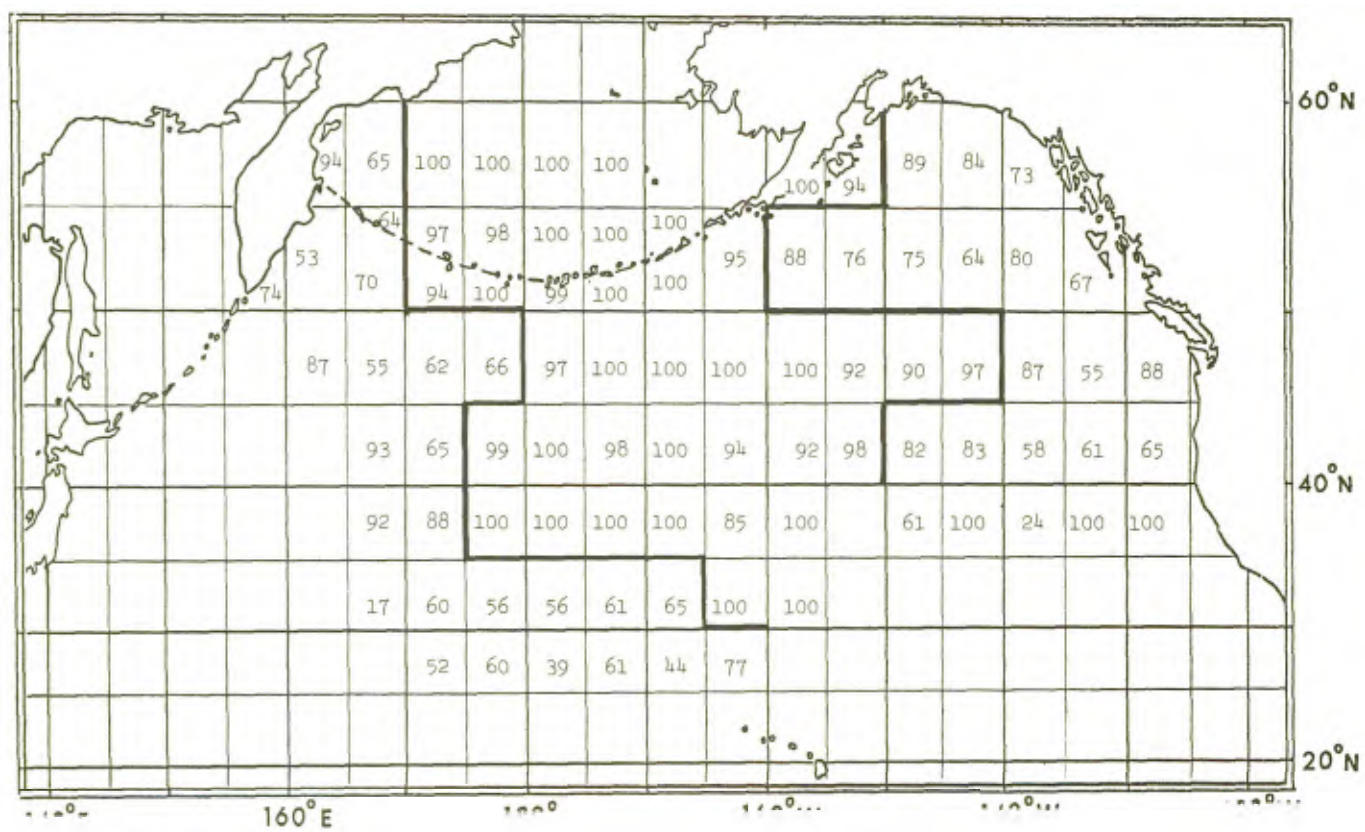


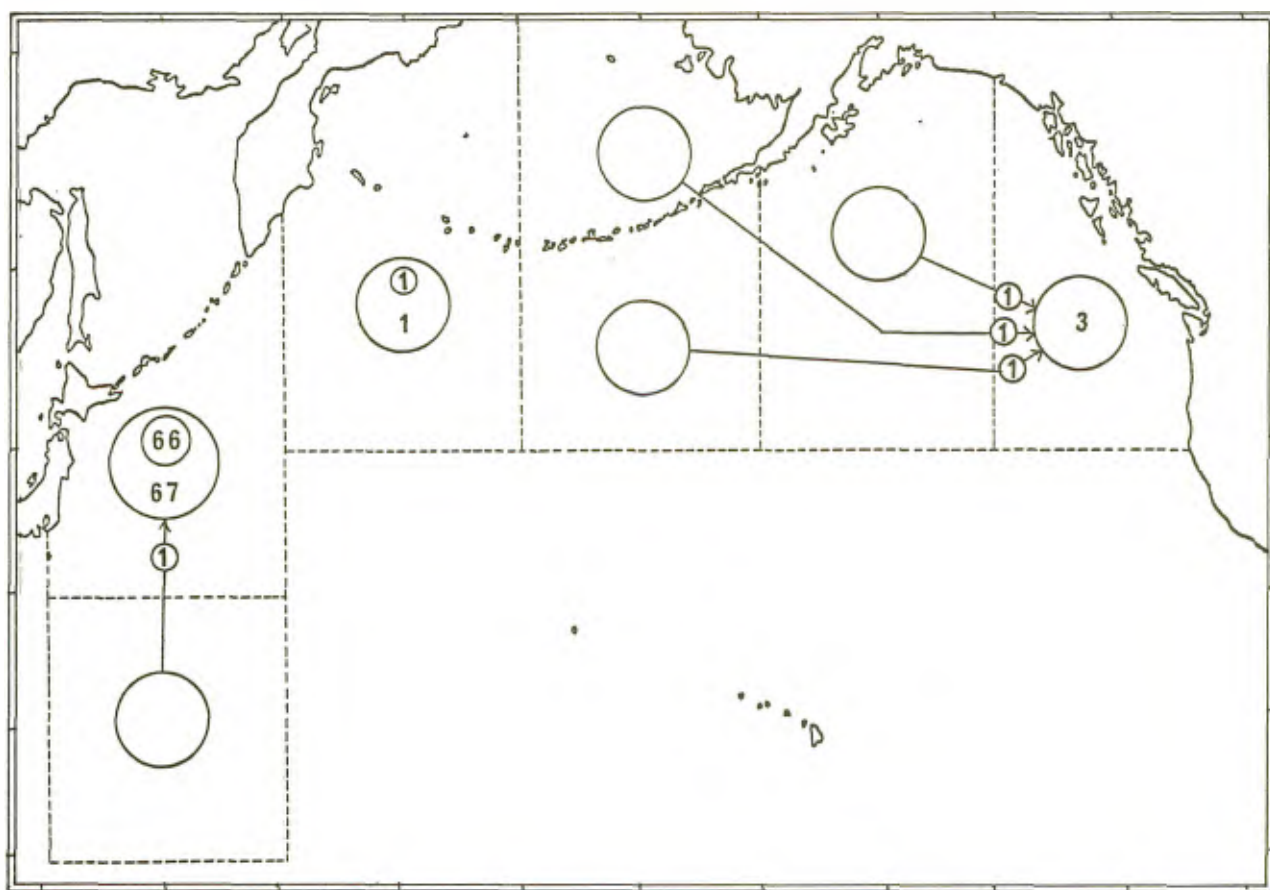
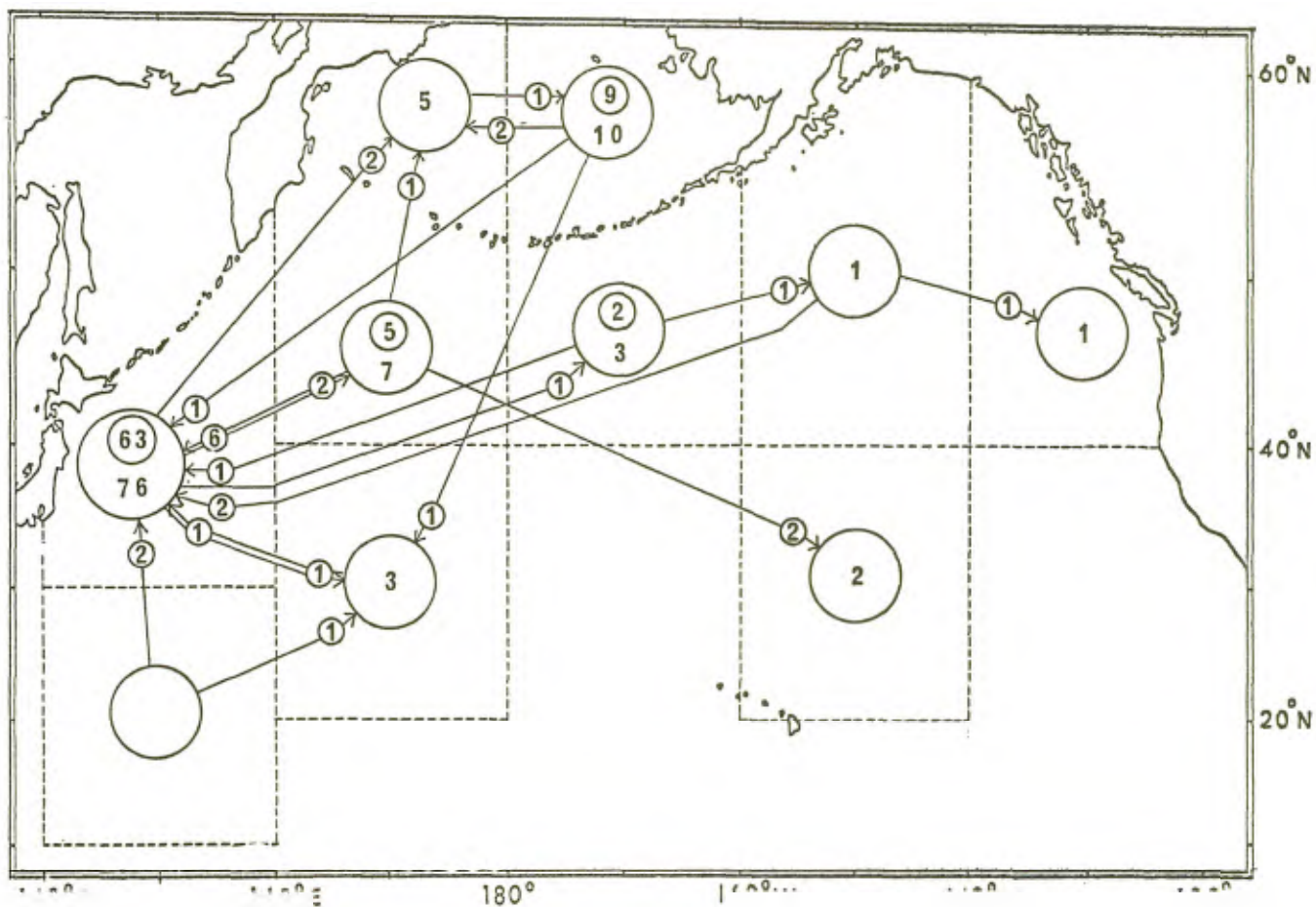




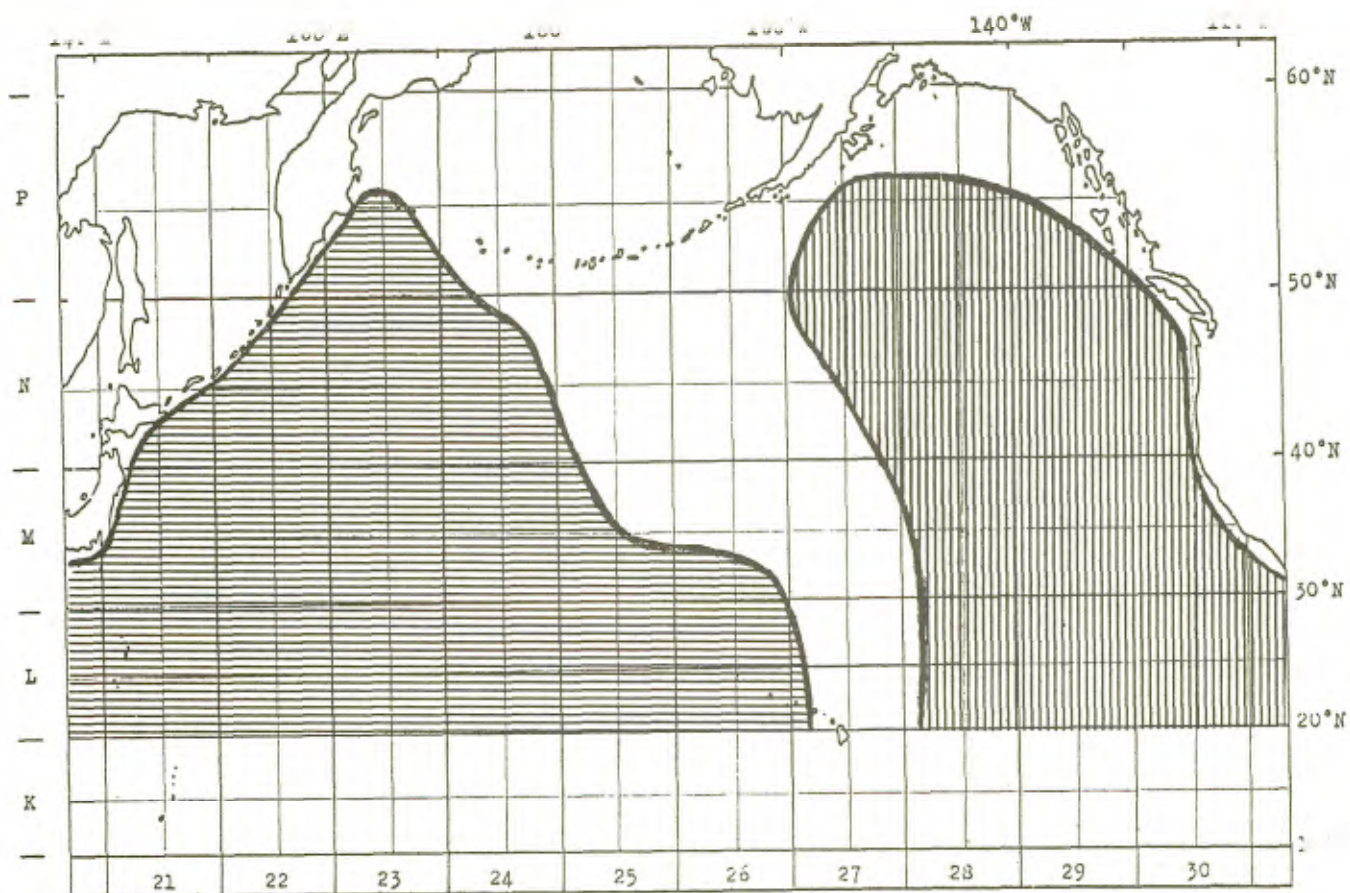
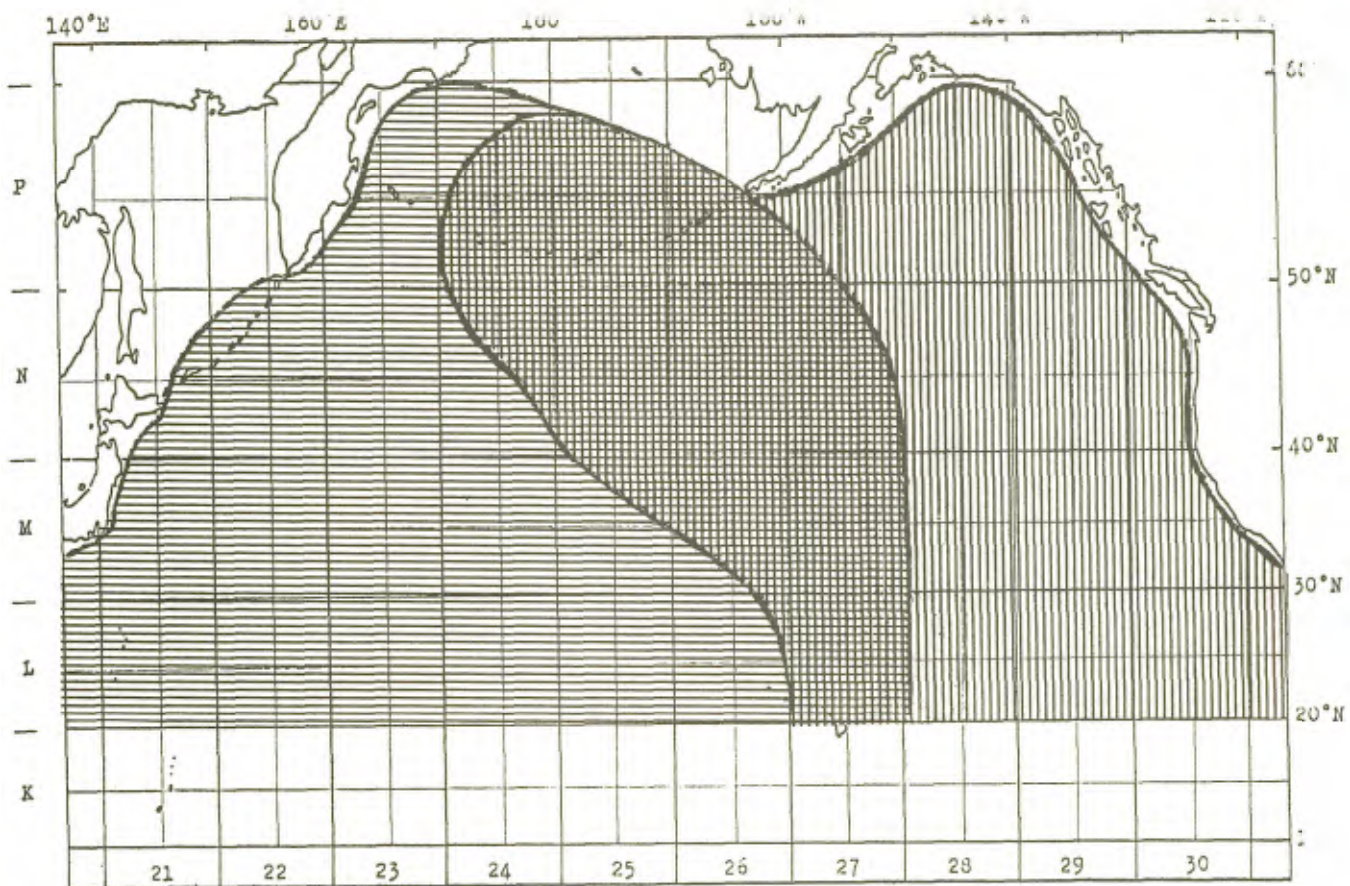


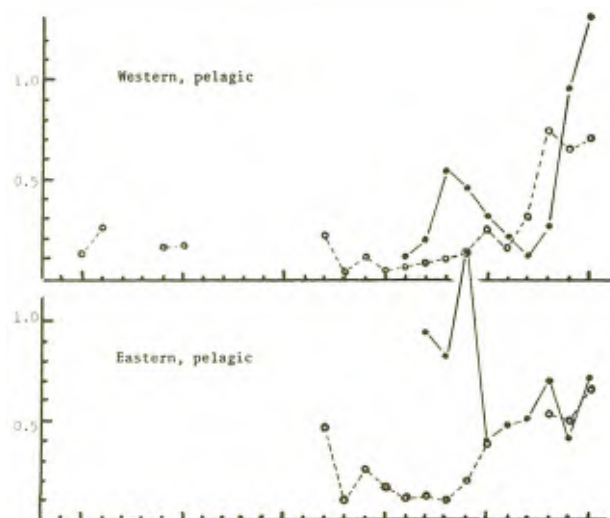
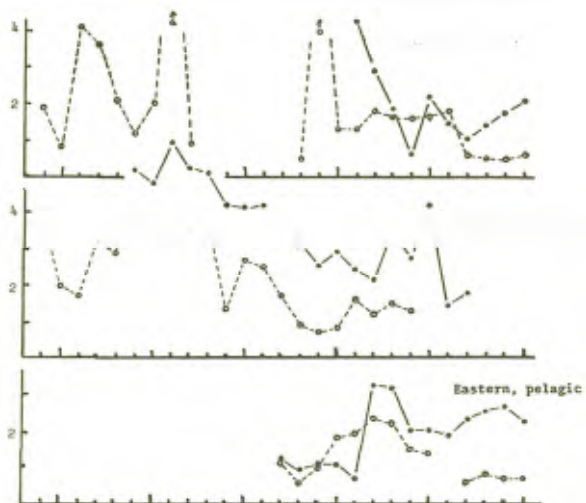




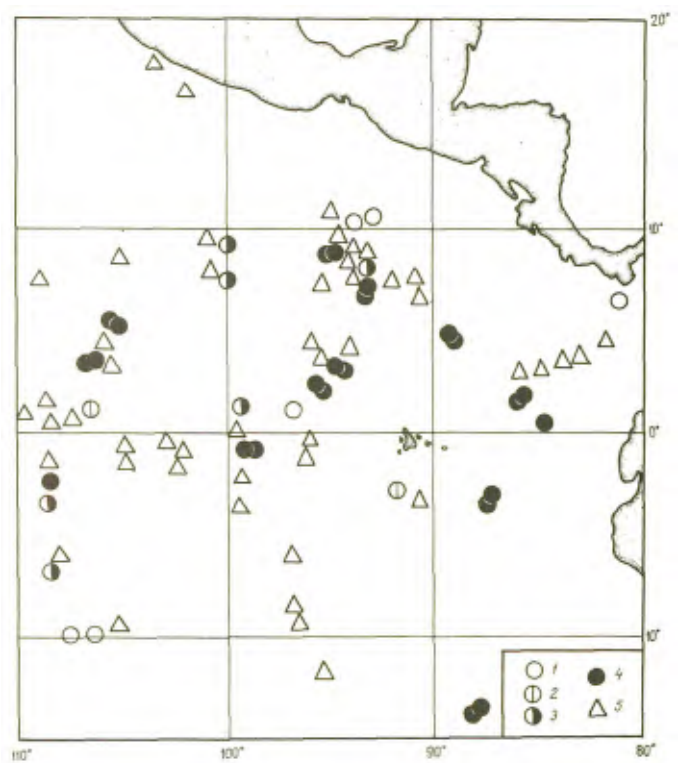


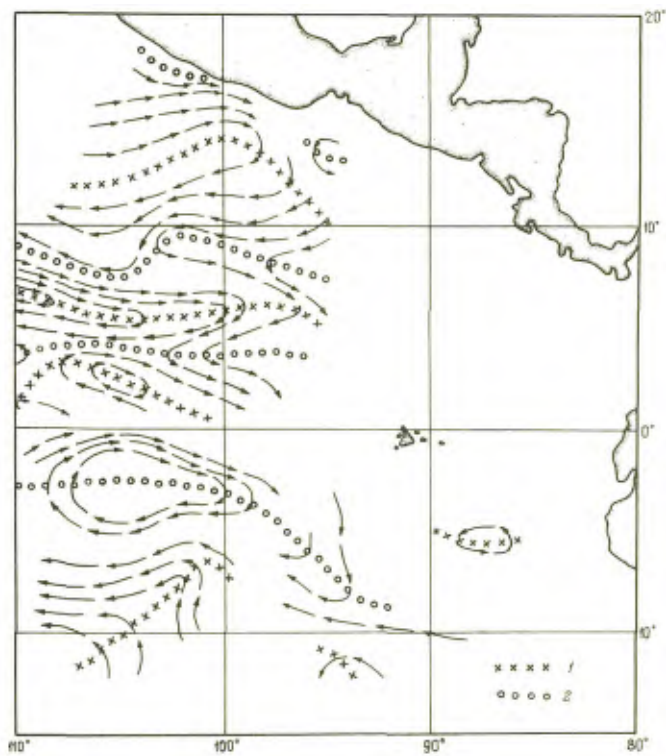


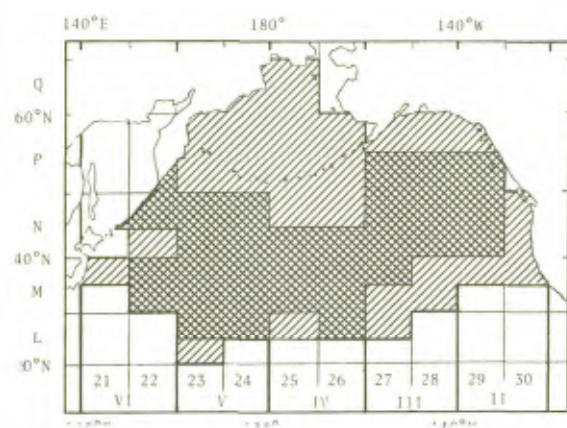








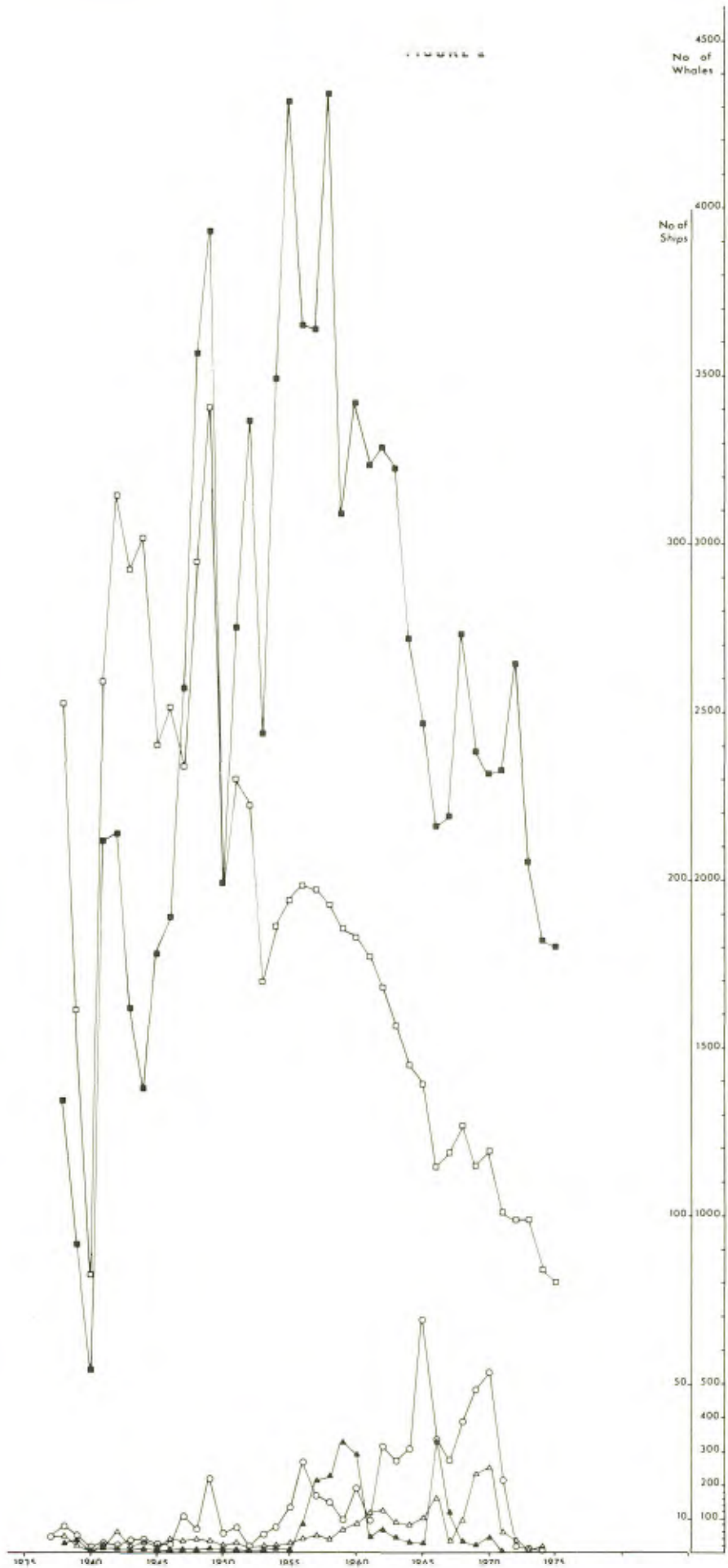






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DEEP DIVING, BENTHIC FEEDING

KEY:

FIGURE 1



= GEOGRAPHICAL/SPACIAL DISTRIBUTION AND AGGREGATIONS.



= FILTER, LIMITING FACTORS.



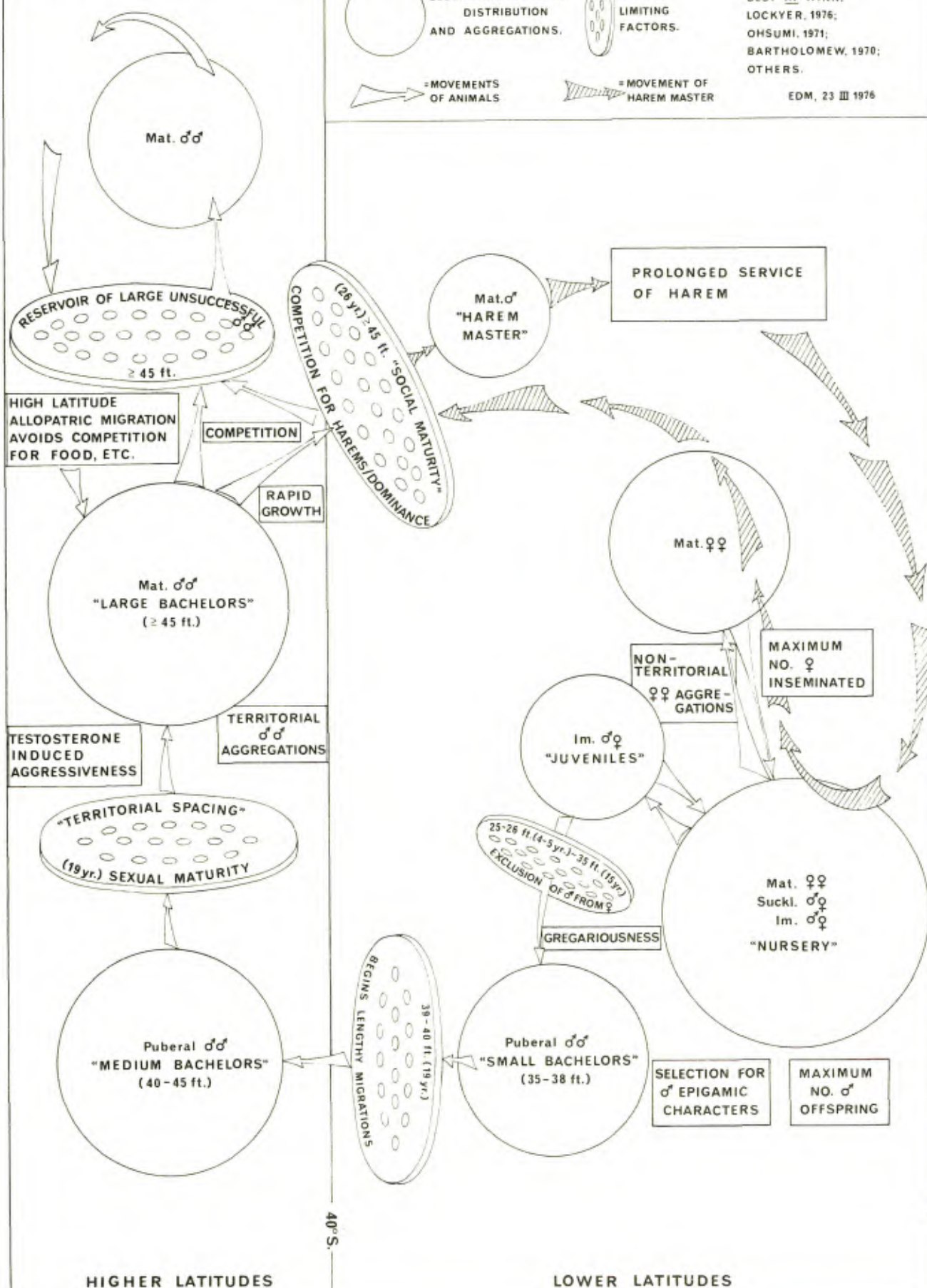
= MOVEMENTS OF ANIMALS

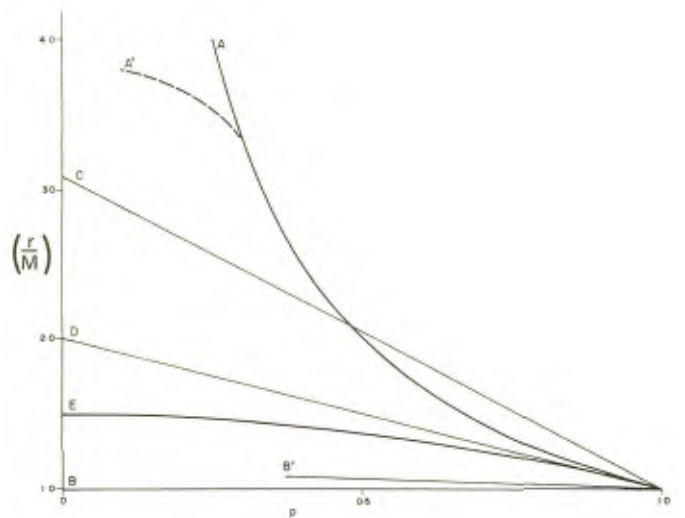


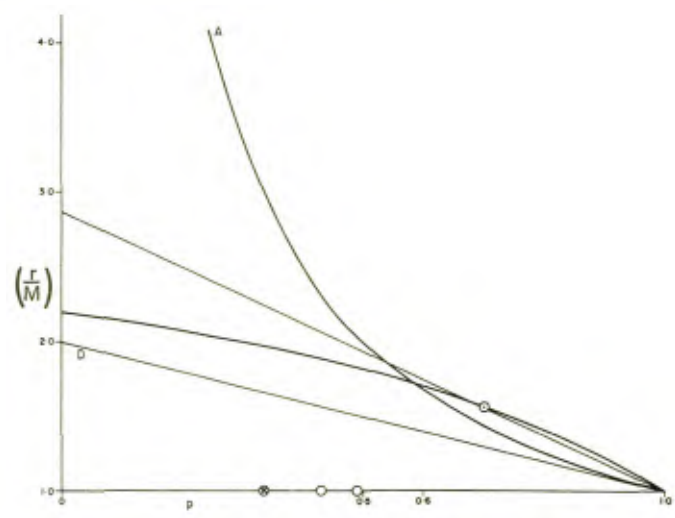
= MOVEMENT OF HAREM MASTER

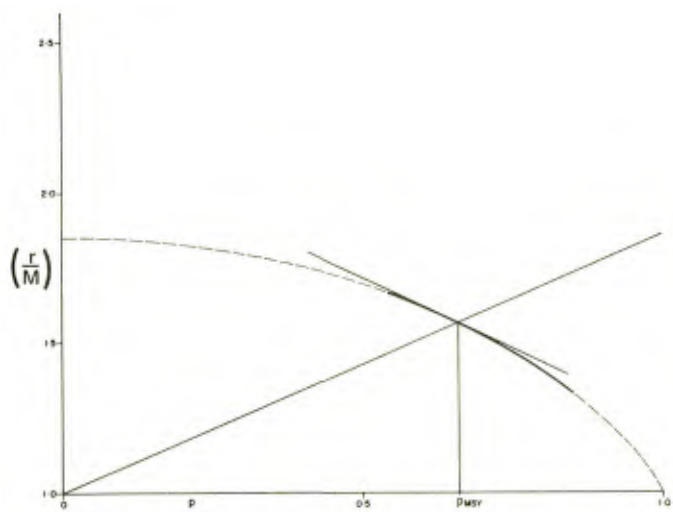
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LOCKYER, 1976;
OHSUMI, 1971;
BARTHOLOMEW, 1970;
OTHERS.

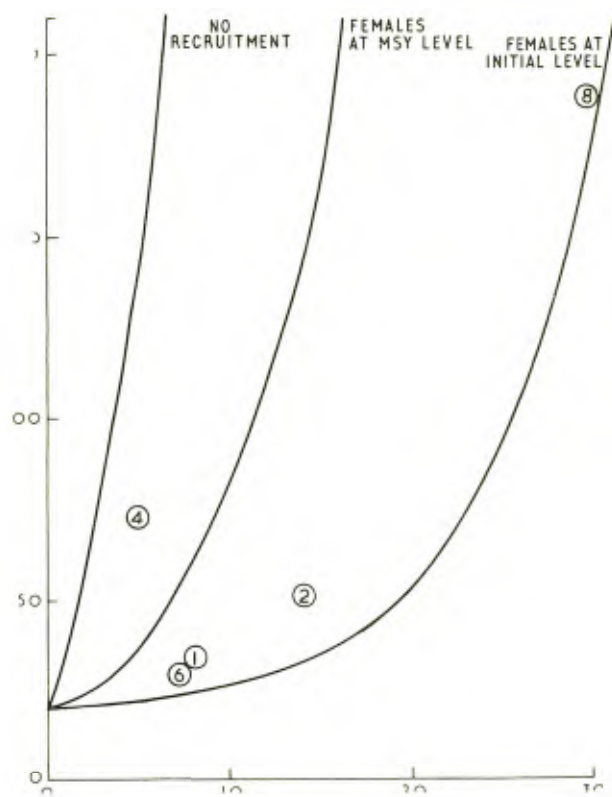
EDM, 23 III 1976

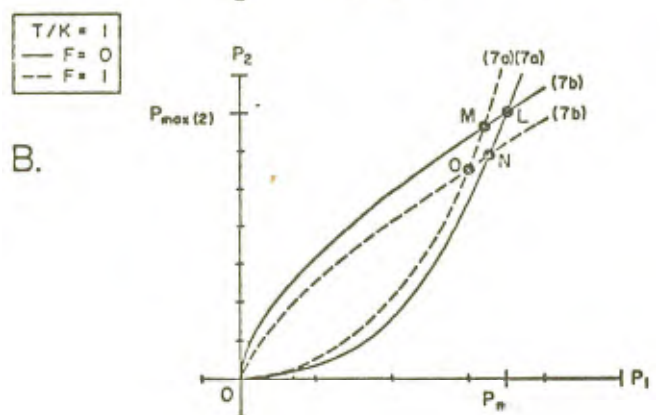
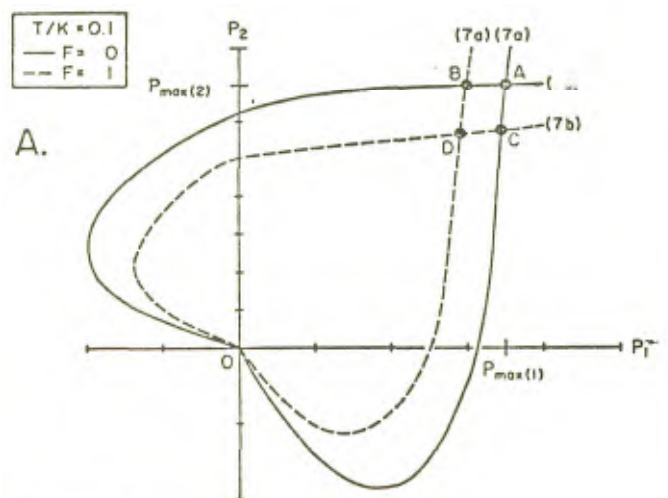






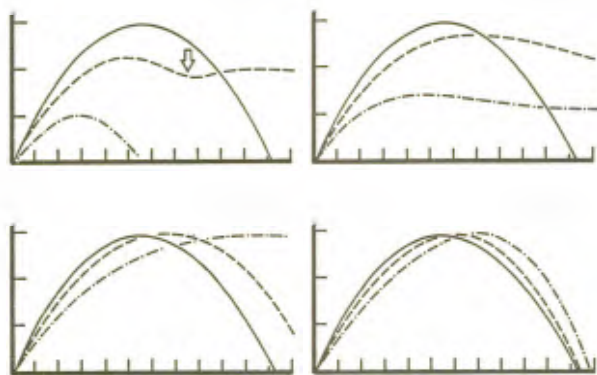






Let $y_1(x)$ and $y_2(x)$ be two solutions of the boundary value problem (10.1). Then $y_1(x) - y_2(x)$ is a solution of the homogeneous problem (10.2). Since $y_1(x) - y_2(x)$ satisfies the boundary conditions $y_1(0) - y_2(0) = 0$ and $y_1(1) - y_2(1) = 0$, it must be the zero function. Therefore $y_1(x) = y_2(x)$ for all x in $[0, 1]$. This shows that the solution to the boundary value problem (10.1) is unique.

Now we consider the existence of a solution to the boundary value problem (10.1). Let $y_1(x)$ and $y_2(x)$ be two solutions of the homogeneous problem (10.2). Then $y_1(x)$ and $y_2(x)$ are linearly independent solutions of the homogeneous problem. Let $y_3(x)$ be a particular solution of the inhomogeneous problem (10.1). Then the general solution of the inhomogeneous problem is given by

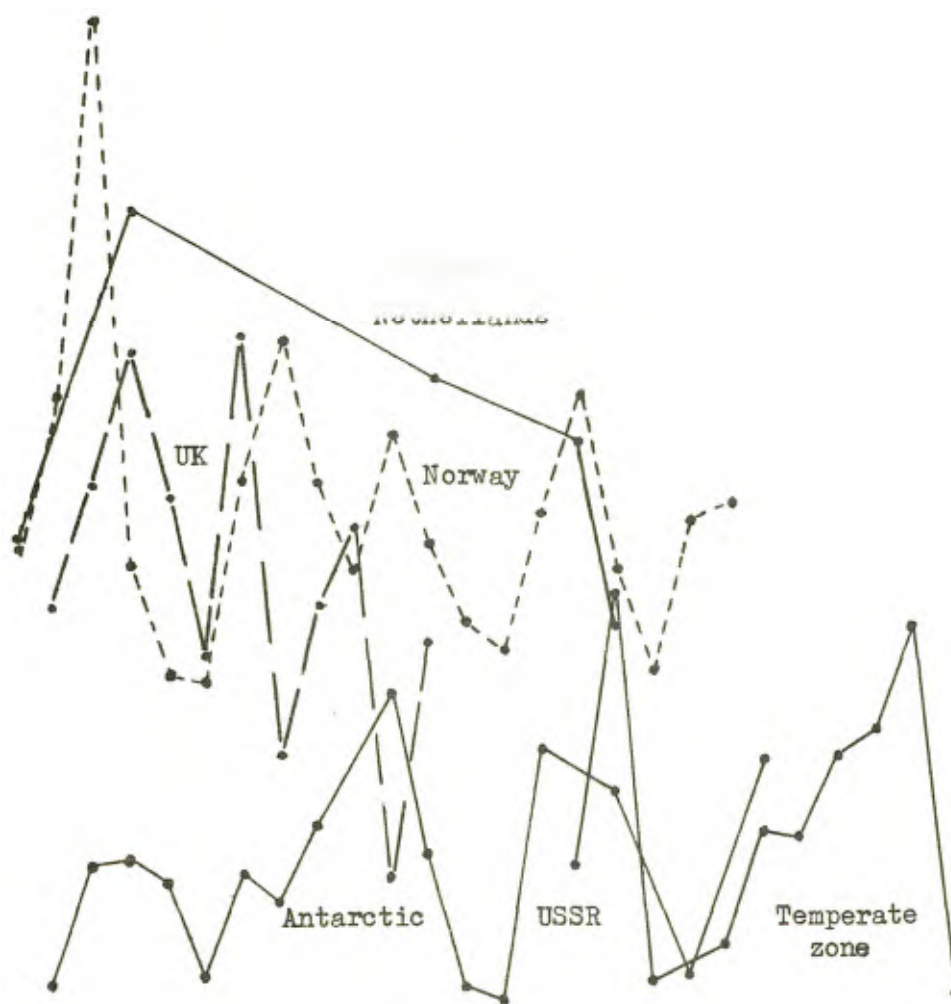
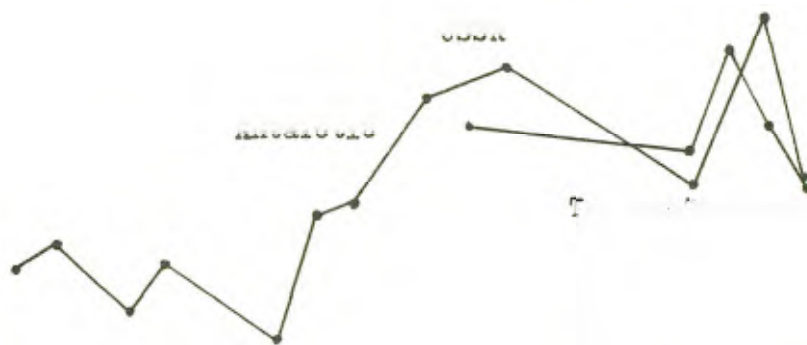


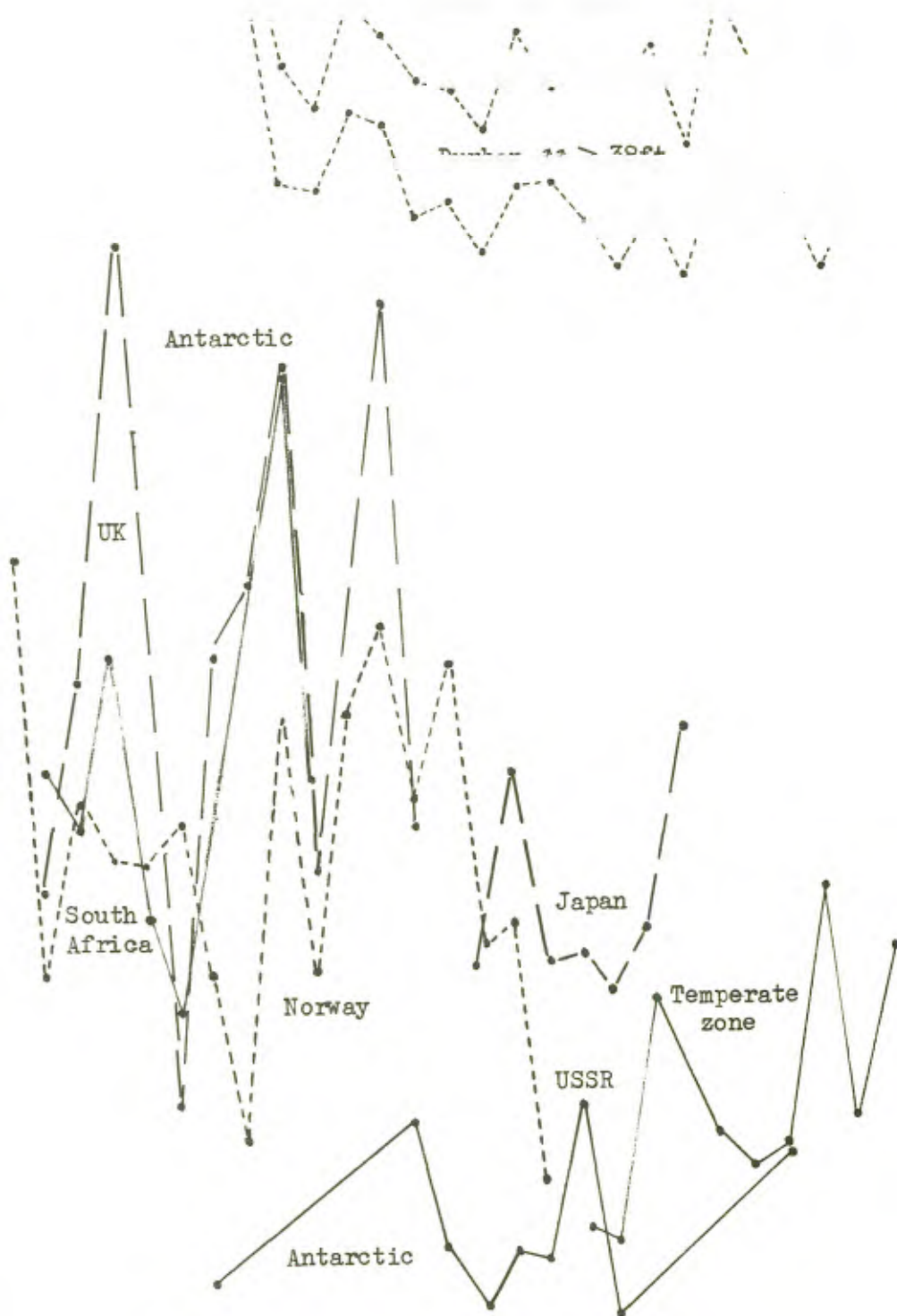
where C_1 and C_2 are constants. The boundary conditions $y(0) = 0$ and $y(1) = 0$ are satisfied if and only if $C_1 = 0$ and $C_2 = 0$. Therefore, the only solution to the homogeneous problem (10.2) is the zero function. This shows that the homogeneous problem (10.2) has only the trivial solution.

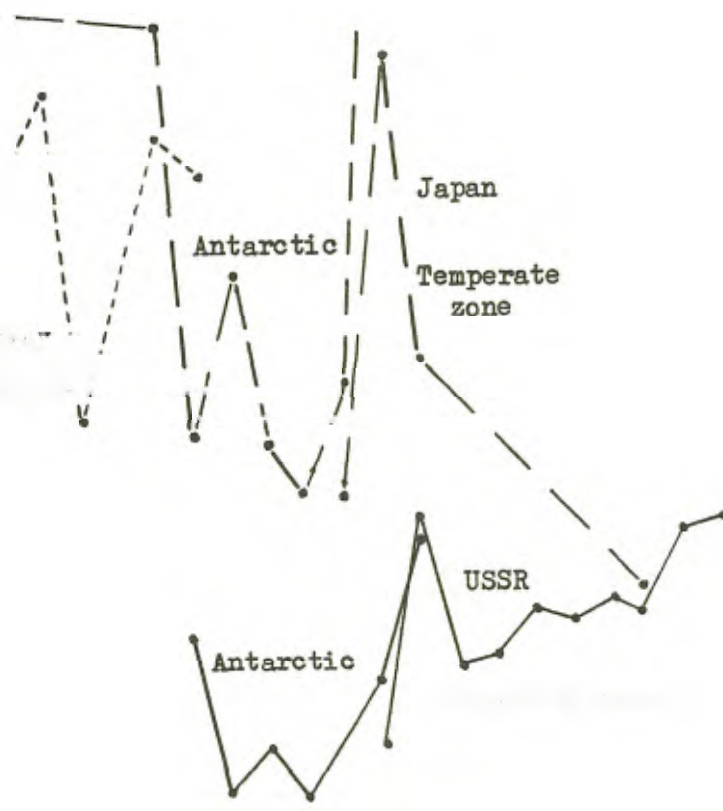
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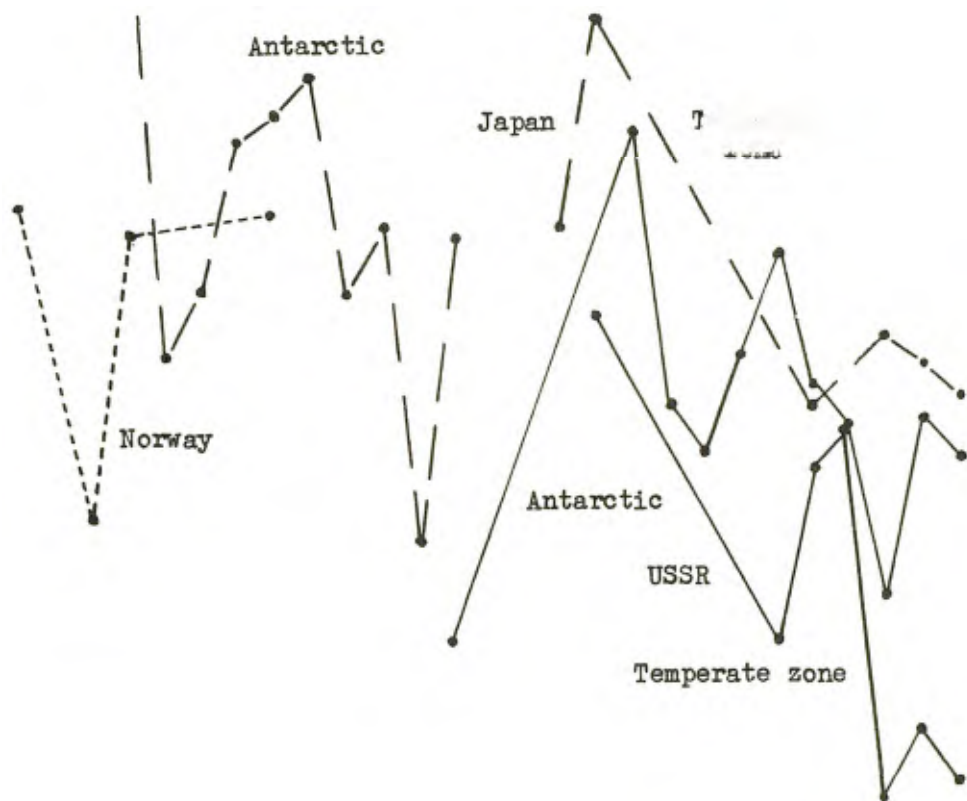
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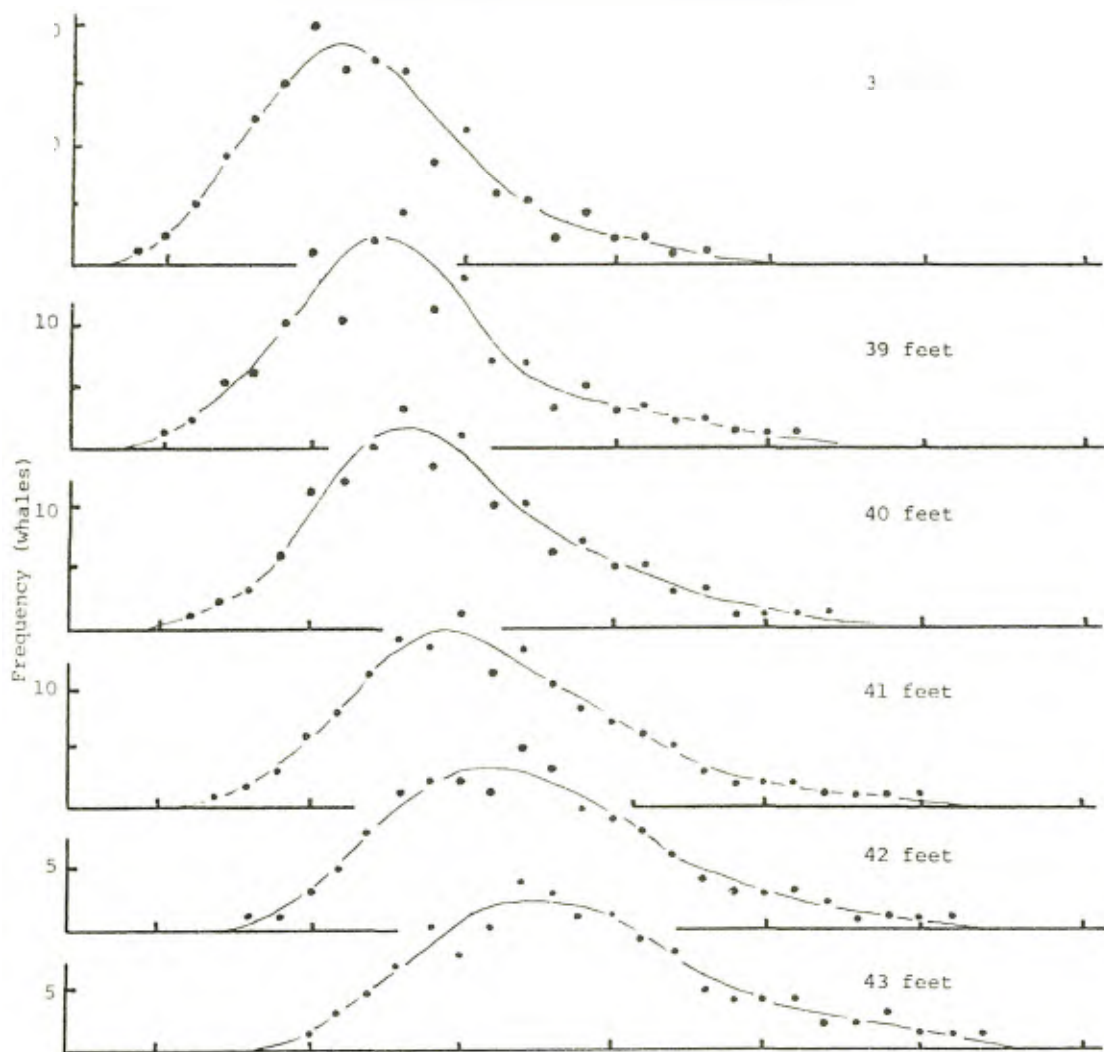












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1 - 2 3
2 10 2 1
2 4 4 1
5 5 2 4
3 5 1 2
- 1 3

Scatter Plot of Data Points with Two Curves

Figure 1: Scatter Plot of Data Points

Figure 1 shows a scatter plot of data points (circles) and two fitted curves, labeled A and B.

The x-axis represents the independent variable, and the y-axis represents the dependent variable.

The data points are distributed across the plot area.

Curve A is a solid line, and Curve B is a dashed line.

Curve A starts at the origin (0,0) and increases monotonically, passing through the data points.

Curve B starts at a positive y-intercept and increases monotonically, passing through the data points.

The data points are scattered around the curves, indicating some variability in the data.

The plot area is bounded by the x-axis and y-axis, with tick marks indicating the scale.

The data points are represented by small circles.

The curves are labeled A and B.

The x-axis is labeled with values 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10.

The y-axis is labeled with values 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10.

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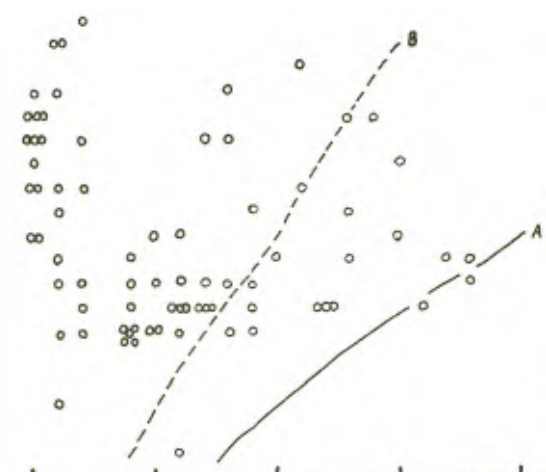
The data points are scattered around the curves.

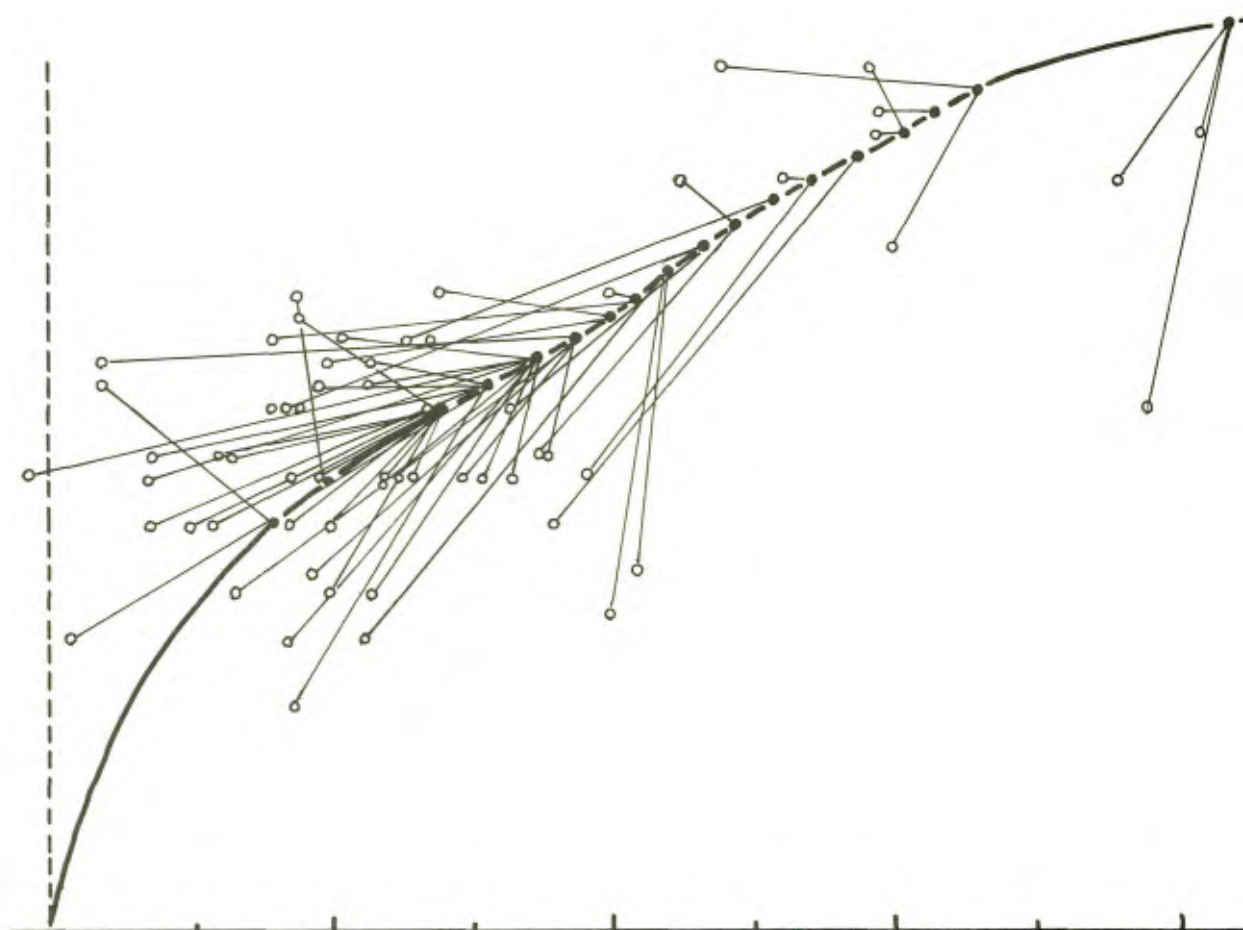
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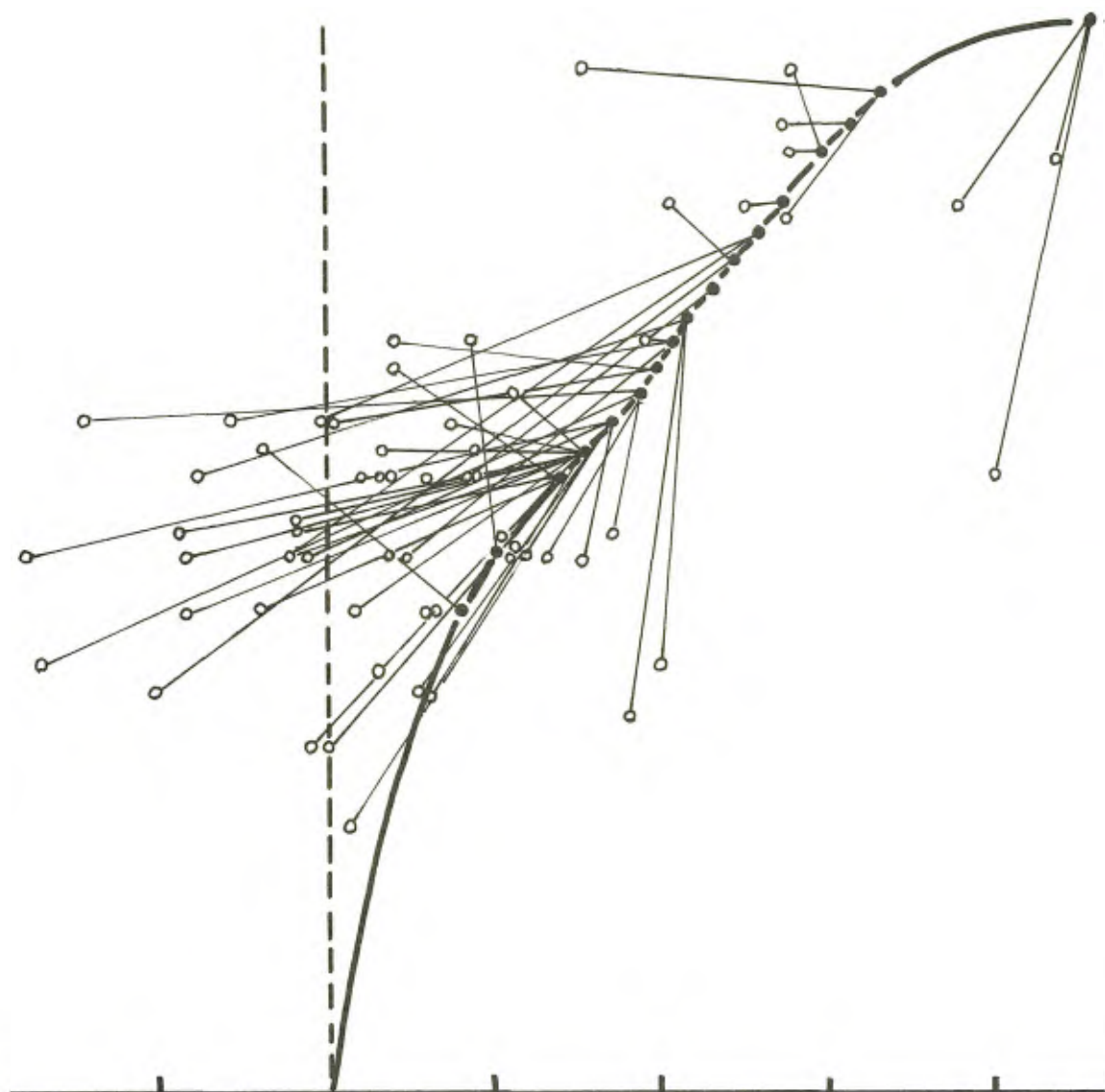
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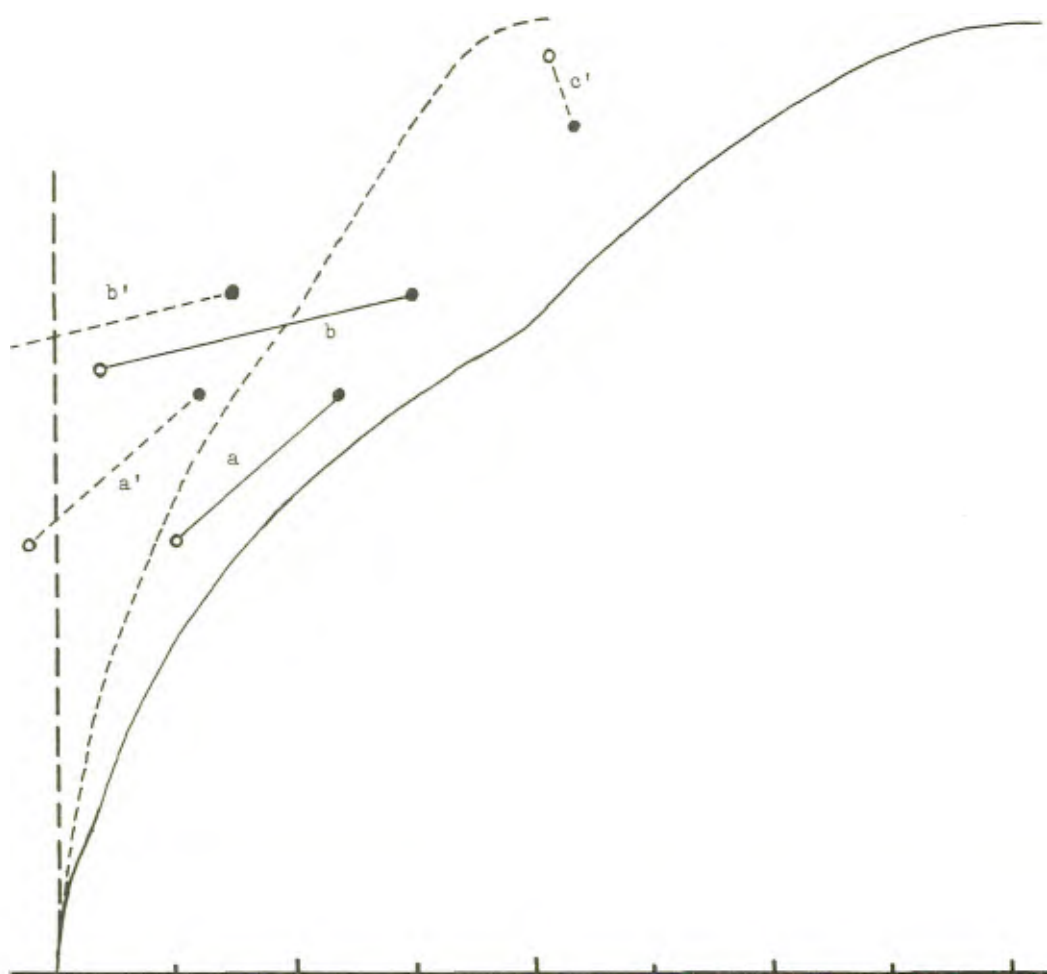
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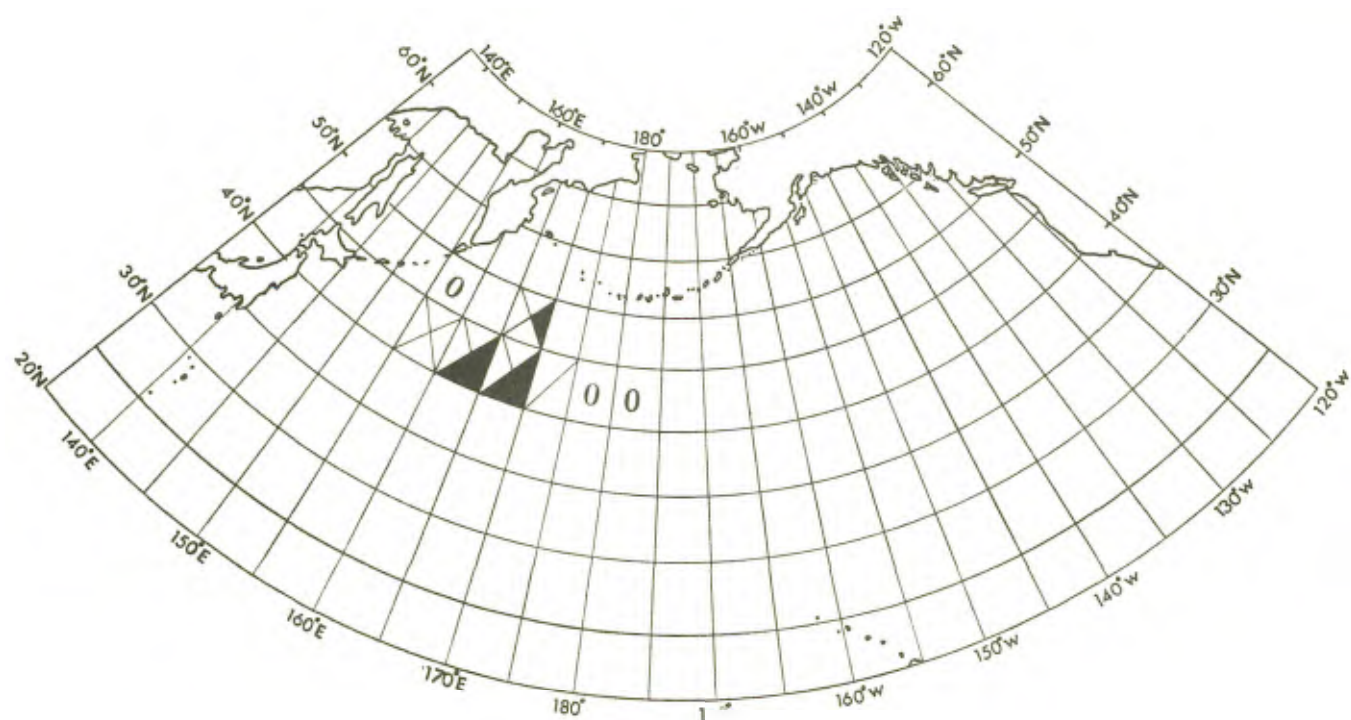
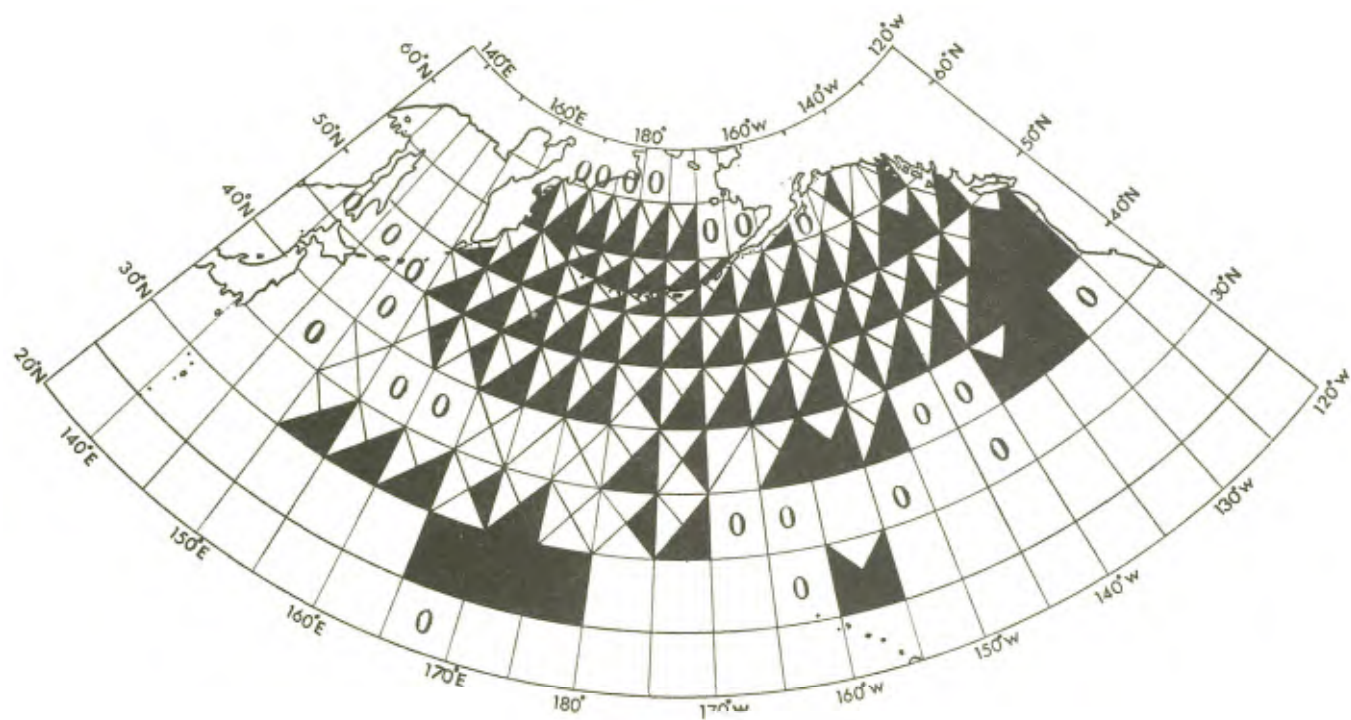
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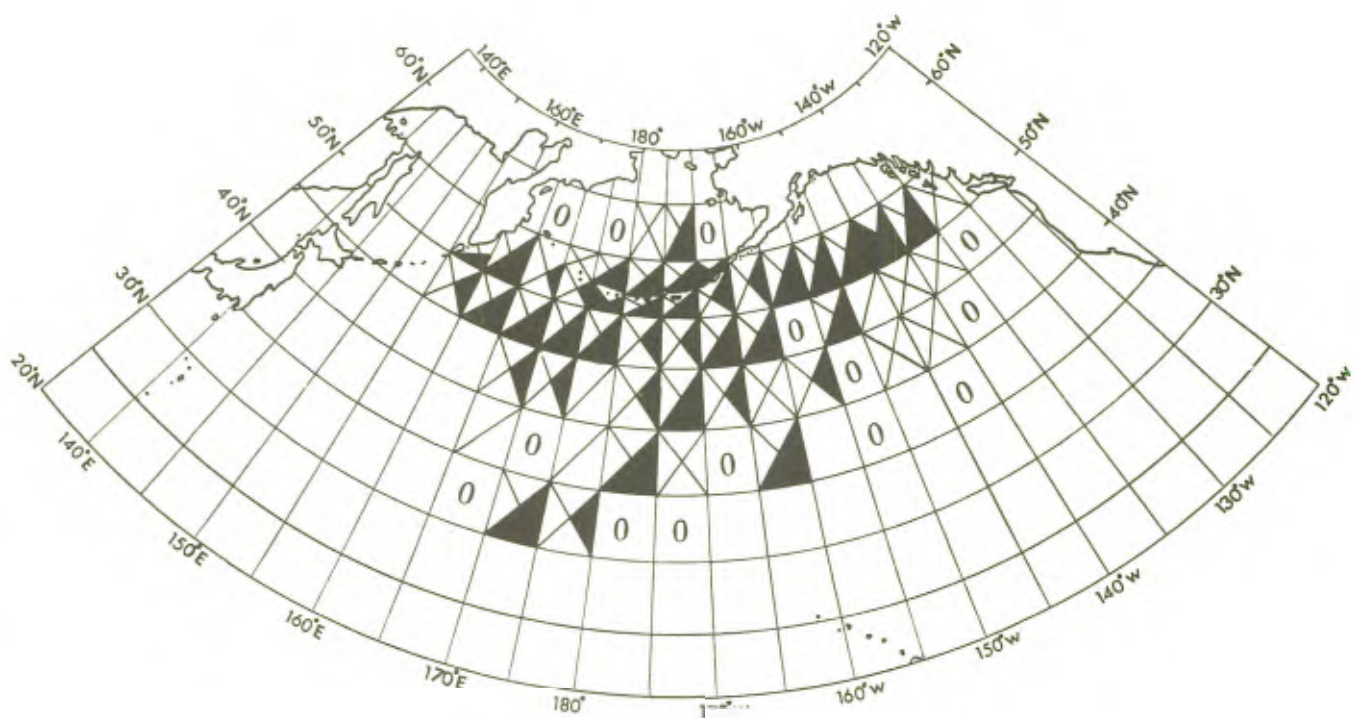
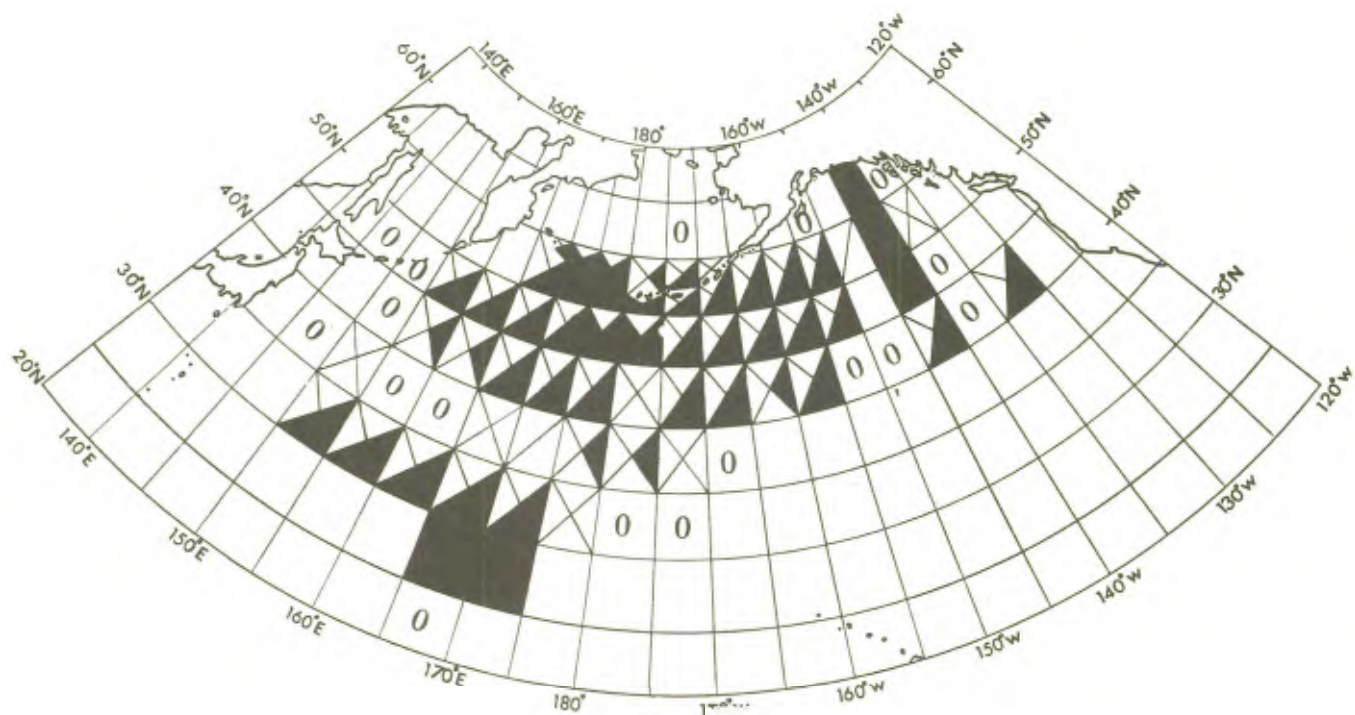


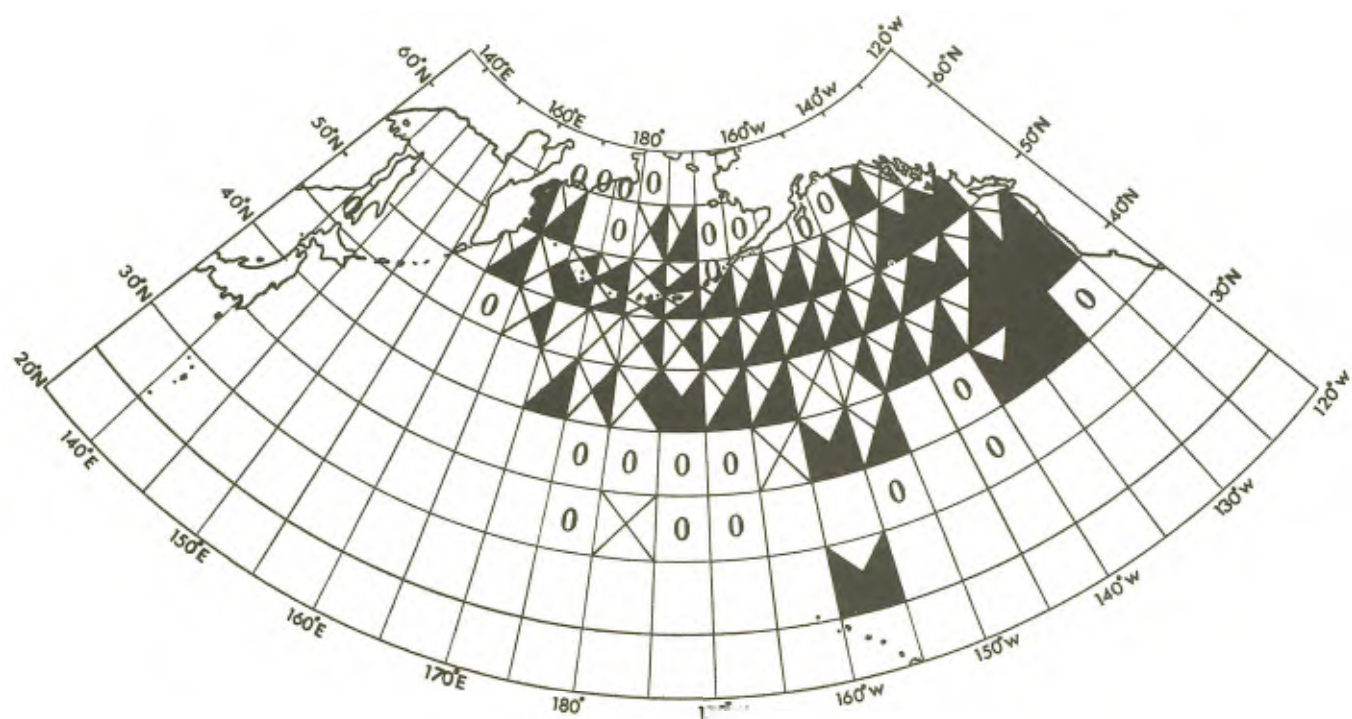
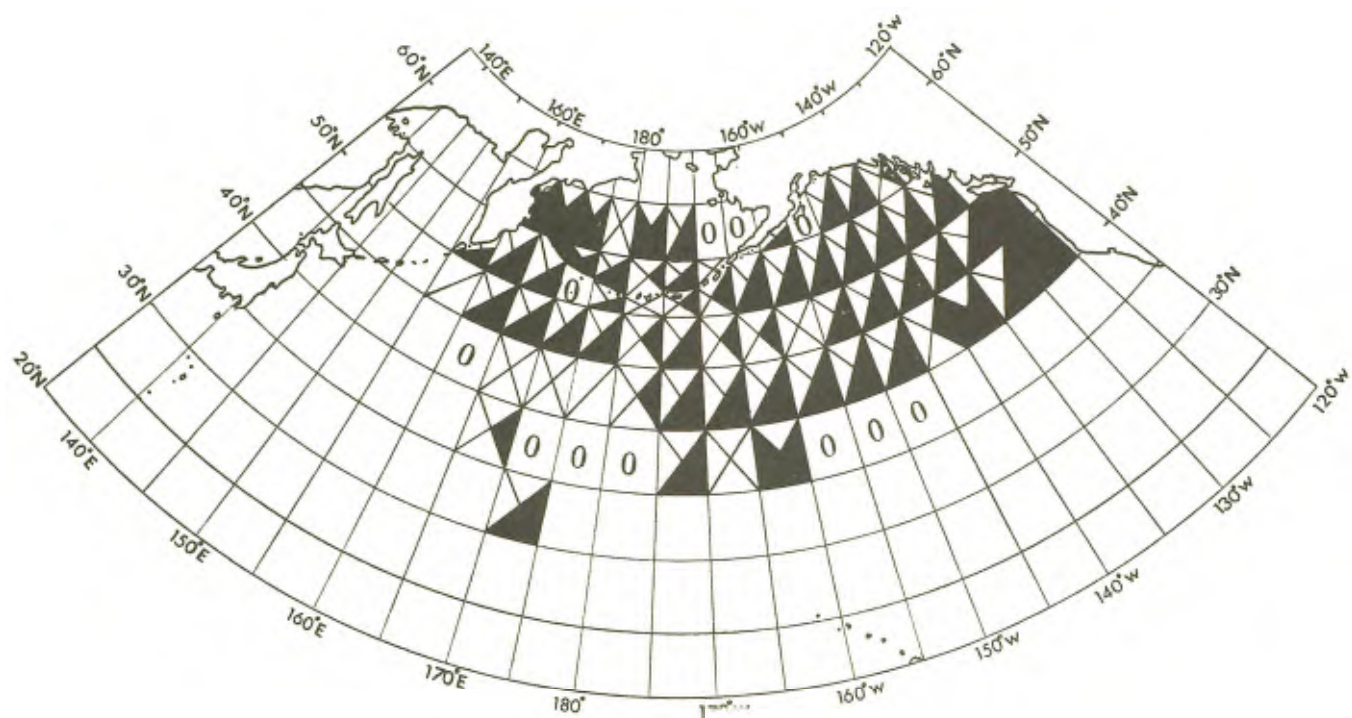


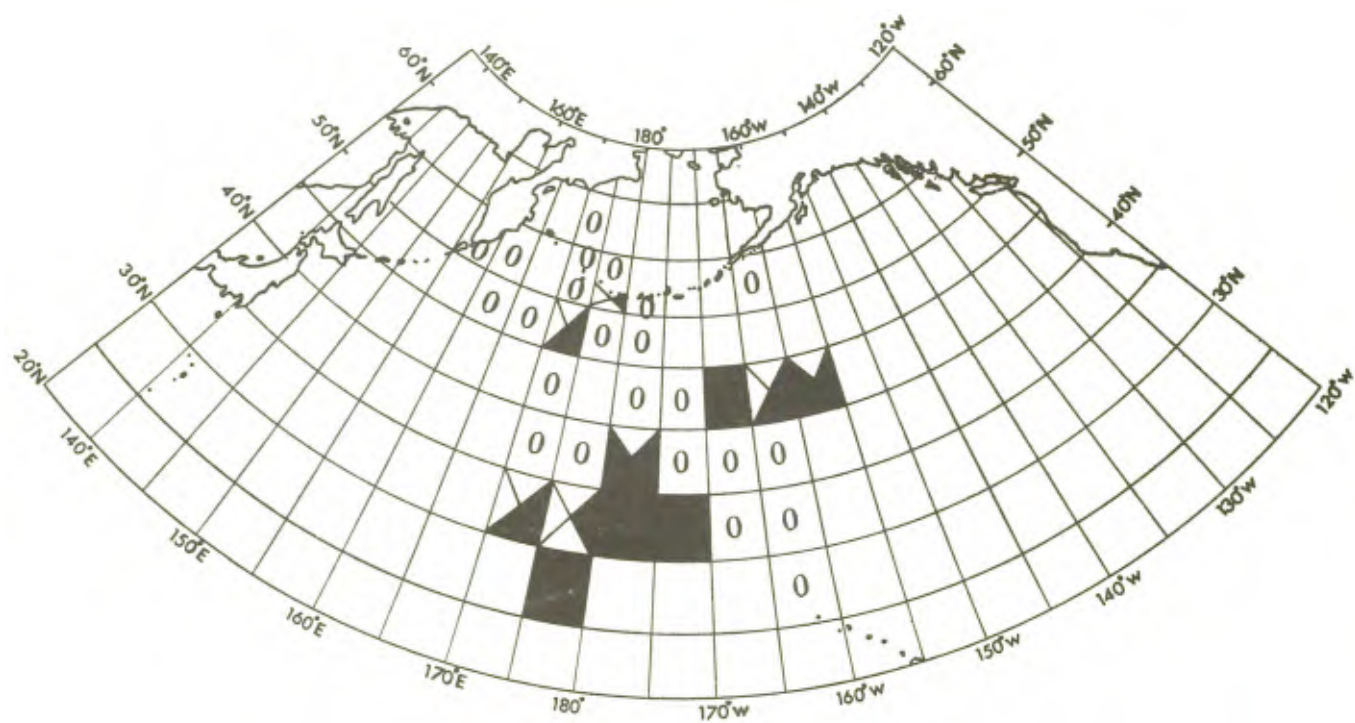


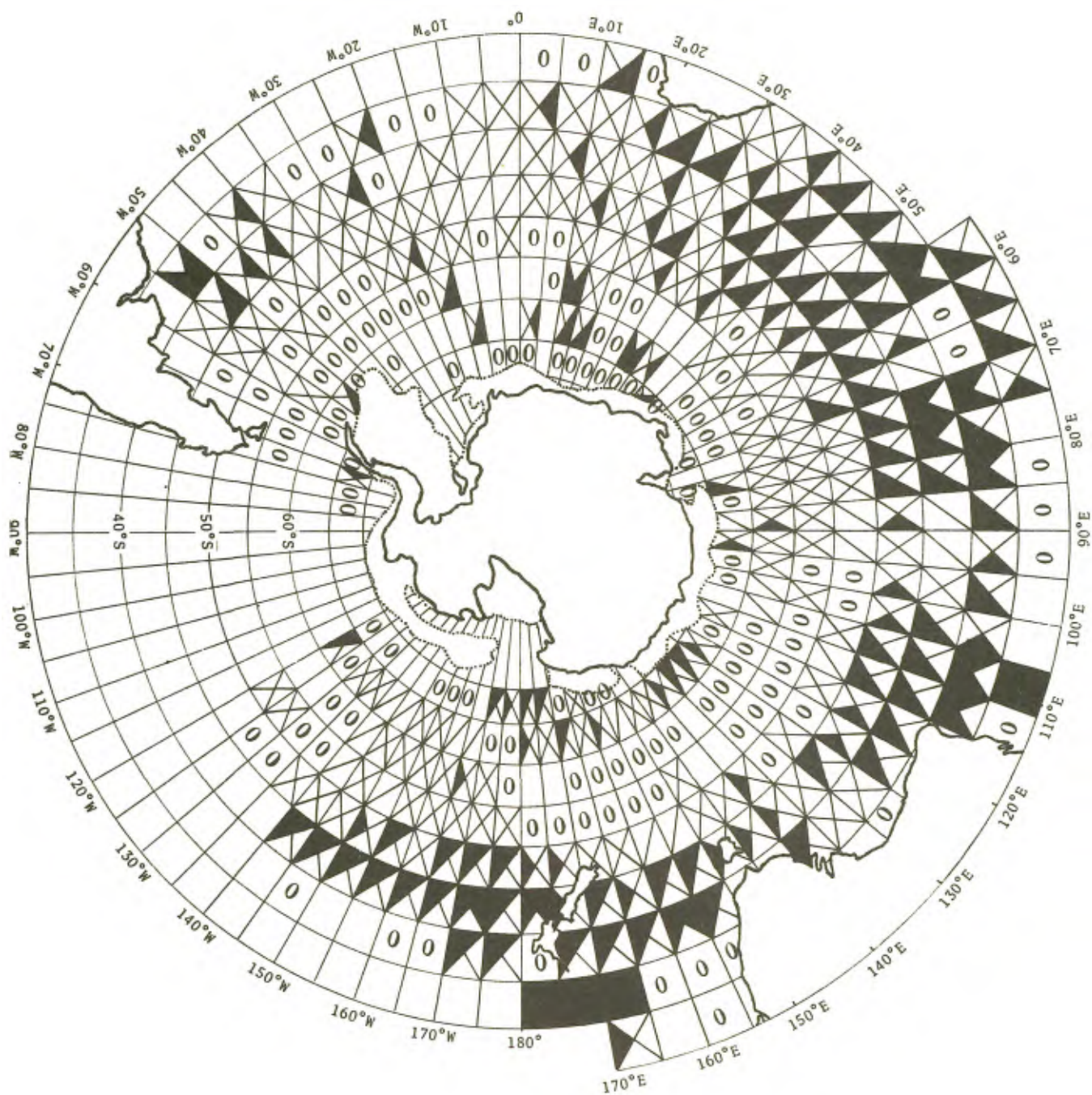


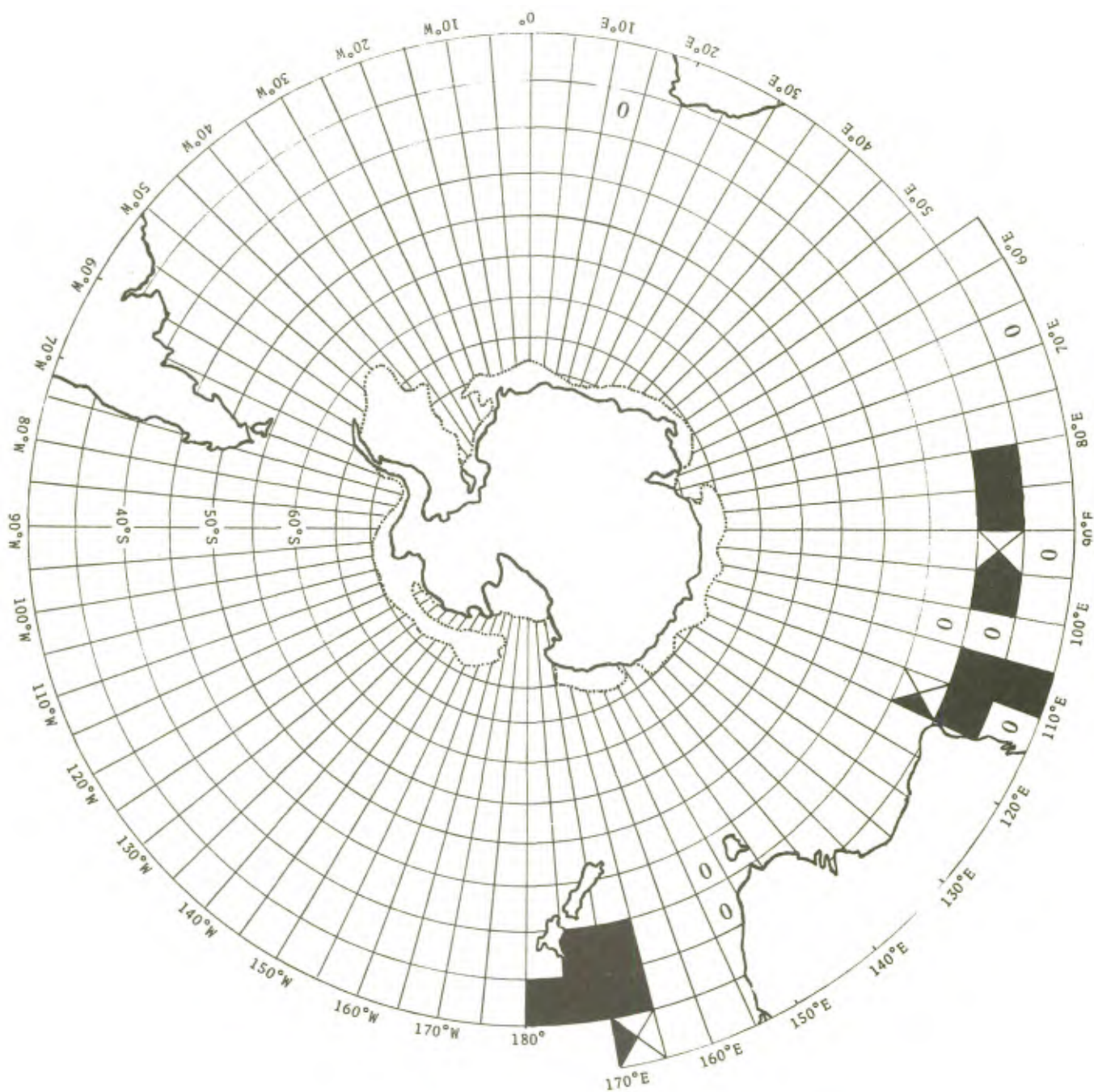


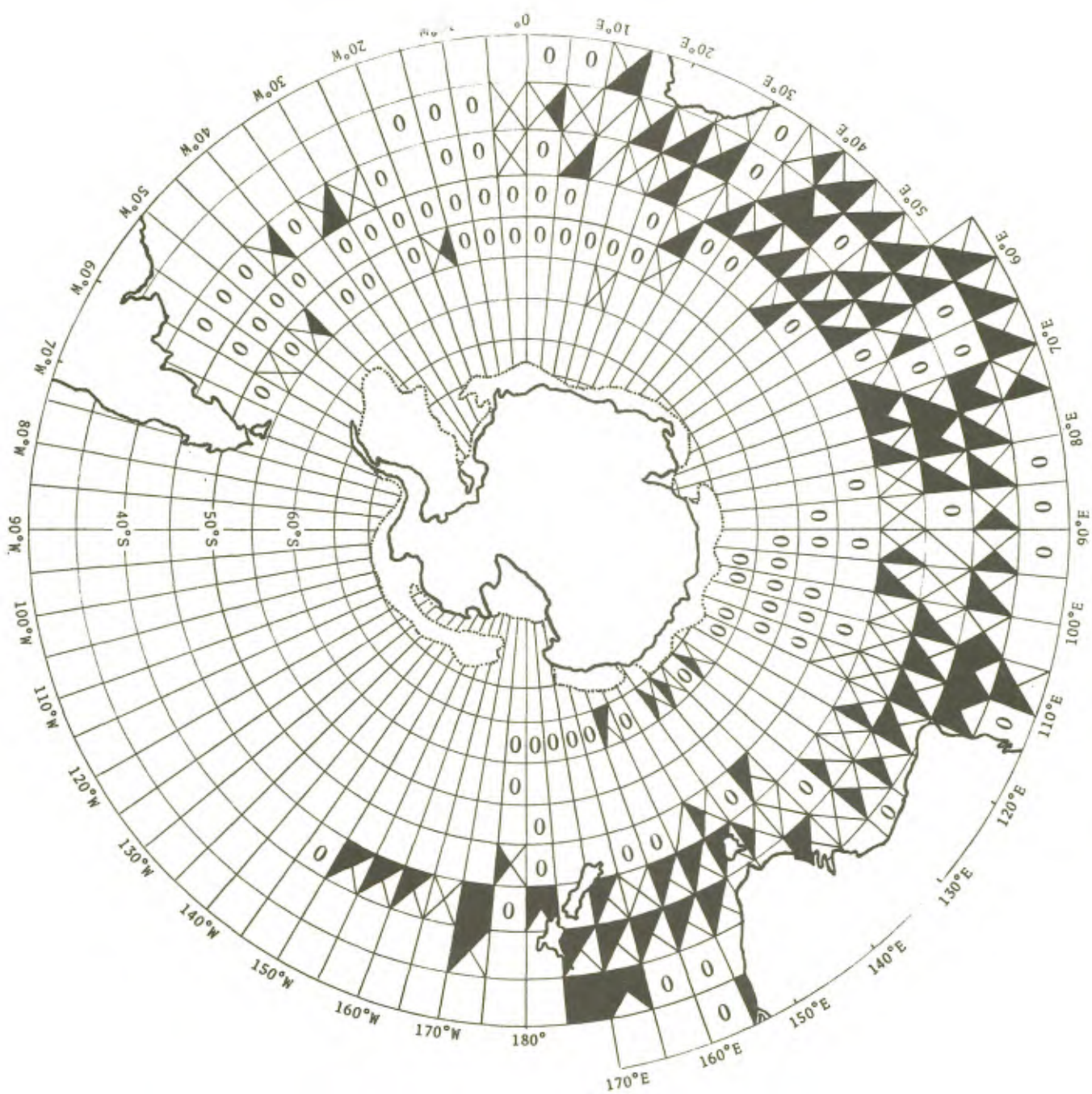


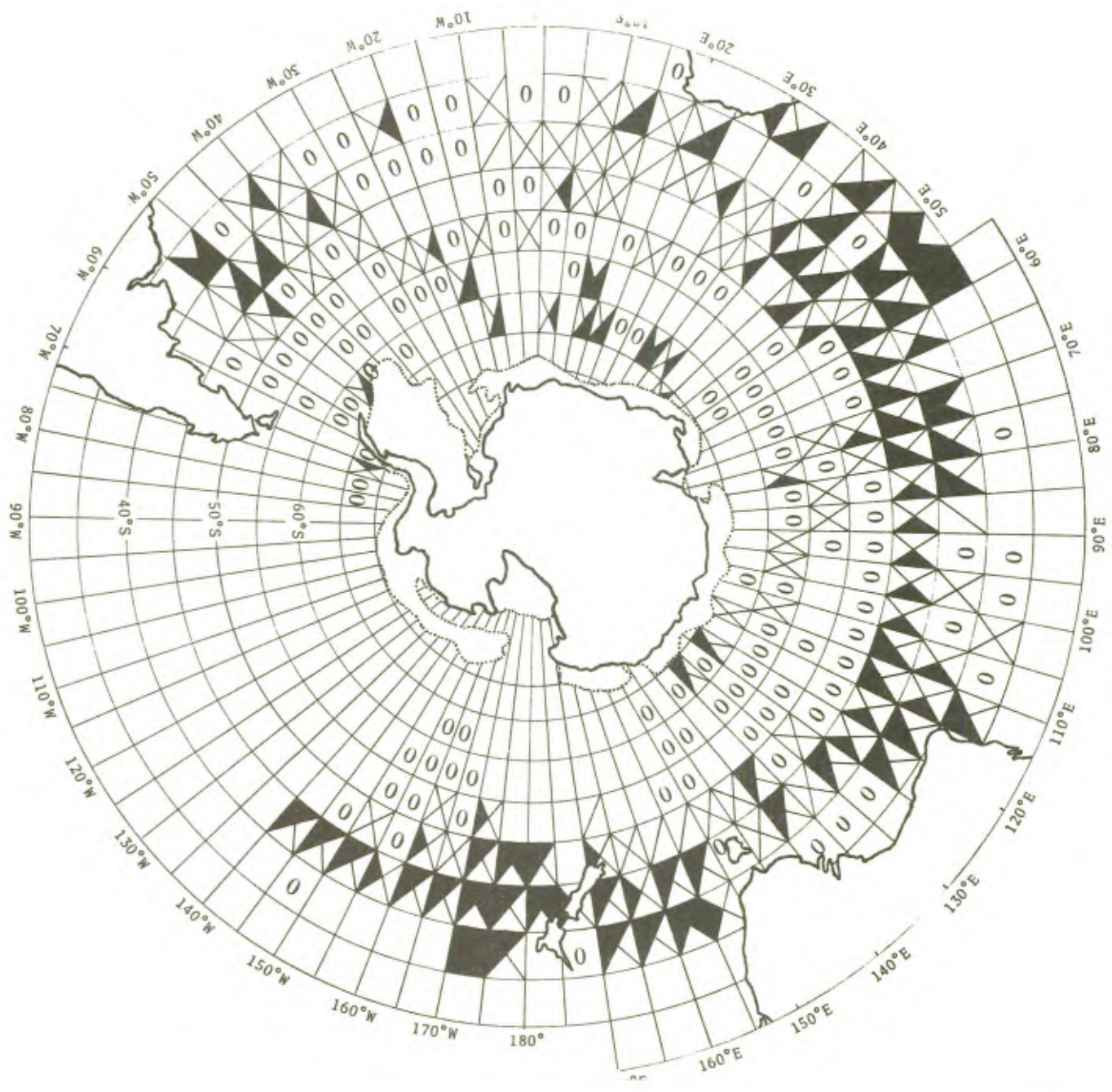


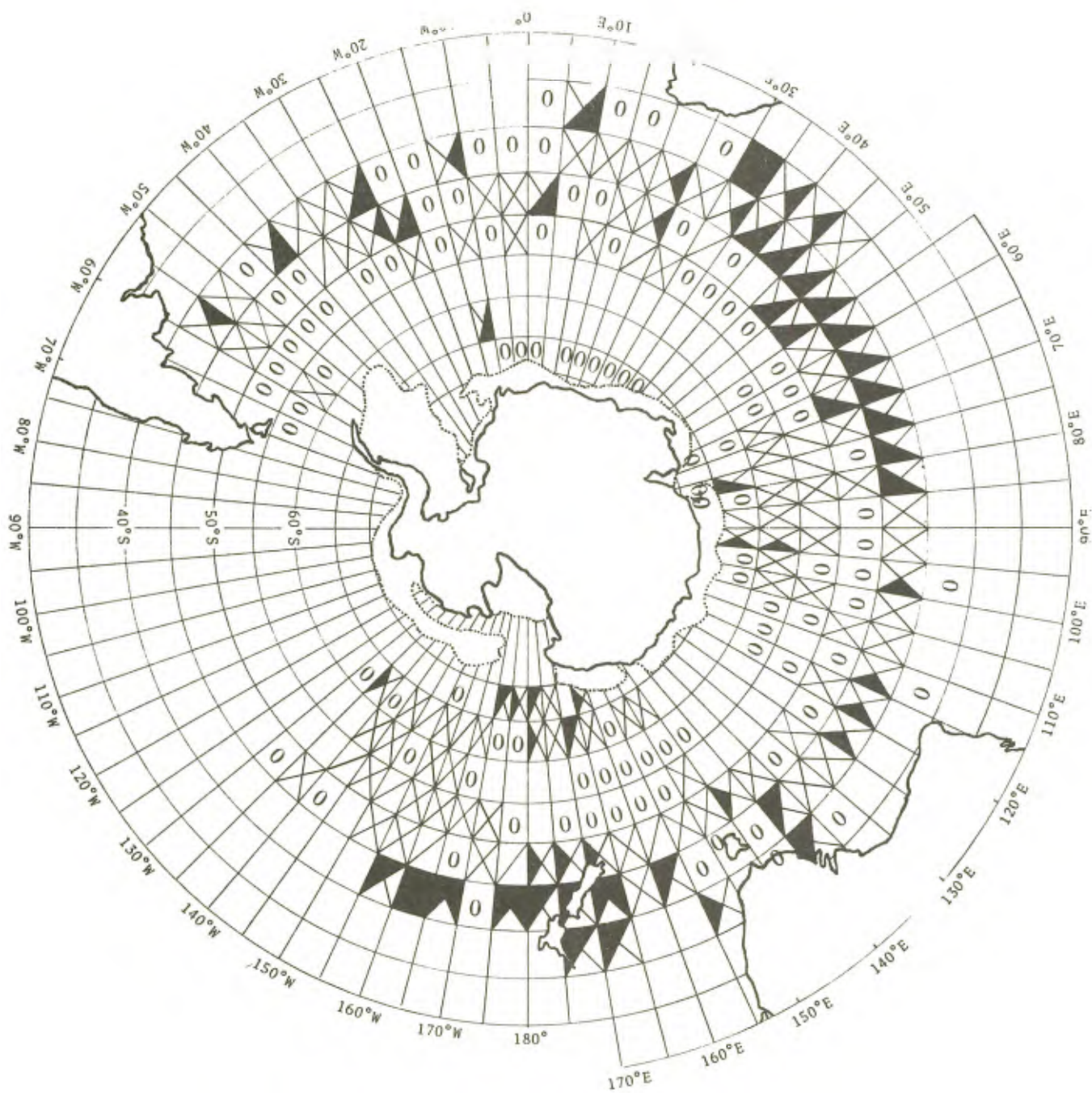


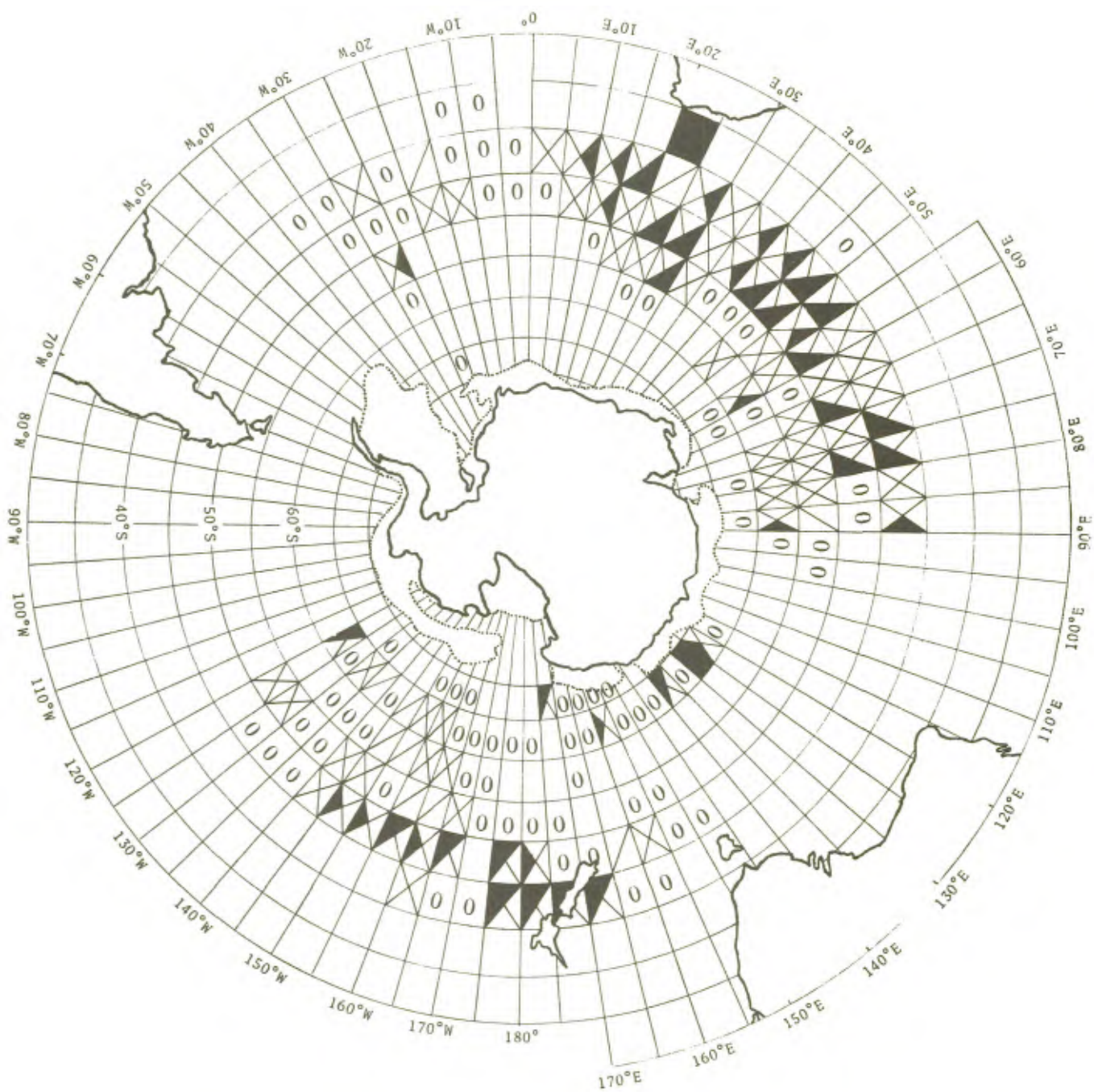


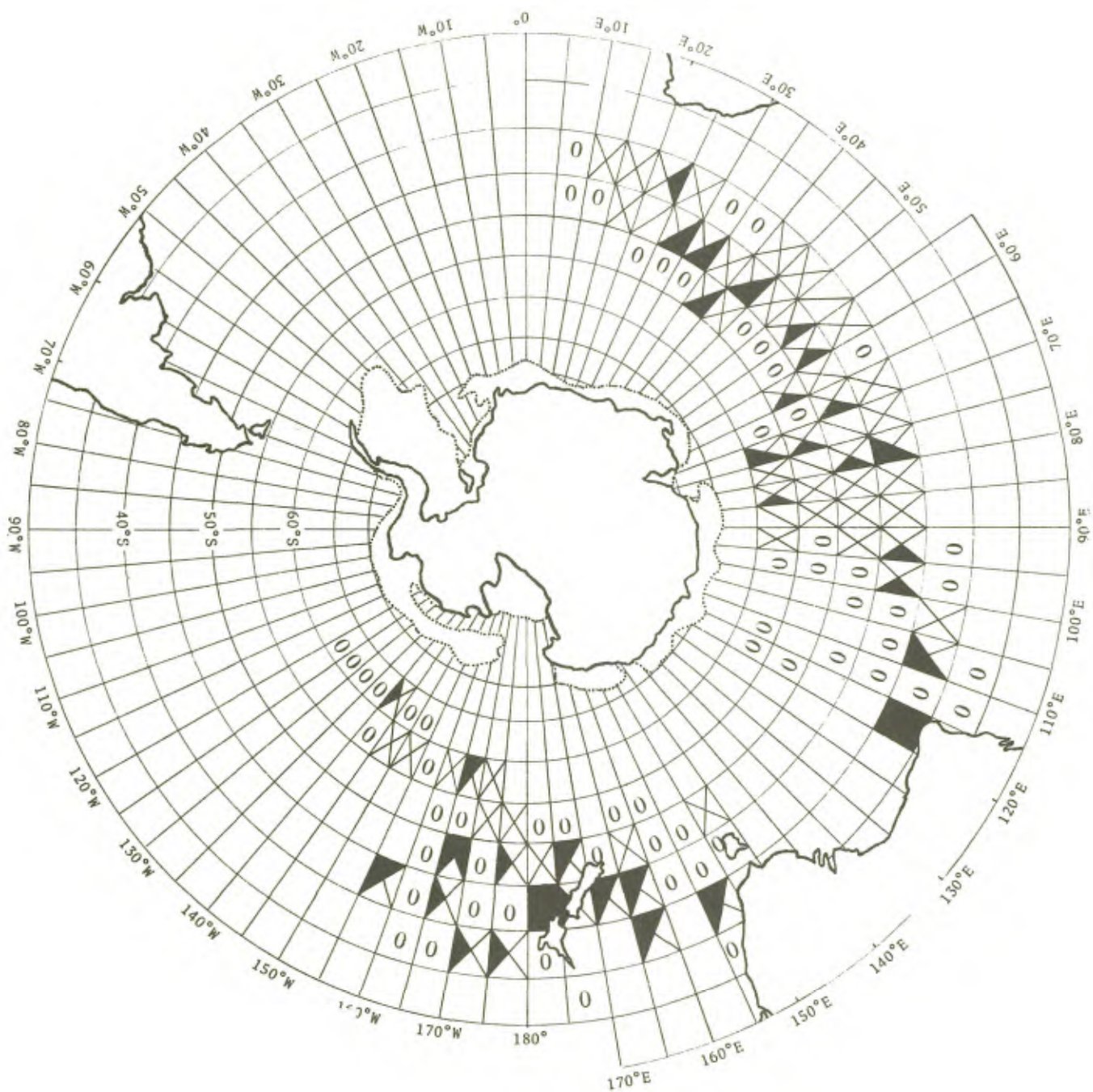


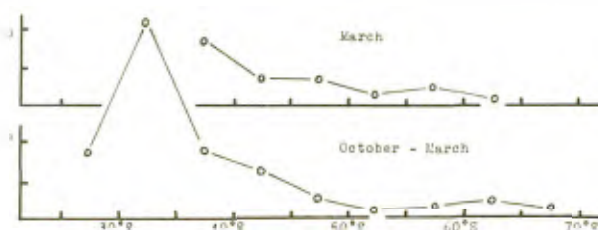
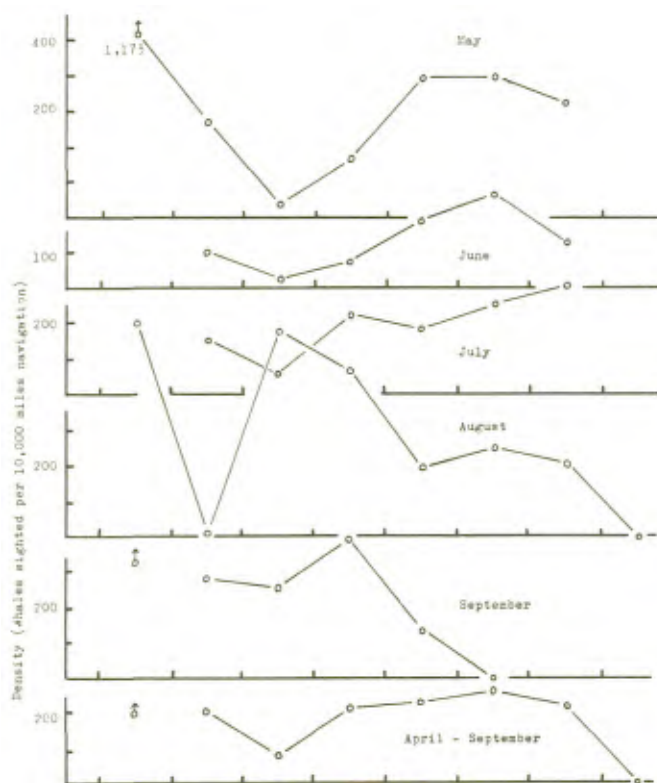
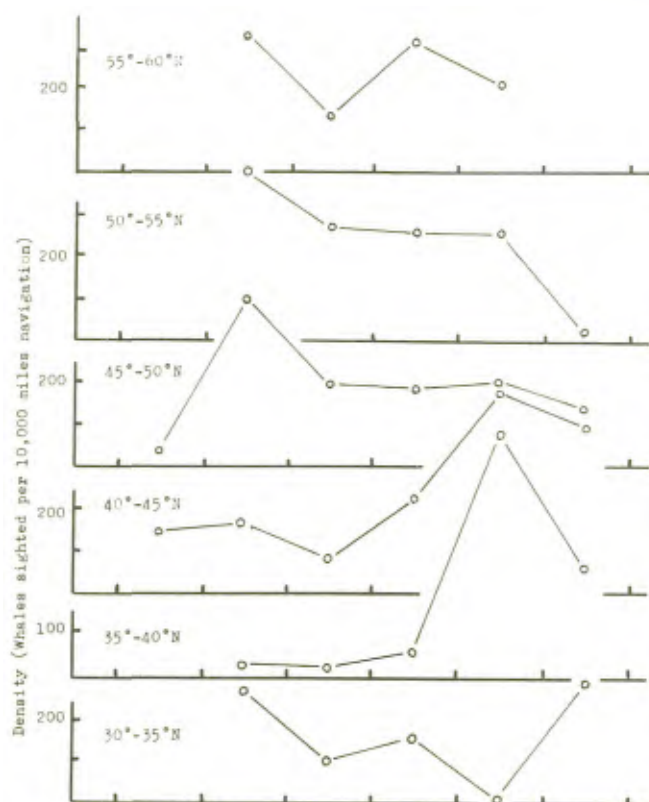


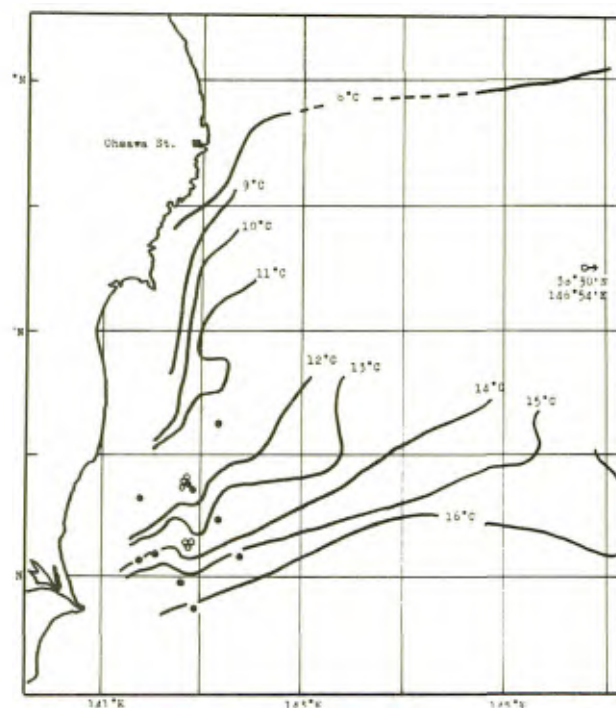
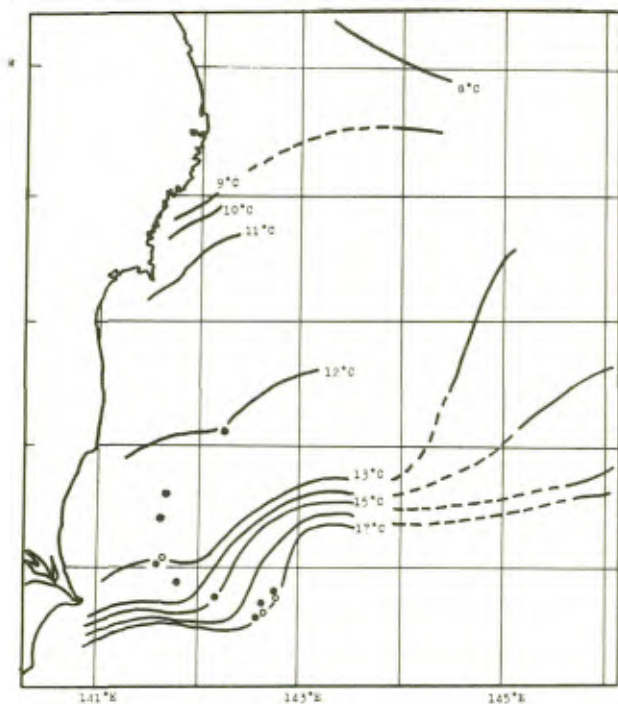


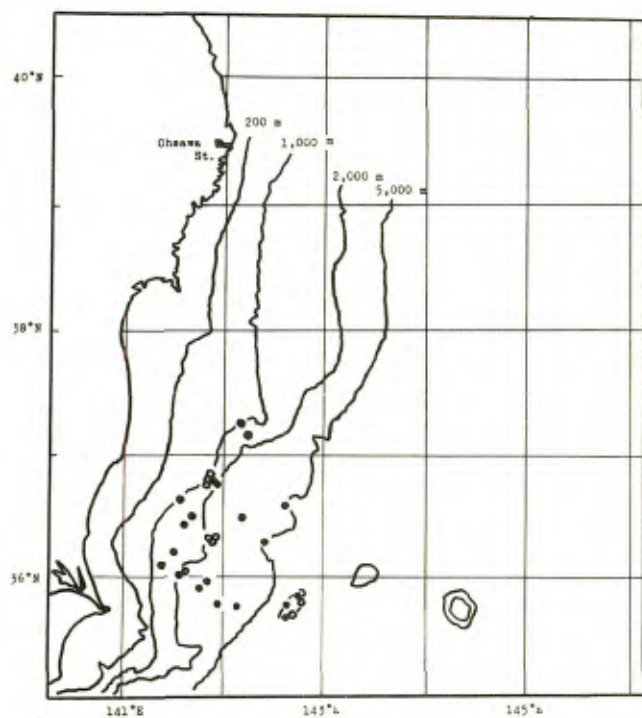












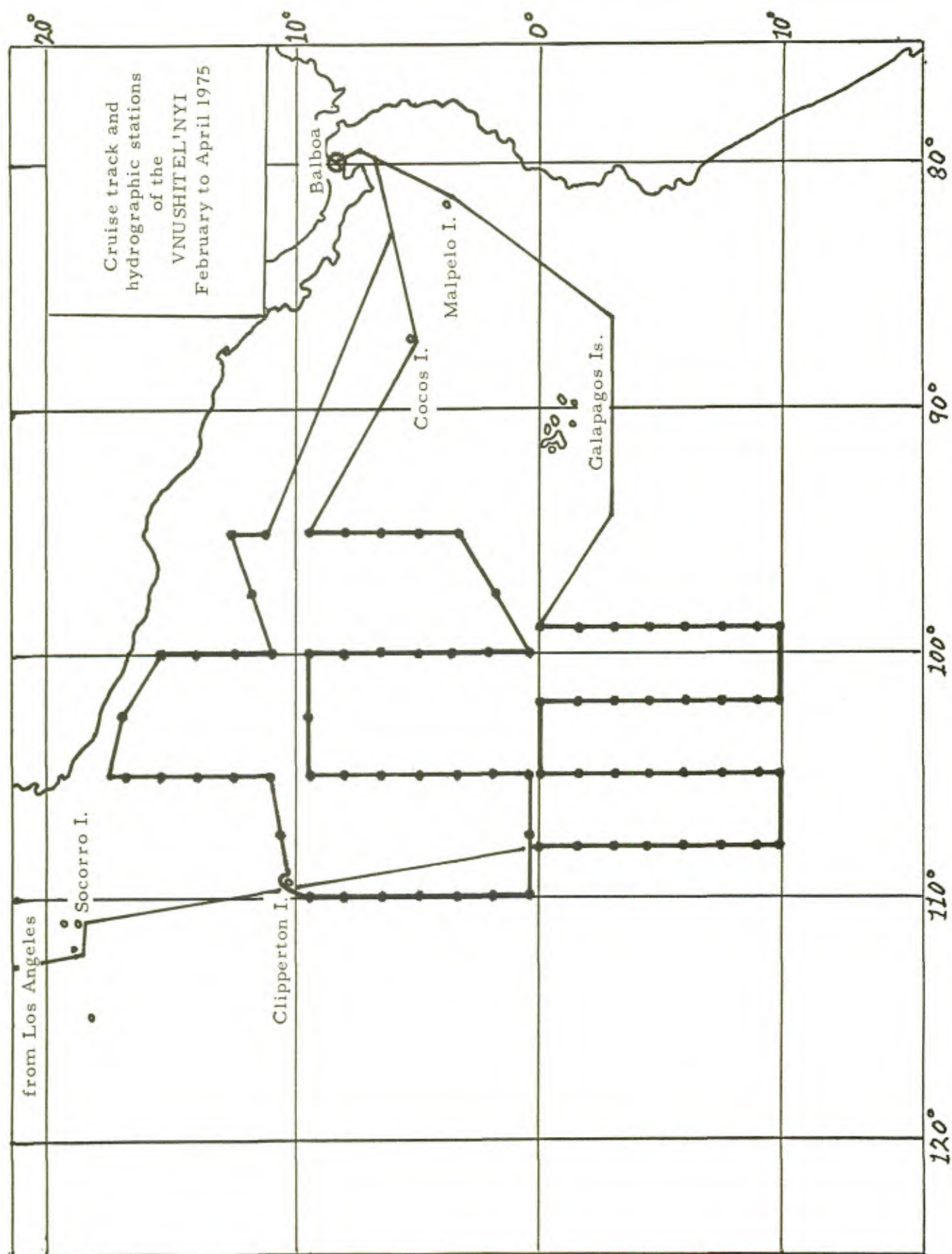
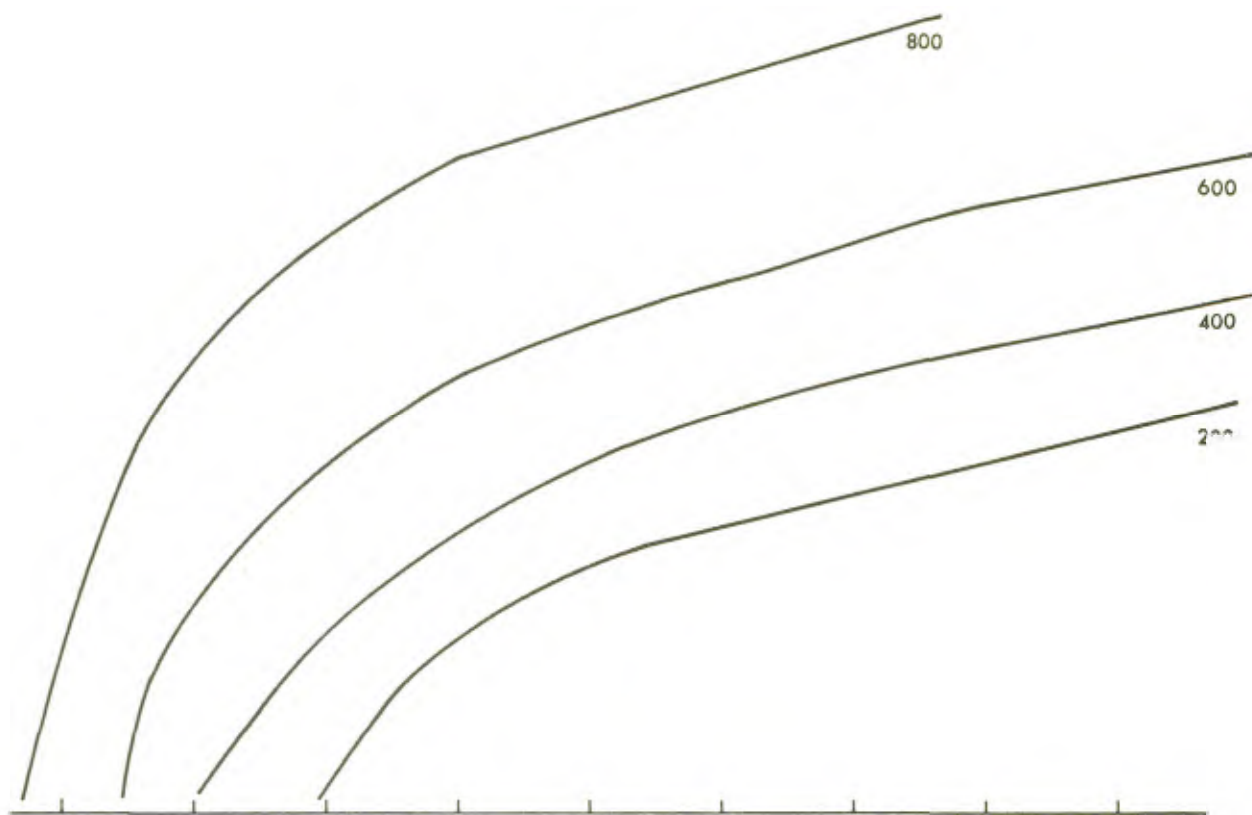
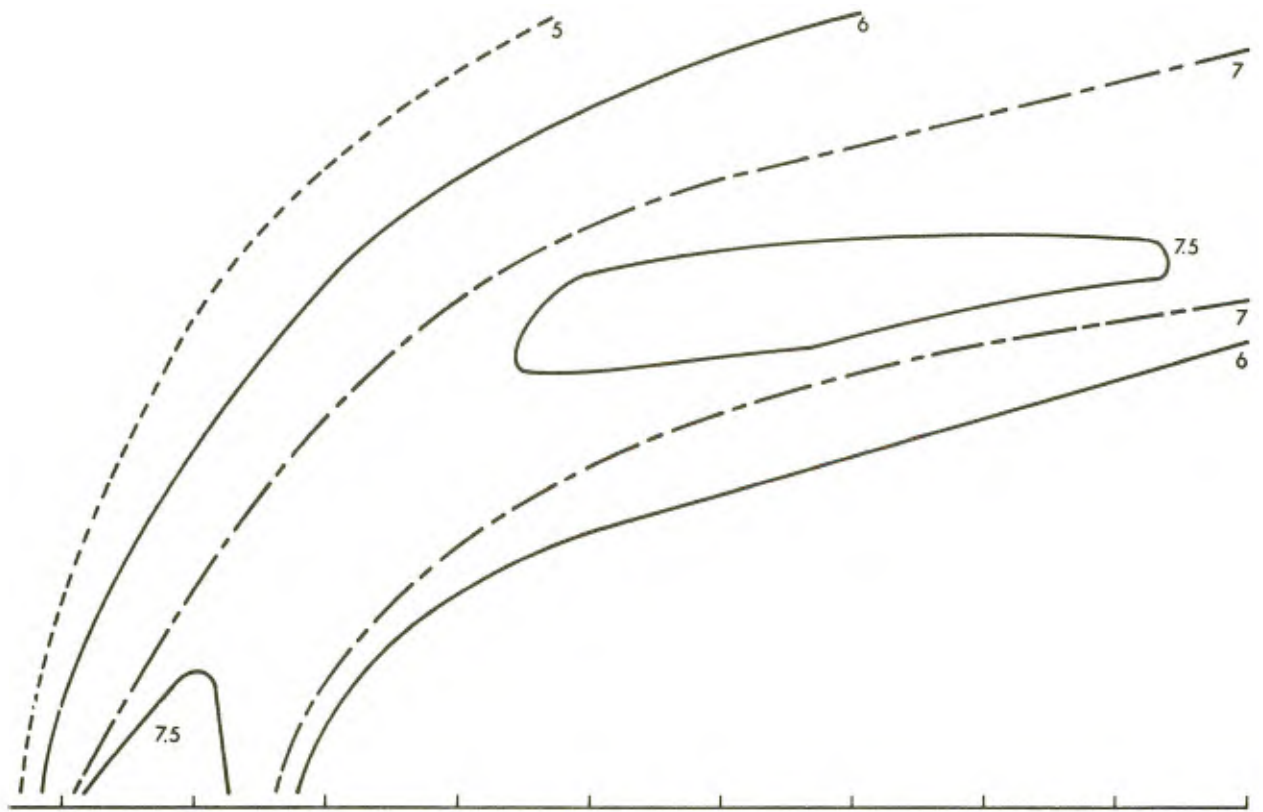
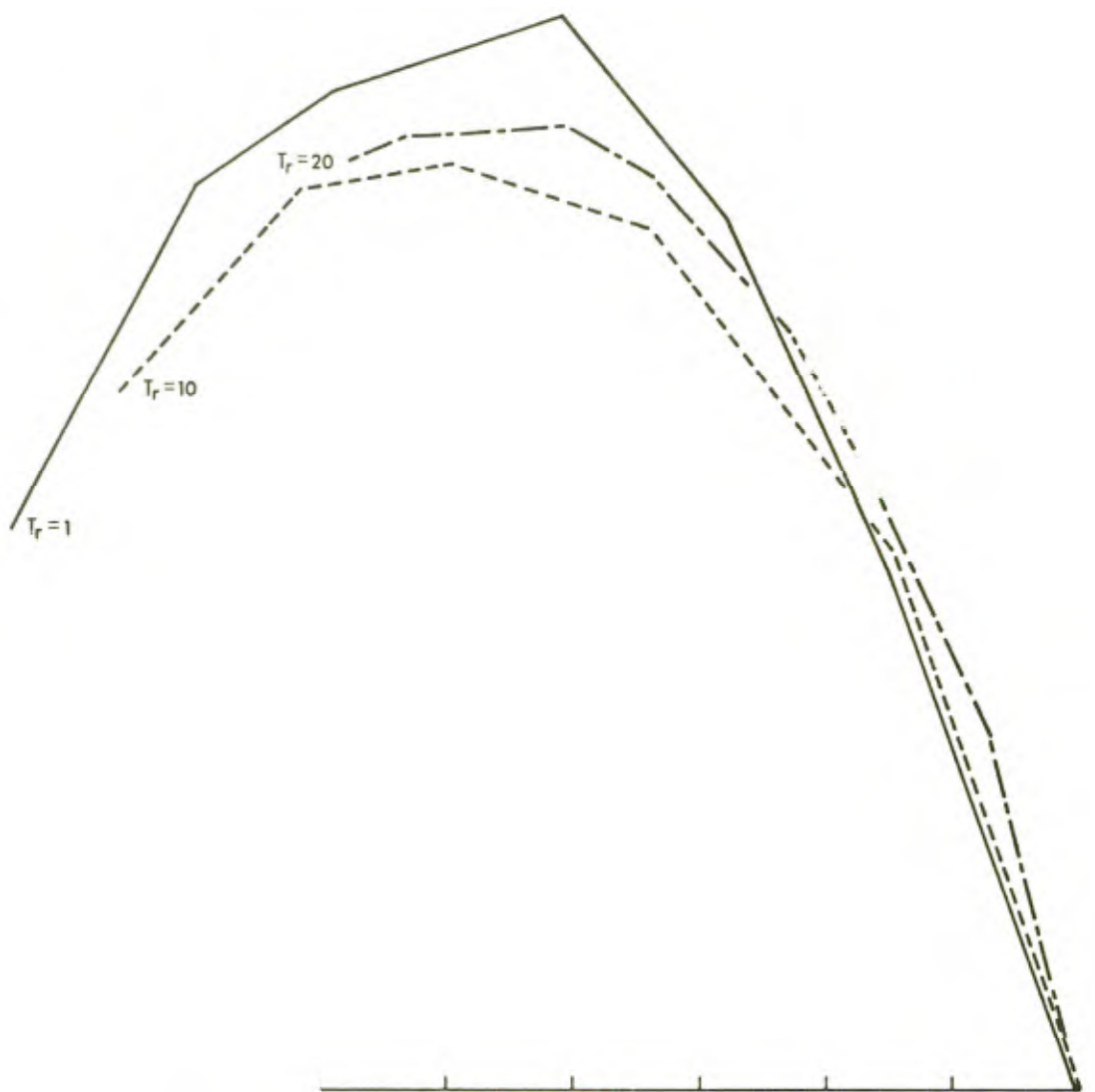
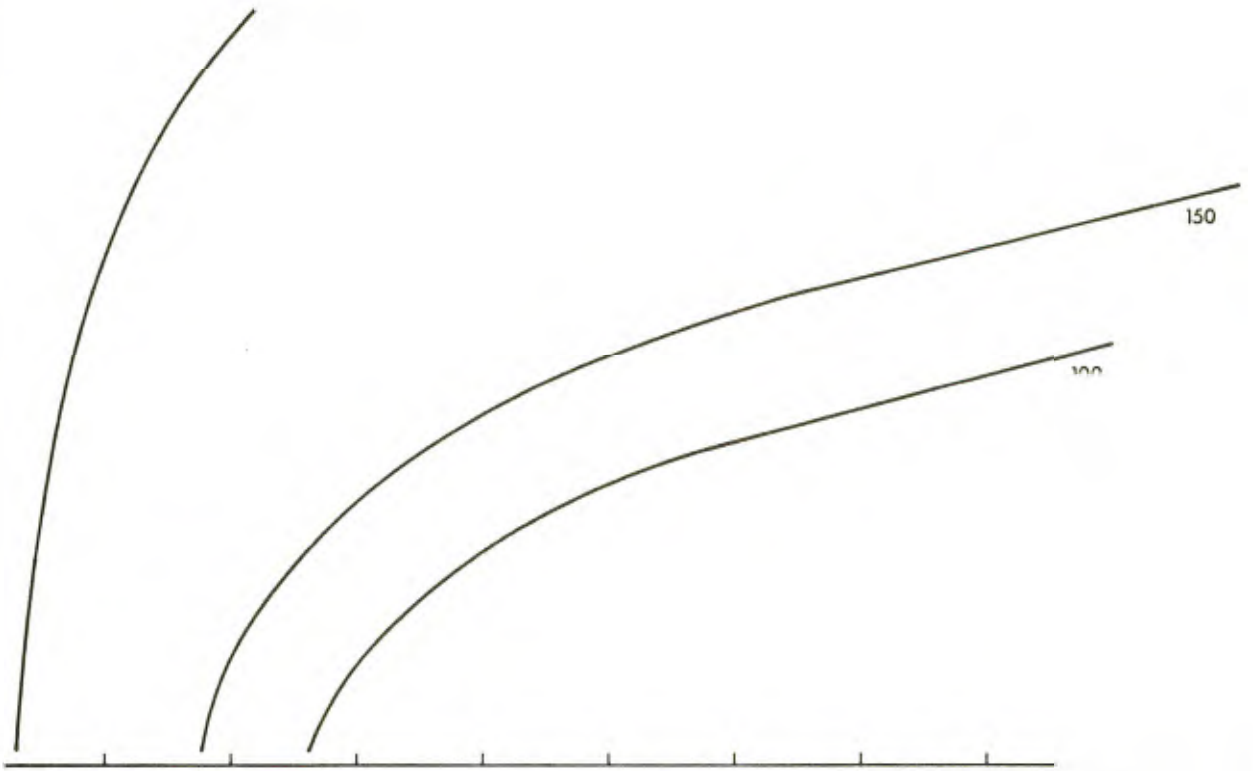


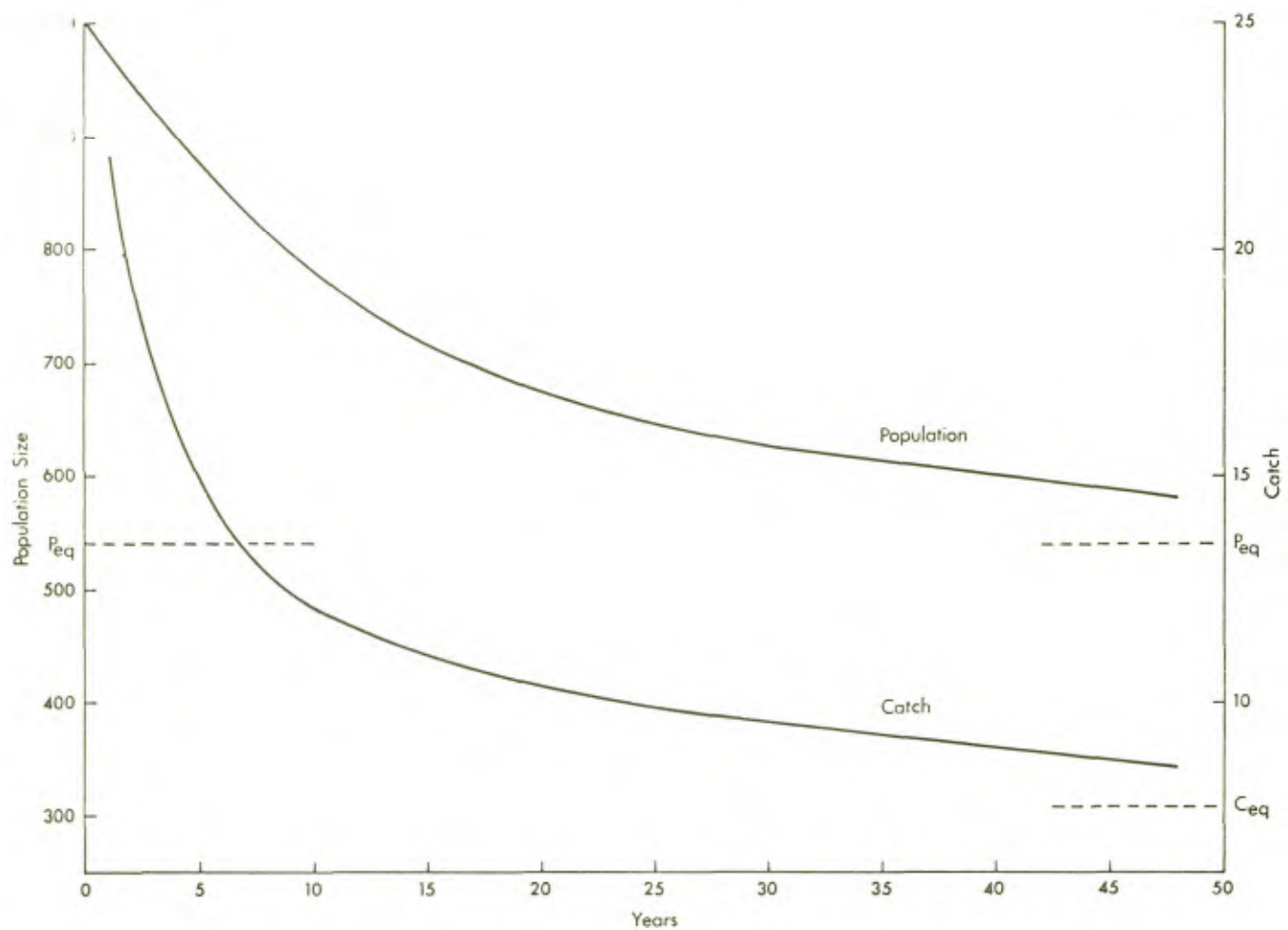
Fig. 1.

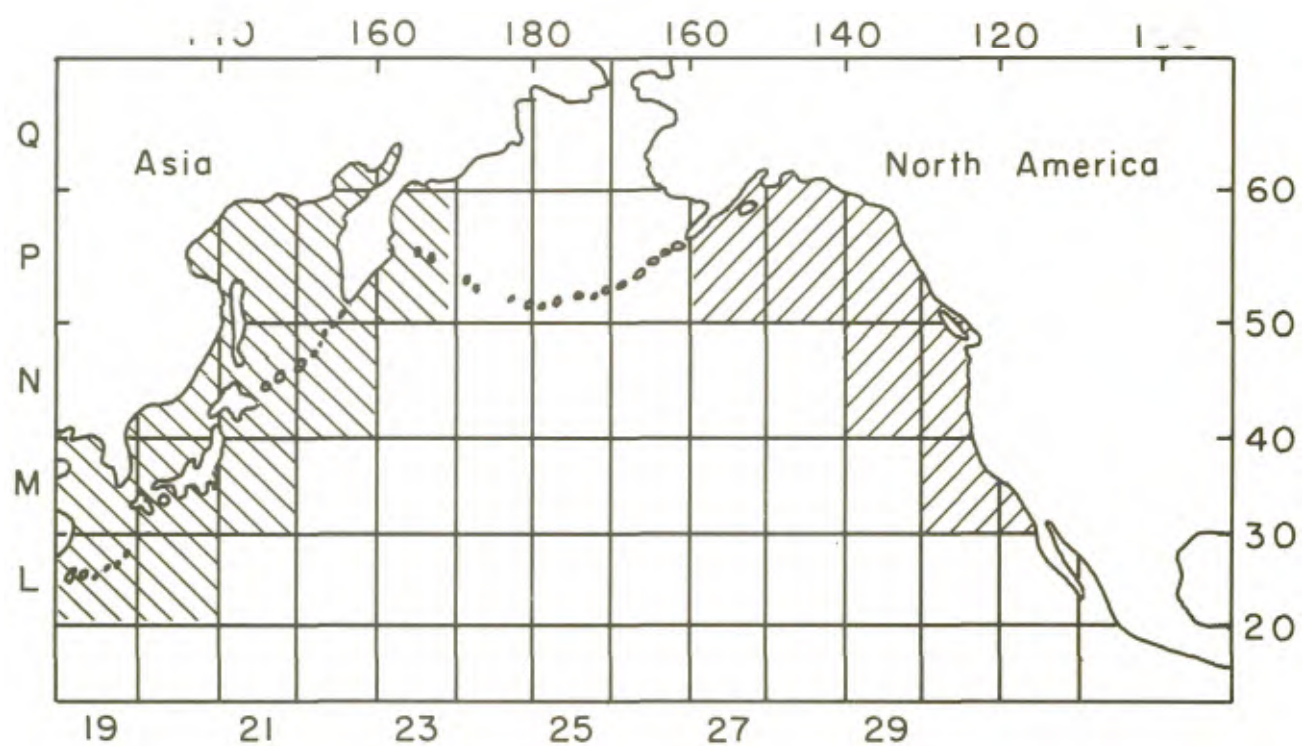




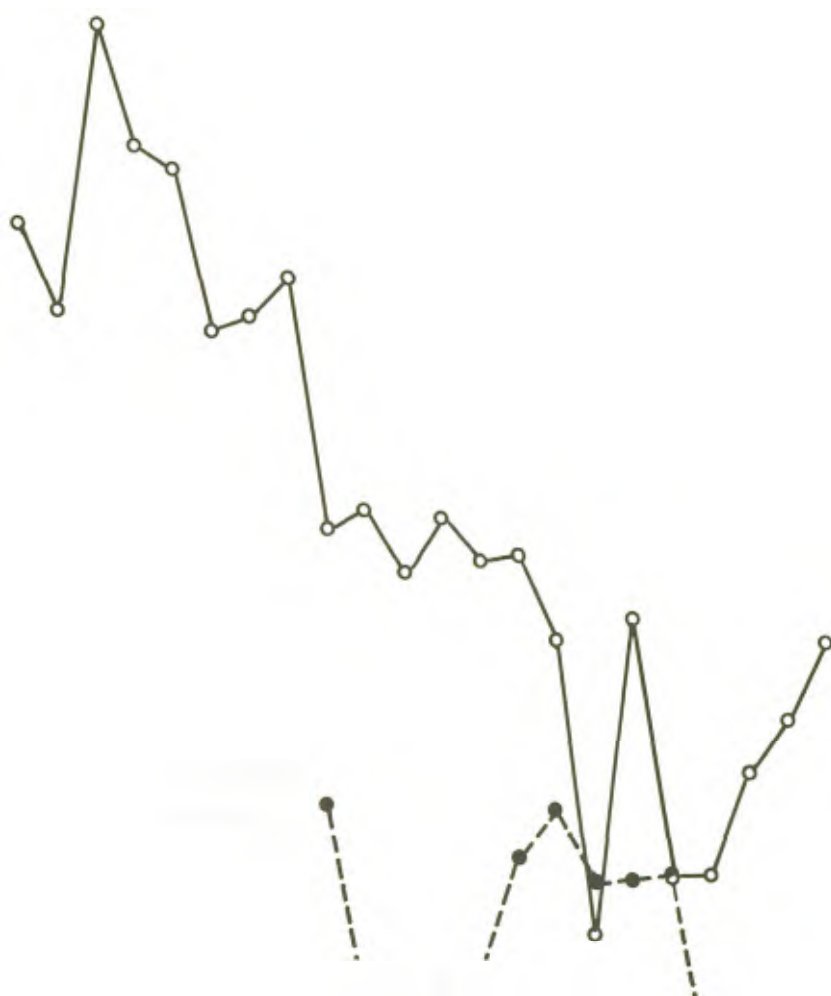




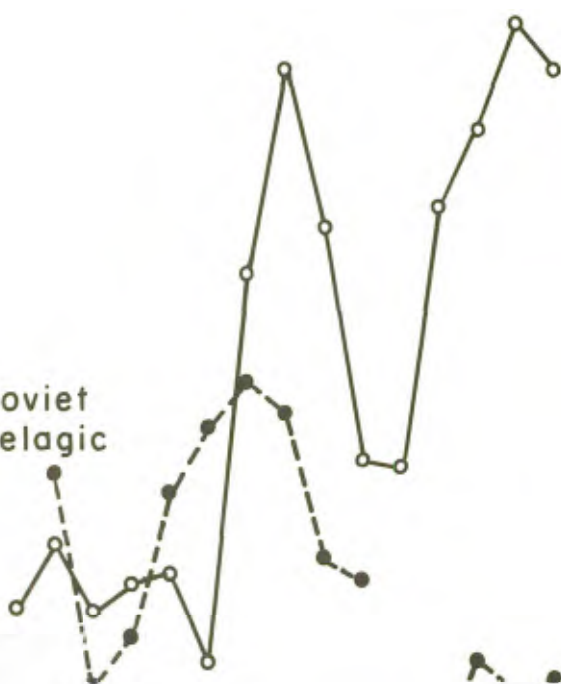


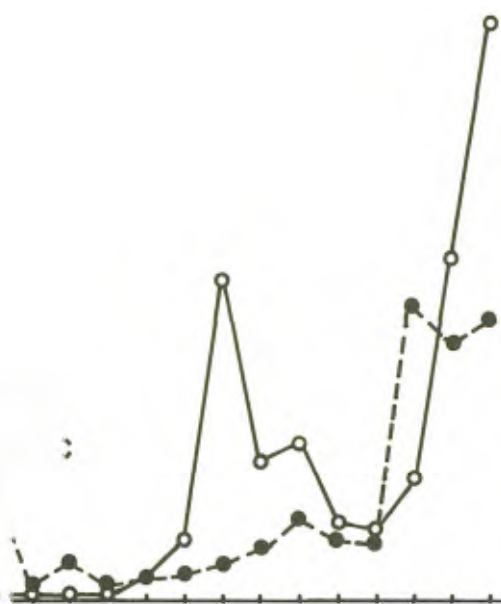
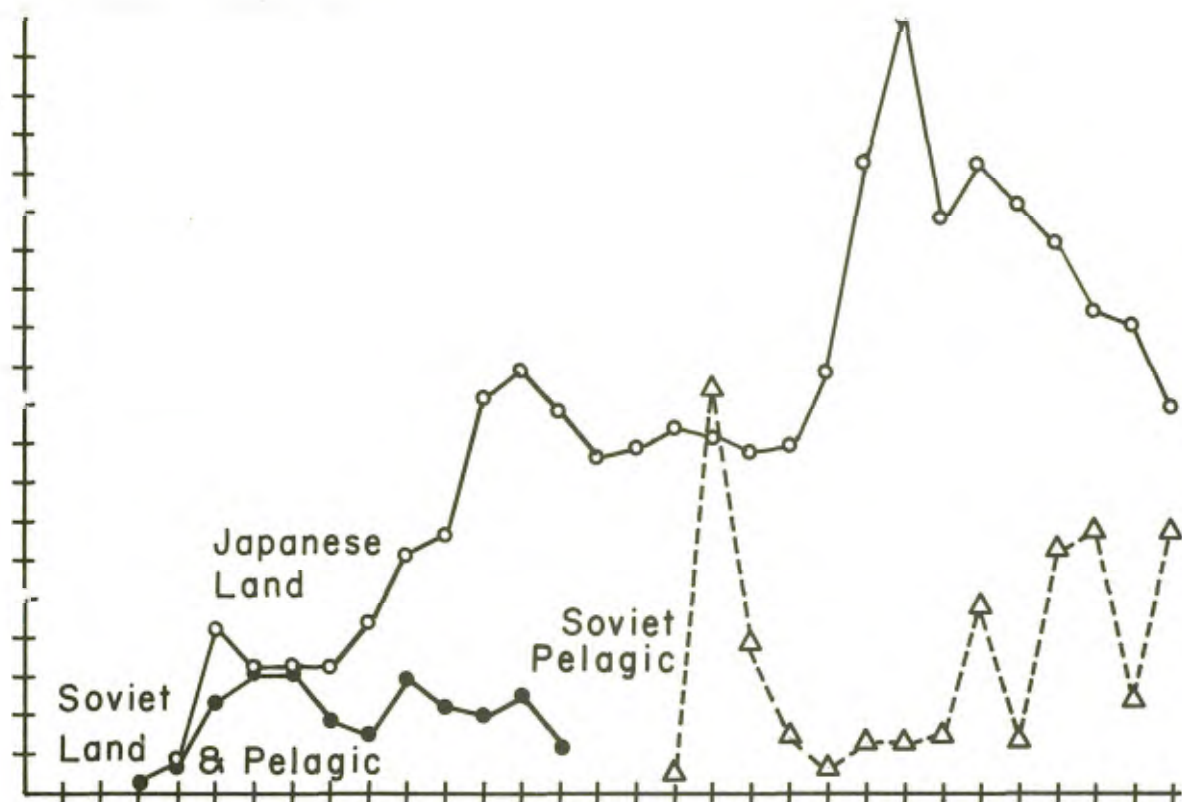


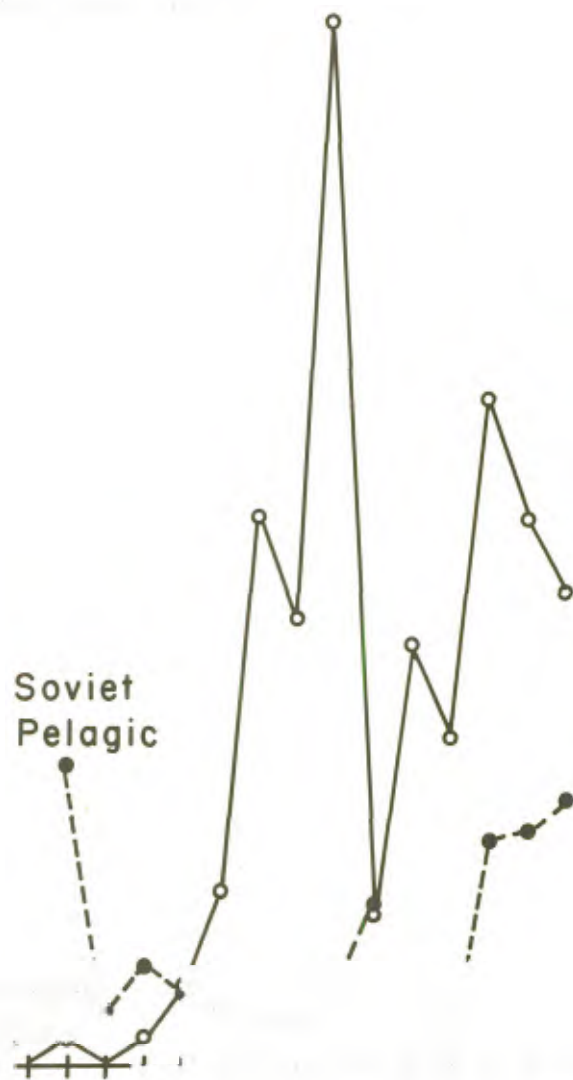


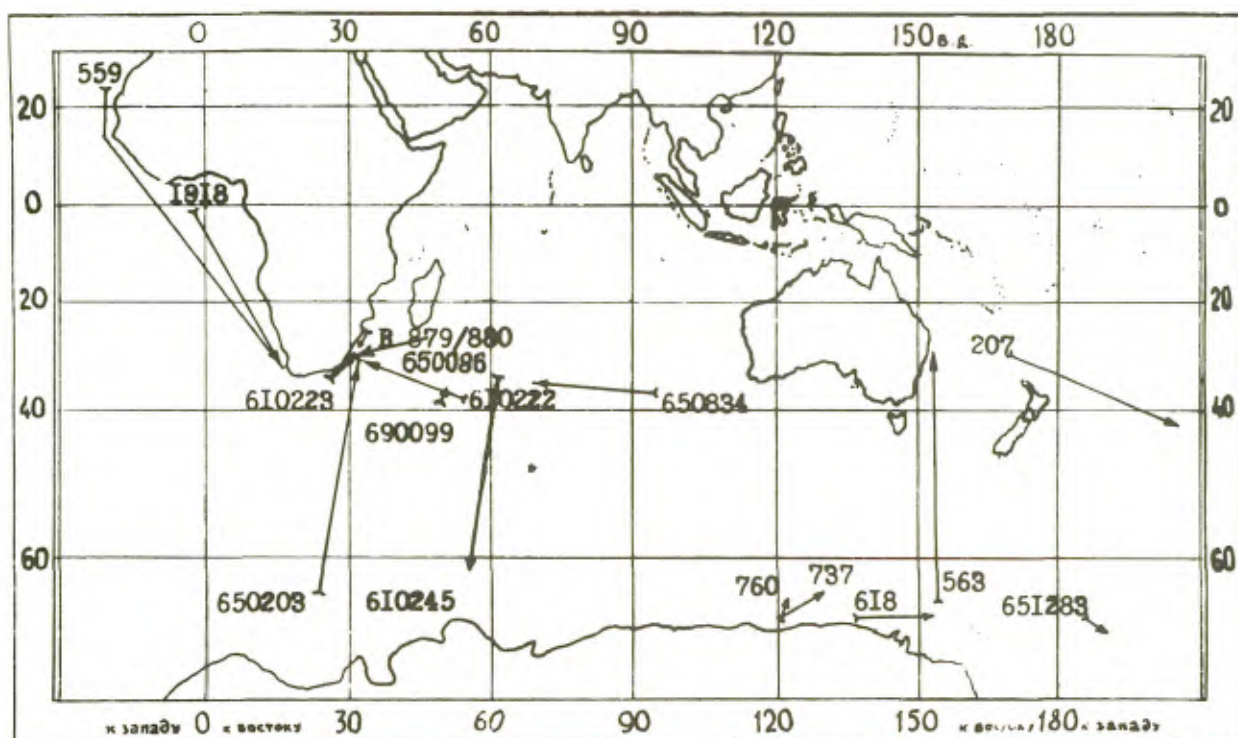


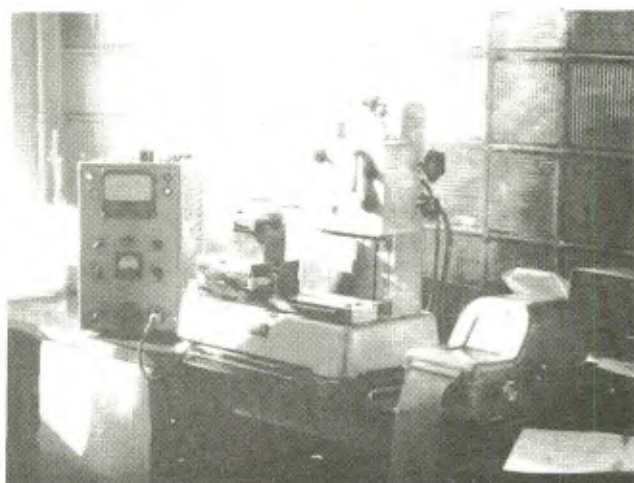
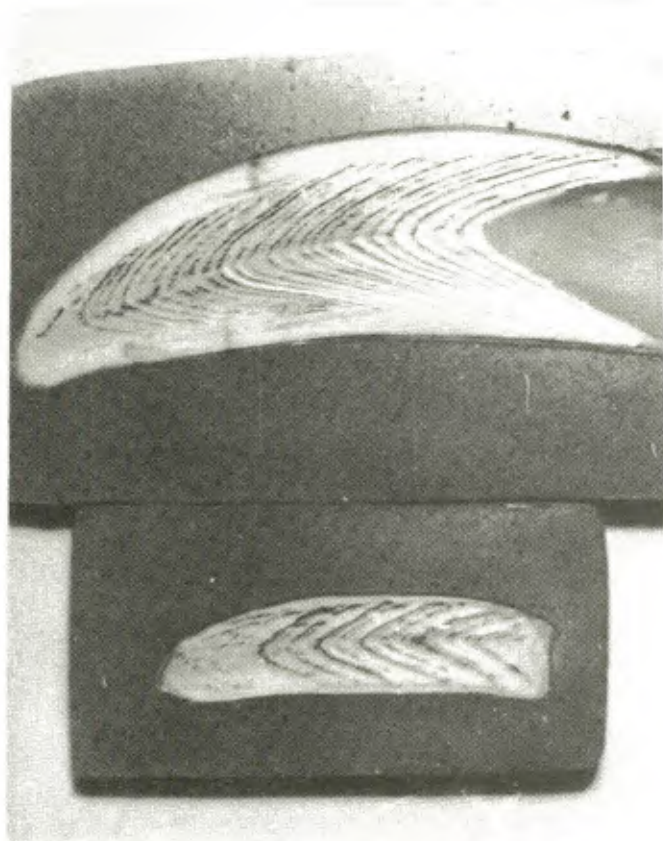
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Pelagic

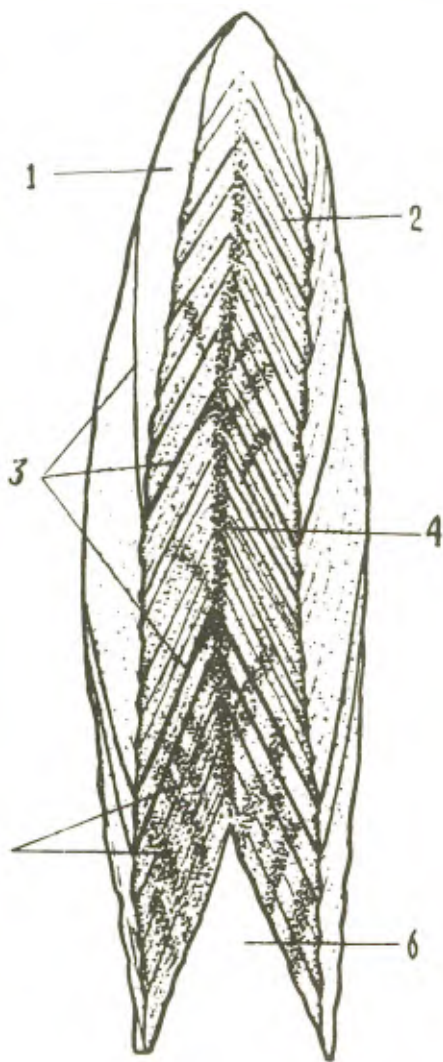










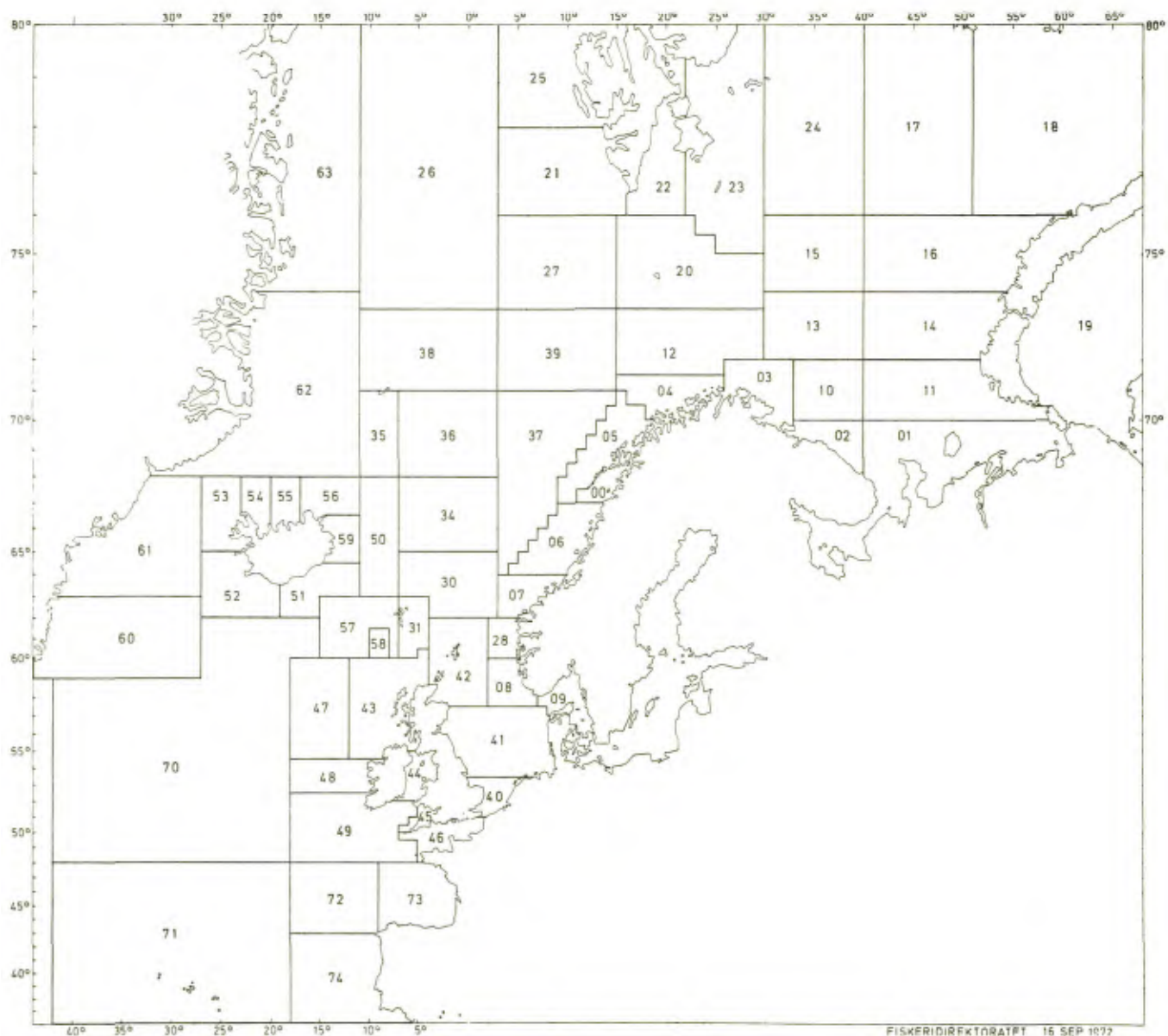


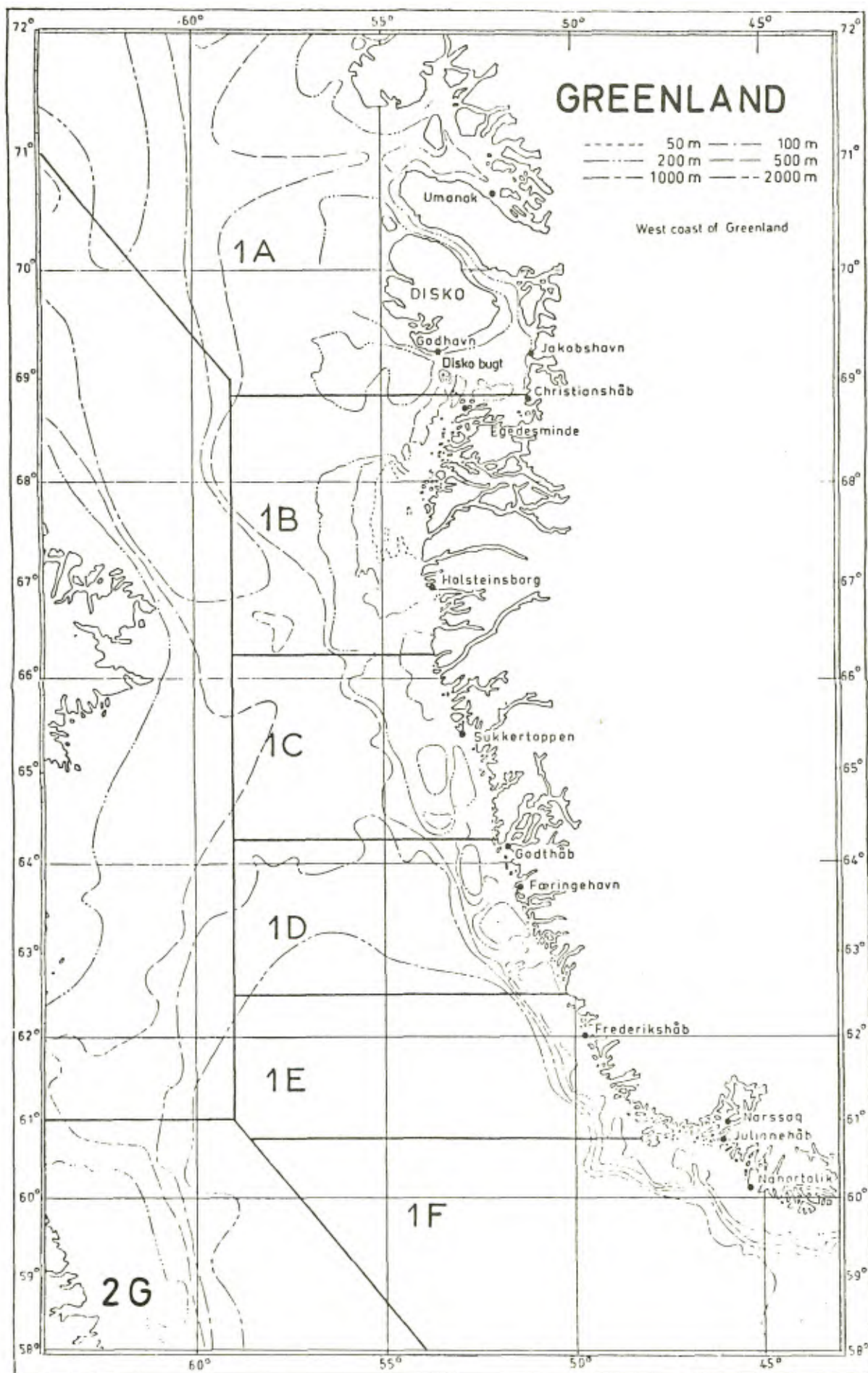


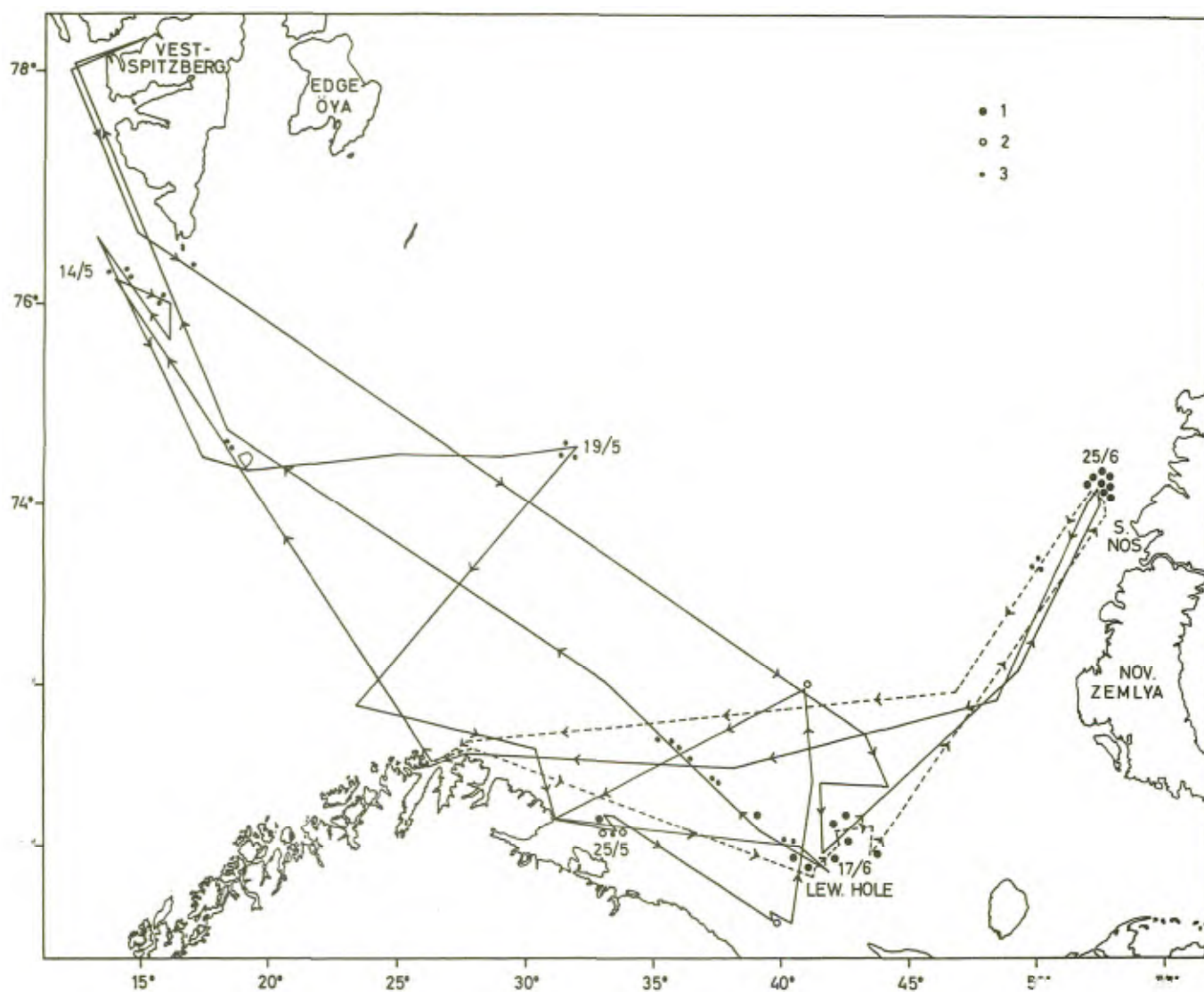
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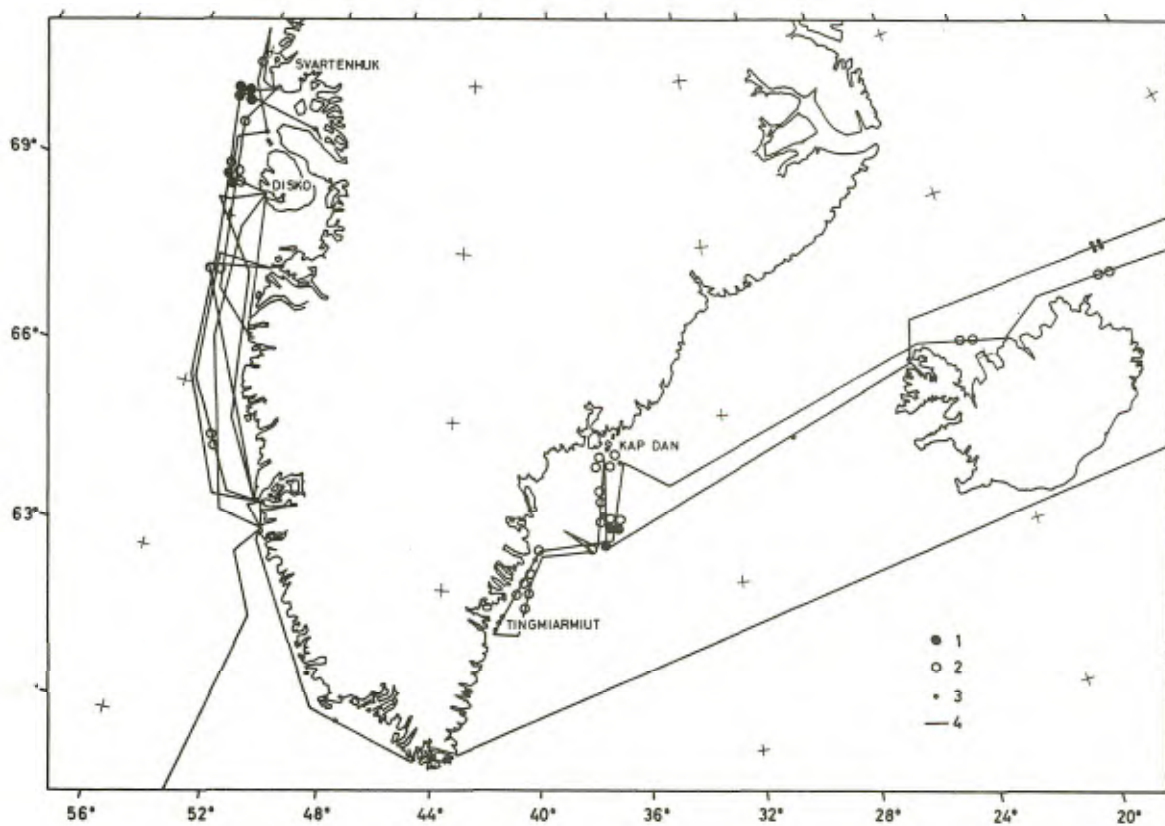
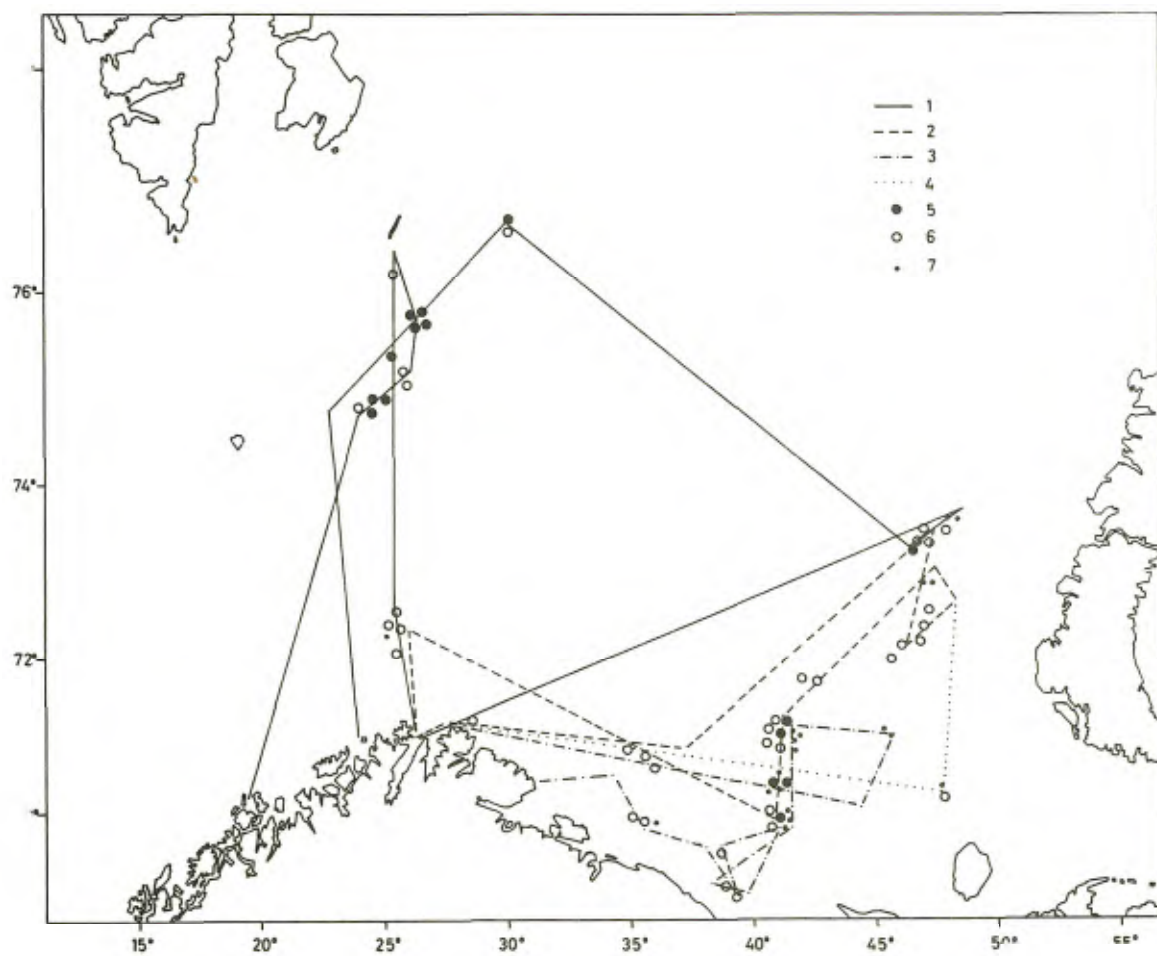


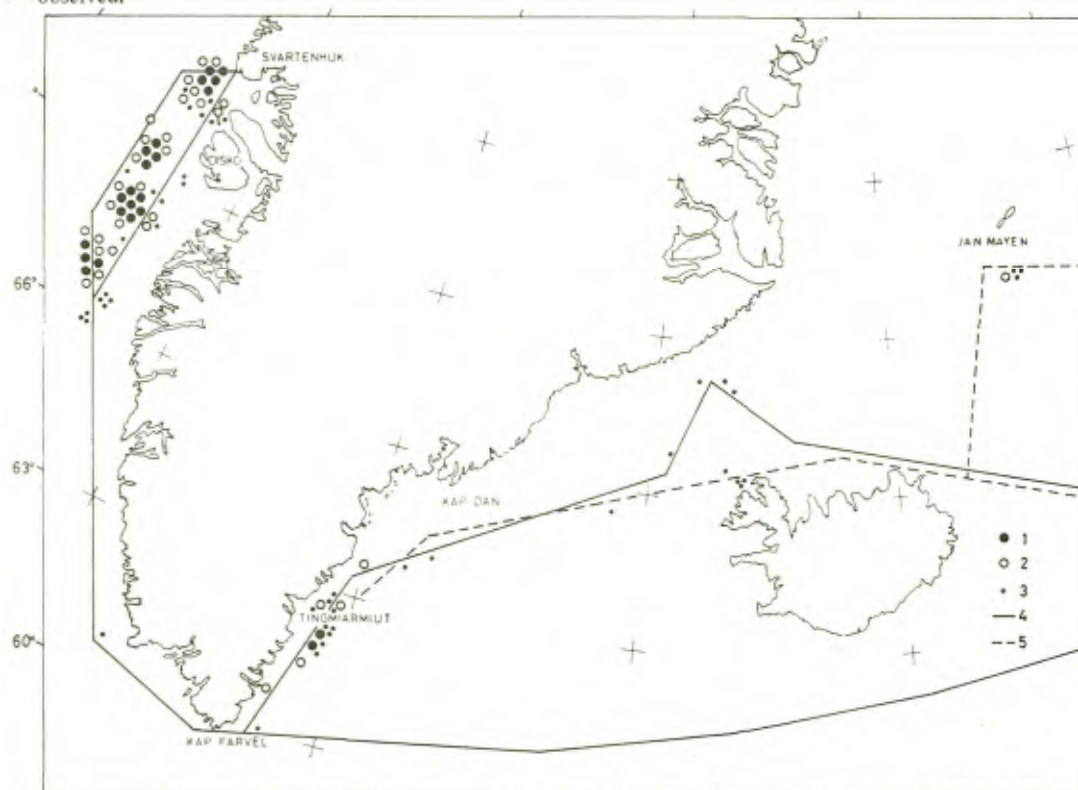
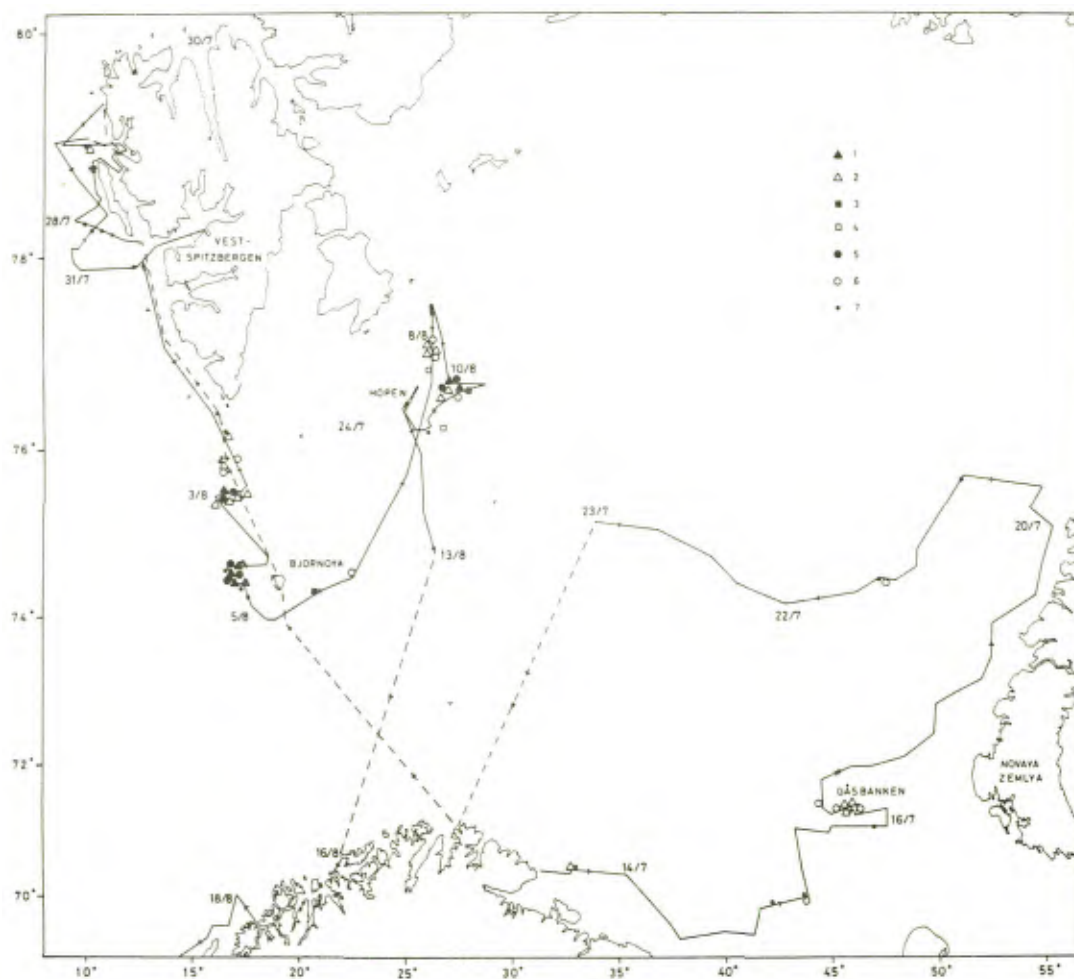


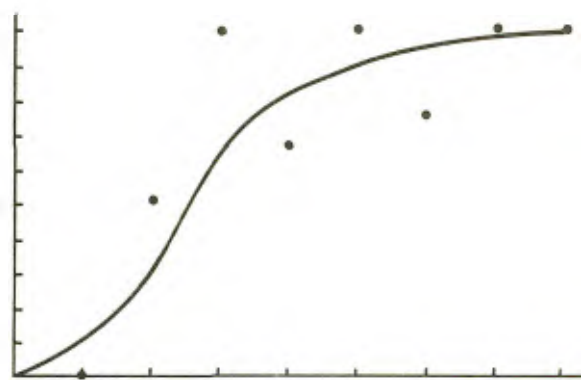


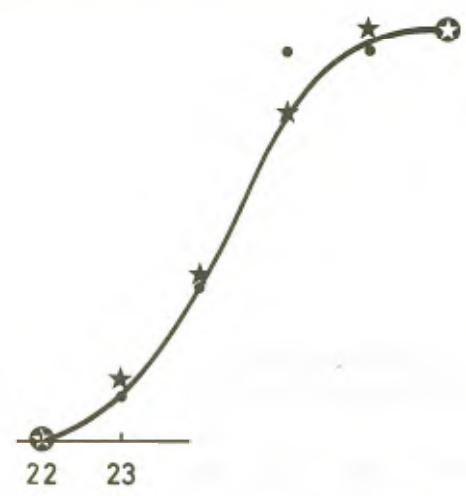










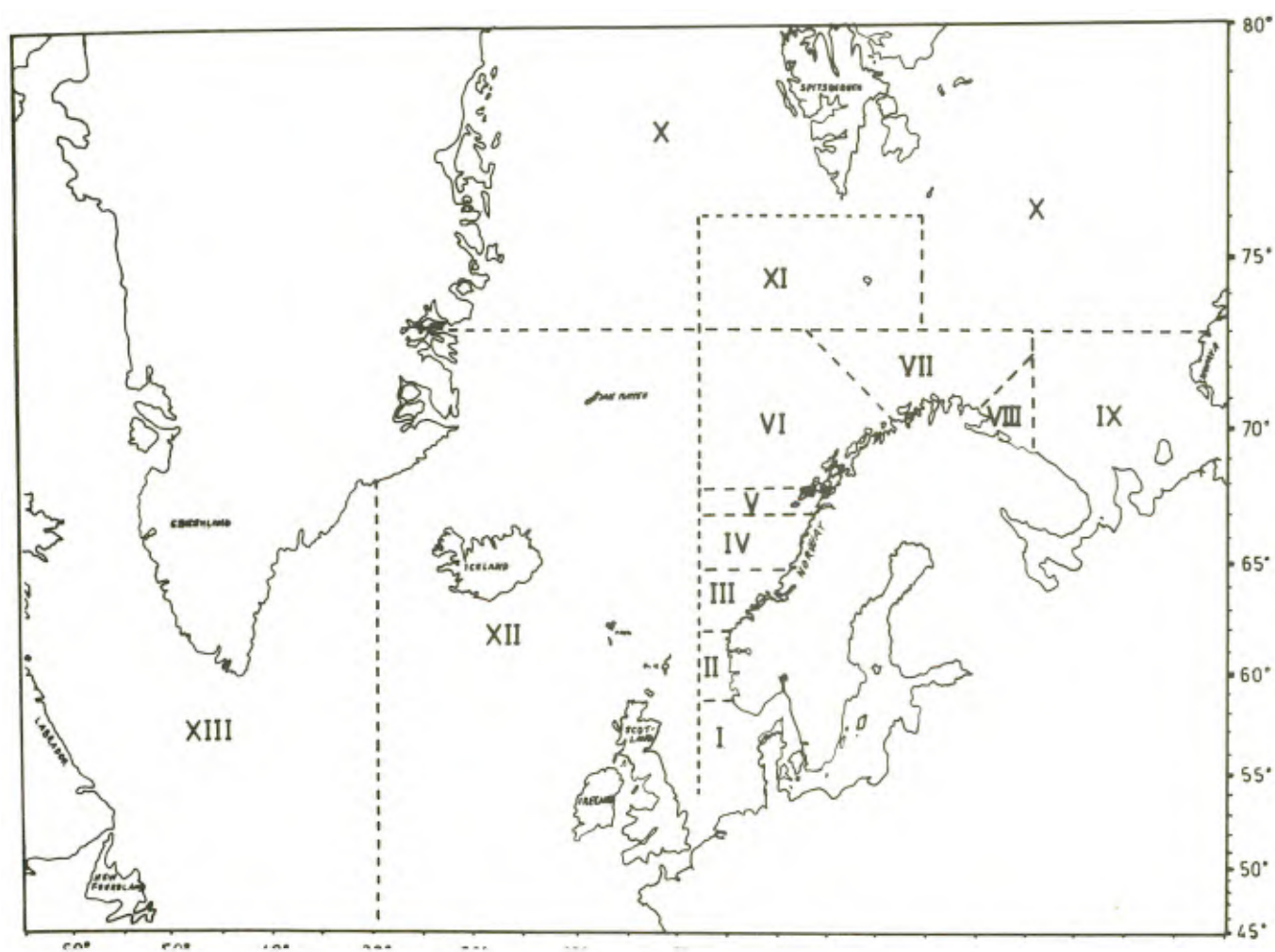


$$k_4 = - \left(1 + \frac{\frac{1}{\theta} + \frac{C_2}{C}}{1 - M} \right)$$

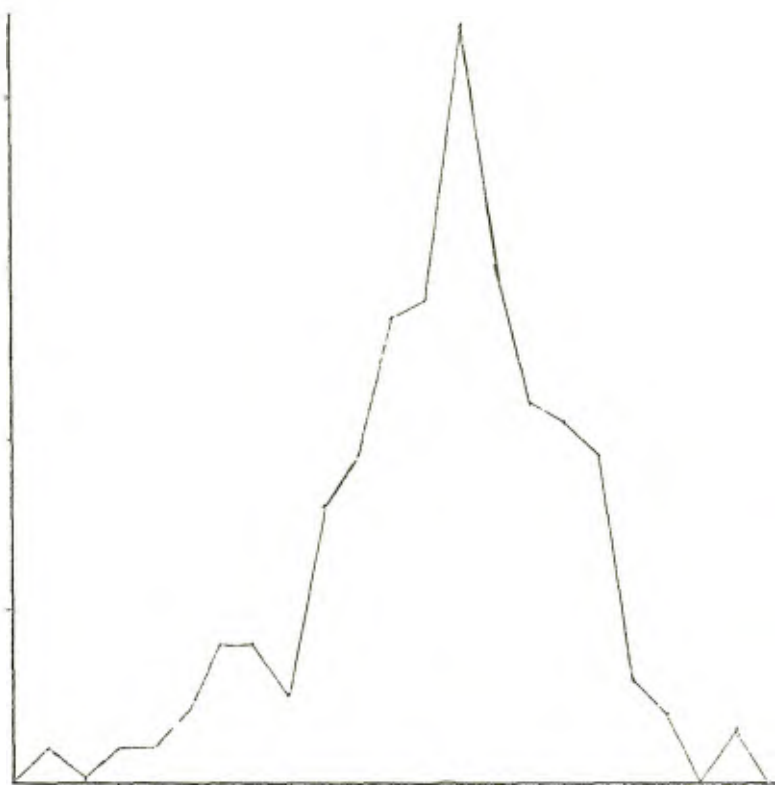
(9), (7) and (31) give

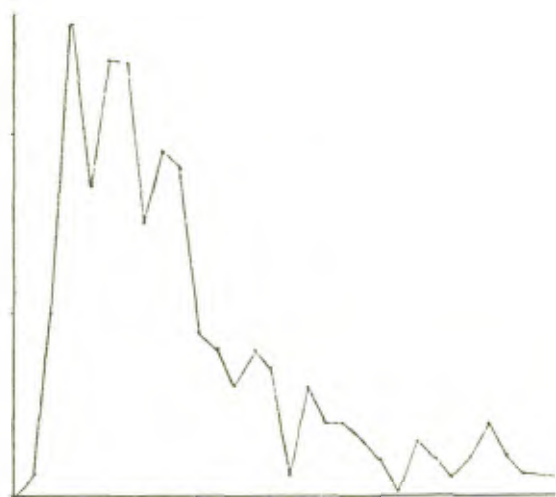
$$S_1 \text{ pa}_1 = \left(\frac{\frac{1}{\theta} + \frac{C_2}{C}}{1 - M} - \frac{1}{\theta} \right) a_0.$$

$$= \left(1 + \frac{\frac{1}{\theta} + \frac{C_2}{C}}{1 - M} \right) (1$$





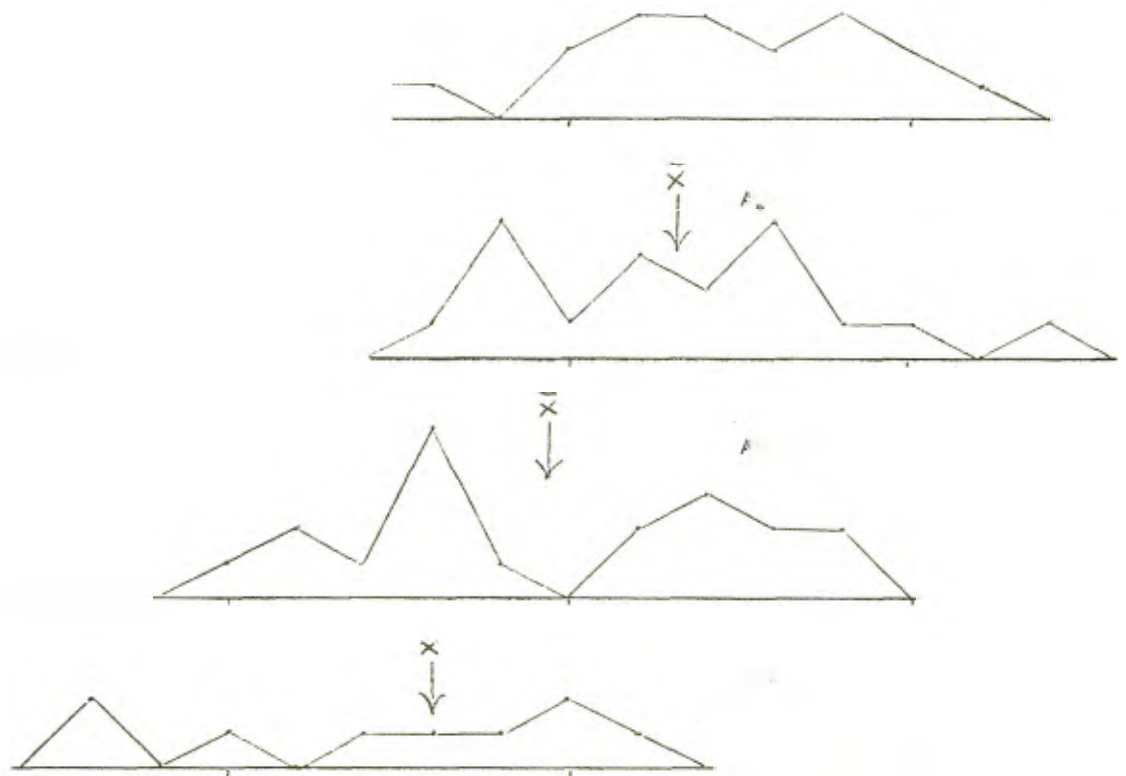


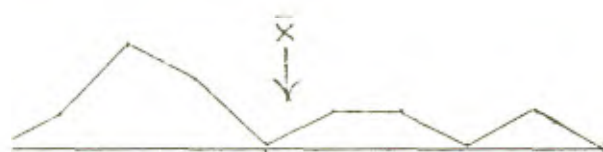
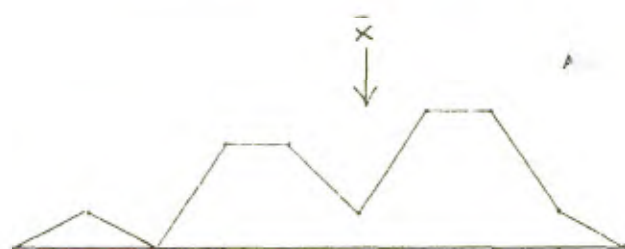
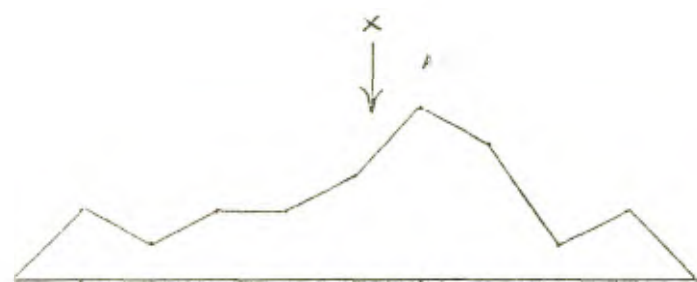


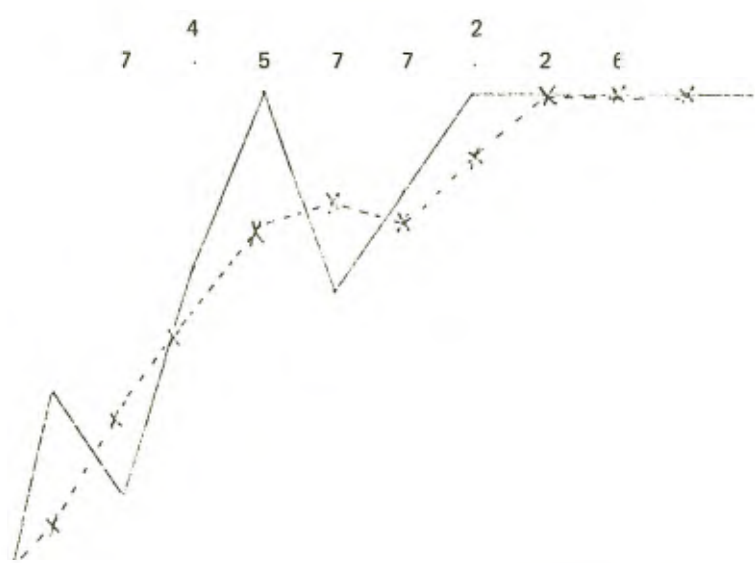


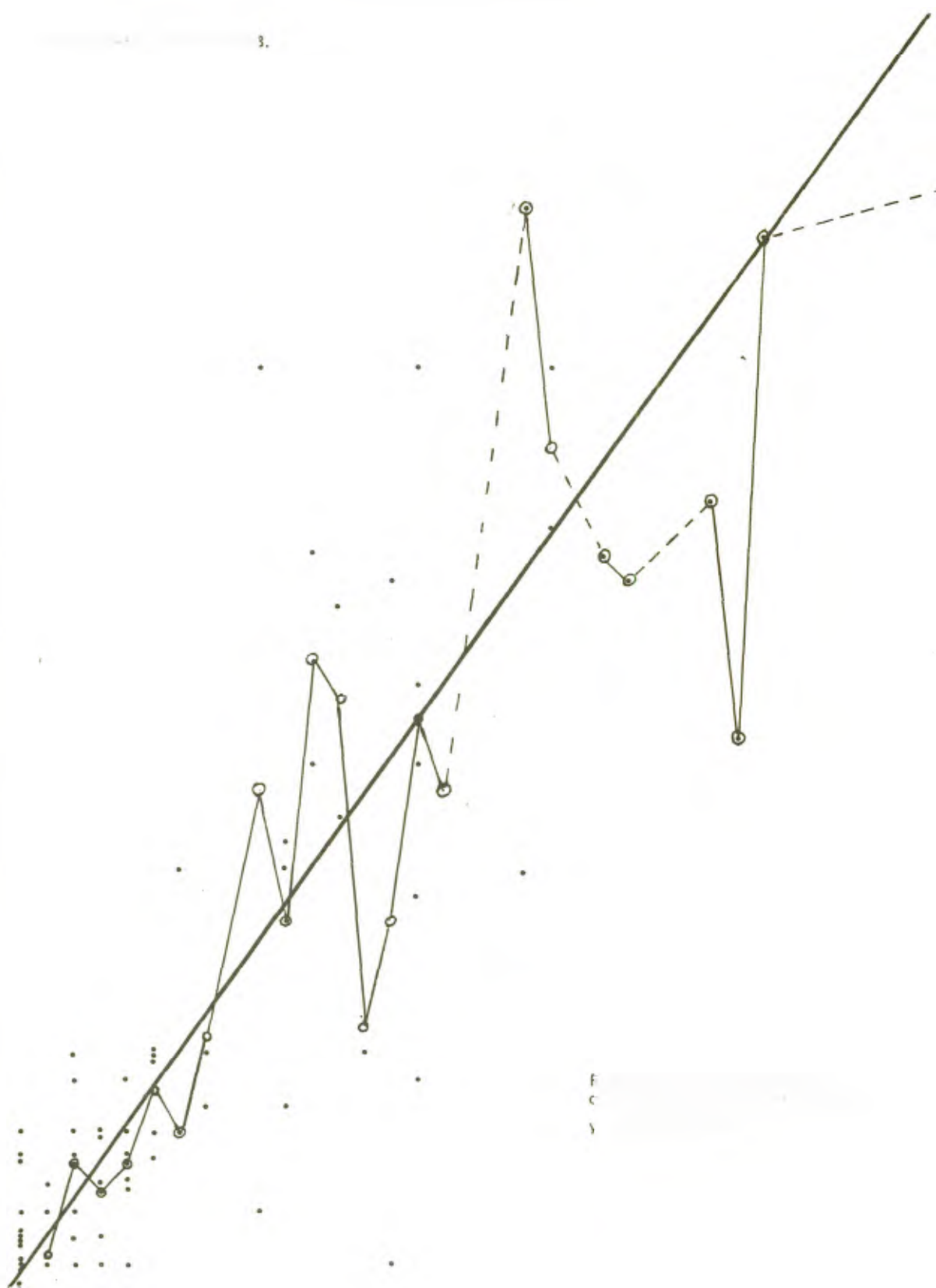
66 sample 4



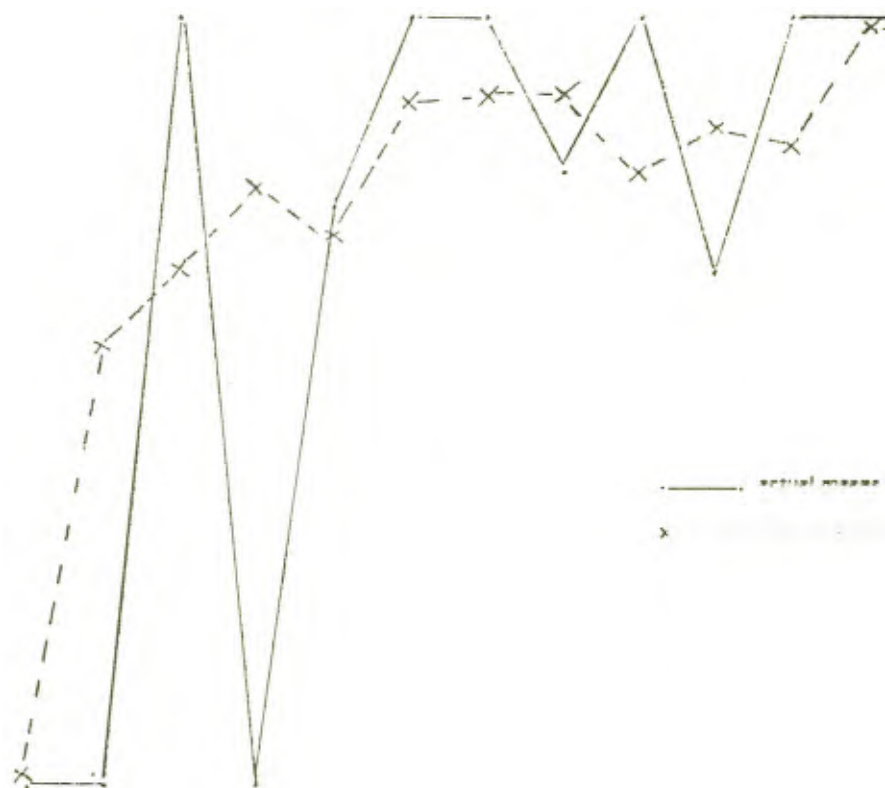






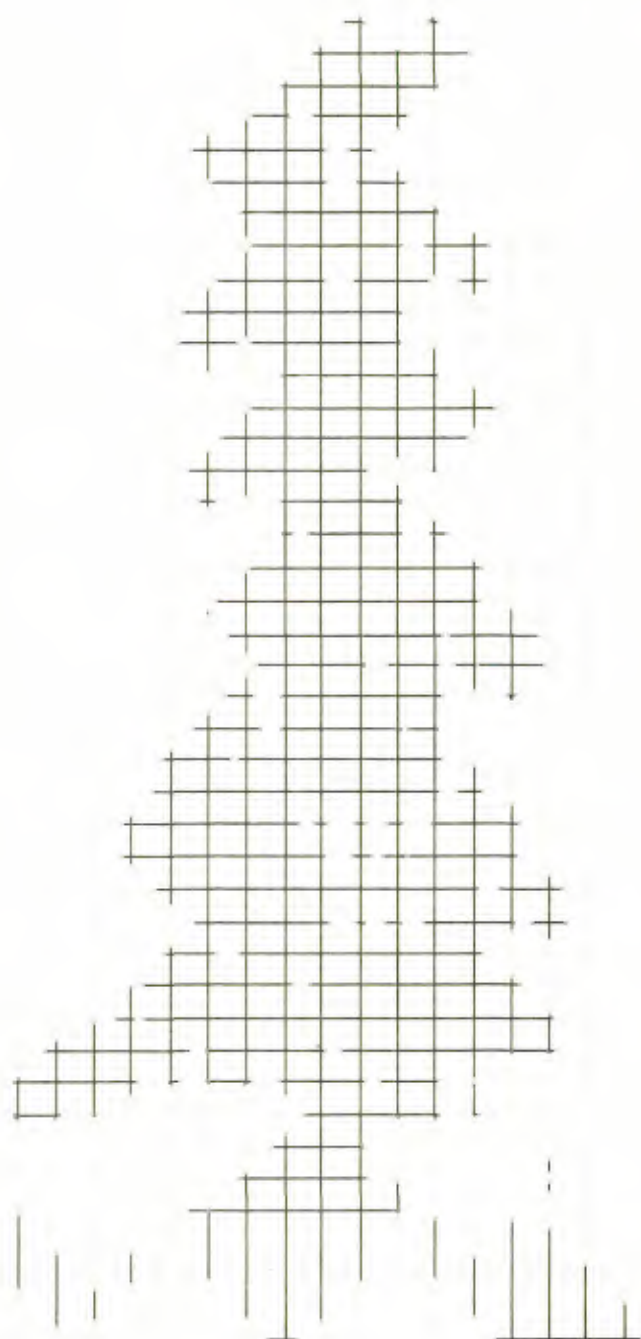
F
C
Y

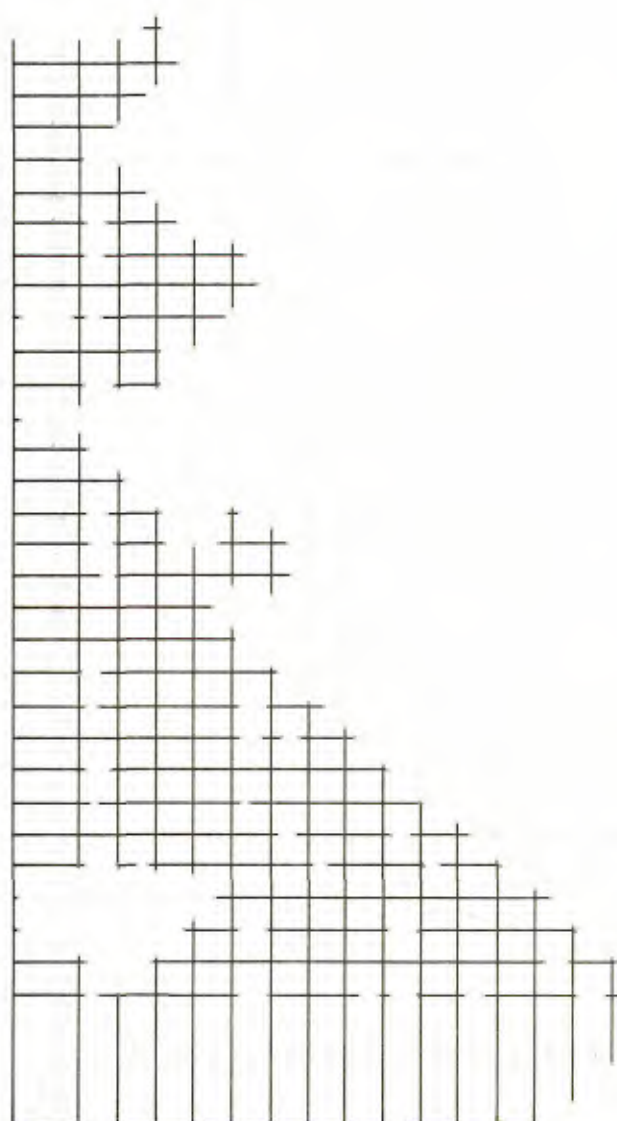




———, actual answer

x, predicted answer





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