

Reanalysis of Recruitment Estimates of the Peruvian Anchoveta in Relationship to Other Population Parameters and the Surrounding Environment

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Abstract

New recruitment estimates of the Peruvian anchoveta are analysed with respect to other population parameters and the surrounding ocean environment. The inshore and offshore environmental variables differ in their dynamics, and the inshore series vary north to south. For the inshore locations, it is not possible to resolve if a wind-related effect is due to transport or turbulence. The new recruitment estimates differ significantly from the old estimates, partly due to mackerel consumption acting as a surrogate for SST. Models using the monthly data were not possible due to correlations in the populations that could be spurious. On a yearly basis, a nonlinear additive model using parent biomass and transport at Trujillo explained 75% of the variance in the recruitment estimates.

Resumen

Nuevos estimados de reclutamiento de la anchoveta peruana se analizan en relación con otros parámetros poblacionales y el ambiente en que habita. Las variables ambientales costeras y distantes de la costa difieren en su dinámica, y las series costeras varían de norte a sur. Para las localidades costeras, no es posible establecer si un efecto relacionado con el viento es ocasionado por el transporte o la turbulencia. Los nuevos estimados de reclutamiento difieren significativamente de los estimados antiguos, debido parcialmente al consumo del jurel que actúa como un indicador de la temperatura. No ha sido posible aplicar modelos que utilizan datos mensuales debido a que las correlaciones en la población pudieran ser espurias. Un modelo aditivo no lineal usando la biomasa parental y el transporte de Trujillo, sobre una base anual, explica el 75% de la variancia de los estimados del reclutamiento.

Introduction

One of the main goals of the contributions in Pauly and Tsukayama (1987) was to estimate the demographic parameters of the Peruvian anchoveta, taking into account all sources of mortality. Thus, estimates of anchoveta consumption by birds (Muck and Pauly 1987), marine mammals (Muck and Fuentes 1987) and bonito (Pauly et al. 1987) were included in the estimation algorithms. Muck and Sanchez (1987), however, presented evidence that mackerel and horse mackerel are major predators of the anchoveta, with consumptions levels approaching that of the fishery at its highest levels. As the mackerel consumption was not included in the original estimates, new population estimates have been calculated (Pauly and Palomares, this vol.).

These new population estimates, as well as the corrected alongshore stress series in Bakun and Mendelsohn (this vol.), are the impetus for redoing the analysis in Mendelsohn and Mendo (1987, hereafter referred to as M&M). Besides examining some models for using population and

environmental parameters to forecast the new estimates of anchoveta recruitment, this reanalysis affords me the opportunity to delve in more detail into some issues glossed over in M&M, as well as to tie together some loose ends. In particular, the interrelationships among some environmental variables mentioned in M&M are discussed here in more detail.

M&M used a form of non-parametric regression that estimated transformations for both the dependent and the independent variables. The algorithm did not produce tables analogous to the ANOVA tables in linear regression. Non-parametric regressions are also used in this paper, but in a form more analogous to standard regression analysis, even allowing "error bars" on the estimated transformations. This should make the resulting models more easily interpreted. Cury and Roy (1989) estimate optimal environmental windows for a number of eastern boundary current regions, including the Peruvian anchoveta. I reestimate these windows for the new data. Finally, Bohle-Carbonell (this vol.) examines fractal dimensions for some of the time series in Pauly and Tsukayama (1987). I estimate a related parameter, fractional differencing, for a larger number of the environmental series, and show how these estimates relate to the models of this paper.

Many of these issues were examined in my original efforts with Jaime Mendo, but were only alluded to in M&M. My knowledge of the Peruvian ecosystem derives from my working with J. Mendo, and while we did not work on this reanalysis together, I would like to acknowledge my debt to him and indicate that this paper would not have been possible otherwise.

Data and Methods

For the population data, I use the estimates of recruitment, parent and female biomass, and egg production in Pauly and Palomares (this vol.) and Pauly and Soriano (this vol.). For the environmental series, I use the corrected alongshore stress given in Bakun and Mendelsohn (this vol.), the turbulence series ("wind speed cubed") in Bakun (1987), the Southern Oscillation Index (SOI) in Brainard and McLain (1987), and the estimates of upwelling and turbulence for Trujillo and Callao in Mendo et al. (1987). For convenience, I will refer to the Bakun estimates of transport and turbulence as the "oceanic" estimates, while the estimates of Mendo et al. (1987) will be referred to by location.

Spectral estimates were calculated for the mean corrected series by first tapering the series using a split-cosine bell taper (Bloomfield 1976)

$$u_t = \begin{cases} .5 \left(1 - \cos \left(\pi (t-.5)/m \right) \right), & t=0, \dots, m-1 \\ 1, & t=m, \dots, n-m-1 \\ .5 \left(1 - \cos \left(\pi (n-t+.5)/m \right) \right), & t=n-m, \dots, n-1, \end{cases} \quad \dots 1)$$

where m is chosen so that $2m/n$ is the desired proportion of the data to be tapered. I have used a 20% taper. Tapering data reduces leakage between frequencies, but tends to make spectral peaks flatter and broader. The discrete Fourier transform of each tapered series was calculated as

$$d_x(\lambda_j) = \frac{1}{T} \sum_{t=0}^{T-1} e^{-i\lambda_j t} x(t) \quad \dots 2)$$

where $\lambda_j = (2\pi j)/T$ is the j th Fourier frequency. The raw (cross)-periodogram is then calculated as

$$p_{xy}(\lambda_j) = d_x(\lambda_j) d_y^*(\lambda_j) \quad \dots 3)$$

where the notation d^* denotes conjugate (transpose). Spectral density matrices were then calculated as the overlapping moving average of the raw periodograms,

$$f_{xy}(\lambda_j) = \sum_{l=-m}^m \rho_{xy}(\lambda_{j+l}). \quad \dots 4)$$

I have used a value of $m = 5$, giving 22 degrees of freedom.

Most analyses of time series data assume stationarity, or that stationarity can be achieved after applying a relatively short-term filter to the data. This assumption may not be valid for natural processes. Hurst (1951) studied the flows of rivers. Let x_1, x_2, \dots, x_T be the historical sequence of flows. Then the cumulative flows up to time t are

$$Su_t = \sum_{j=1}^t x_j, \quad t = 1, 2, \dots, T. \quad \dots 5)$$

Related to reservoir construction is the sequential range

$$R = \max Su_t - \min Su_t \quad \dots 6)$$

Hurst (1951) looked at the normalized sequential range (or "rescaled adjusted range") where Su_t has the mean flow removed and the result is divided by the standard deviation of the flows. If the flows are independent over long time scales, then one would expect that $R/S \sim (T/2)^{-.5}$. However, Hurst (1951) found that for a wide range of river flows $R/S \sim (T/2)^H$ for H in the range (.6,.8). This can be explained in terms of fractional Gaussian noise (fGn) (Mandelbrot and Van Ness 1968, Mandelbrot 1971). Let $B(s)$ be Brownian motion, a stochastic process such that $B(s+u) - B(s)$ are $N(0,1)$ and independent. Then fractional Brownian motion takes the form

$$B_H(t) = \int_{-\infty}^t (t-a)^{H-.5} dB(s), \quad -\infty < t < \infty \quad \dots 7)$$

or

$$B_H(t) - B_H(0) = \int_{-\infty}^t (t-s)^{H-.5} dB(s) - \int_{-\infty}^0 (-s)^{H-.5} dB(s). \quad \dots 8)$$

Discretizing the equation yields

$$b_t(H) = B_H(t) - B_H(t-1). \quad \dots 9)$$

Fractional Gaussian noise can be described by its autocorrelation function

$$C(s) = \frac{1}{2} (|s-1|^{2H} - 2|s|^{2H} + |s+1|^{2H}). \quad \dots 10)$$

Fractional Gaussian noise also exhibits the self-similarity property, that is

$$x(t\lambda) \sim (\lambda)^d x(t). \quad \dots 11)$$

A concept related to fGn is "fractional differencing" (Granger and Joyeux 1980, Hosking 1981) described as

$$(1-B)^d x(t) = e(t) \quad \dots 12)$$

where d is possibly nonintegral, B is the backshift operator, and the $e(t)$ are independently distributed as $N(0, \sigma^2)$. Note that this is not a nonintegral lag operator, but rather an infinitely lagged polynomial in B whose weights die out at a rate given in the autoregressive representation (14). The spectral density of this model is

$$f(\lambda) = \frac{\sigma^2}{2\pi} (2(1-\cos(\lambda)))^{-d}, \quad \lambda \neq 0. \quad \dots 13)$$

Granger and Joyeux (1980) derive the following autoregressive representation of a fractionally differenced process

$$\sum a_j x(t-j) = e(t); \quad a_j = \frac{\Gamma(j-d)}{\Gamma(1-d)\Gamma(j+1)} \quad j > 1. \quad \dots 14)$$

Porter-Hudak (1982) and Geweke and Porter-Hudak (1983) show that the power spectrums of the error terms from an fGn process and a fractionally differenced process only differ by a short-term memory component. Thus both models are estimating essentially the same long-term memory component. I find fractional differencing more intuitive, as it is a long-term extension of the usual ideas of differencing and filtering to obtain stationarity. (The first few terms of the expansion of the differencing polynomial are

$$1 - dB - \frac{1}{2}d(1-d)B^2 - \frac{1}{6}d(1-d)(2-d)B^3 \quad \dots 15)$$

The parallels with the usual differencing schemes used to achieve stationarity are immediate.)

Porter-Hudak (1982) and Kashyap and Eom (1988) give methods for estimating the fractional differencing parameter d , based on regressions between the log of the theoretical spectrum and the log of the observed periodogram. The property of concern here is that a process has long-term memory if d is in the range $(0, .5)$; the process has short-term memory if $d < 0$; and the process has infinite variance if $d > .5$ (Granger and Joyeux 1980, Hosking 1981). Both long-term and short-term memory time series models assume that the basic input process is a random variable. The main difference is that in long-memory models any impulse to the system takes a long time to die out. Another way to view this is that the system is sensitive to initial conditions. A small difference in two identical systems at a given time period will be evident for many time periods to come. Depending on the dynamics involved, the difference between the two systems caused by this impulse may grow, rather than disappear through time. The models in M&M as well as the ones in this paper, assume a relationship between anchoveta recruitment and other variables. If this relationship is on the proper scale and is stationary, then long-term memory in any of the predictor variables will not affect the system. However, the length of time ahead that a forecast can be made can be affected by long-term memory, as longer forecast horizons could imply forecasting one of the predictor variables. As errors can propagate in long-memory systems, long-term predictions become unreliable. An alternative is to find another, less direct predictor variable, that is related to anchoveta recruitment at a longer lag. (See also Bohle-Carbonell, this vol., who estimates the fractal dimension of several of the series in Pauly and Tsukayama 1987).

Trends in time-series are estimated using two different algorithms. The first is the "locally-weighted sums of squares" or LOWESS algorithm of Cleveland (1979), and the other is the decomposition algorithm of Kitagawa and Gersch (1984). LOWESS fits to each point a weighted linear regression using some fixed percentage of points surrounding the given point. The regression is then made robust by weighting against outliers. I use a proportion of $F = .05$, which corresponds to two years of data in calculating the smooths in this paper.

Kitagawa and Gersch (1984) assume that an observed time series can be decomposed as

$$y(t) = T(t) + S(t) + A(t) + e(t) \quad \dots 16)$$

where $T(t)$ is a trend component at time t , $s(t)$ is a seasonal component at time t , $A(t)$ is a stationary random component (i.e., and AR component) at time t , and $e(t)$ is an error term. They assume a smoothness prior for the trend and seasonal components, which means that at some level of differencing the component is equivalent to a zero mean normal variate with unknown variance. The degree of differencing and the amount of variance in the random variate causes a tradeoff between the smoothness of the component and the reduction in variance due to that component. This is the same as fitting the discrete equivalent of a smoothing spline for that component (Kohn and Ansley 1988). Kitagawa and Gersch (1984) show that this can be formulated as a state-space model and estimated using a combination of Kalman filtering and maximum likelihood estimation.

The usual regression model has a response random variable Y and p predictor random variables X_1, X_2, \dots, X_p . A set of n independent realizations of these random variables is observed, denoted by $(y_1, x_{11}, \dots, x_{1p}), \dots, (y_n, x_{n1}, \dots, x_{np})$ and it is desired to estimate the conditional expectation $E(Y | X_1, X_2, \dots, X_p)$. Linear regression assumes that the conditional expectation is linear, that is

$$E(Y | X_1, X_2, \dots, X_p) = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p, \quad \dots 17)$$

and given a sample, estimates of the β_i are usually found by least squares. A natural generalization is to consider additive nonlinear models (Hastie and Tibshirani 1986) of the form

$$E(Y | X_1, X_2, \dots, X_p) = \sum_{j=1}^p s_j(X_j) \quad \dots 18)$$

where the nonlinear functions s_j are to be estimated. This is accomplished by estimating the s_j as an "average" of some part of the data surrounding a point, in this case a scatterplot smoother fit using the backfitting algorithm of Breiman and Friedman (1985). In particular, I use the running lines smoother in Hastie and Tibshirani (1986).

When the functions s_j in generalized additive models are estimated using a fixed span smoother, then it is possible to estimate the degrees of freedom used in forming the estimate of s_j , as well as an analysis of deviance table that is directly analogous to the standard analysis of variance table in regression analysis (Hastie and Tibshirani 1986; see Hastie 1987 for a good description of deviance and how it relates to sums of squares). This allows for a comparison of models using measures such as AIC (Akaike 1977), BIC (Schwarz 1978) or cross-validation. A smaller span produces a closer fit to the observed data (smaller variance), but with a greater bias and larger number of degrees of freedom, equivalent to fitting more parameters in a normal regression model. A larger span is smoother, with smaller bias, but greater variance. The choice of the span is thus a tradeoff between variance and bias, as in most situations where extra parameters can be added to the model. Hastie and Tibshirani (1985) show how to construct 95% confidence intervals for the estimated functions s_j .

Environmental Variables

There are a large number of environmental variables that could be used to model the anchoveta, but brute force searching through all of them can lead to spurious results. The environmental variables available for this study in all likelihood are surrogates for the actual physical processes that affect the anchoveta. It is likely, then, that the dynamics of the variables will be the important element in modeling. While each of these large number of series could be argued to be a surrogate variable, it is possible to separate variables that reflect more direct influences on the fish from those with indirect influences. For this reason, the SOI is not used in any of the direct analyses. The SOI reflects processes distant from the environment of the Peruvian anchoveta. The changes reflected in SOI would have to be reflected in changes in the more local environment to have any effect on the anchoveta. If, however, a local variable is a good predictor of anchoveta recruitment, and there is a strong relationship between the SOI and this local variable, then there exists the possibility for a more extended (longer lead time) forecast.

For completeness, I show the major environmental series with trends estimated using LOWESS. SST (Fig. 1), shows a sharp drop through 1954-1956, and then a peak during the El Niño period of 1957-58. SST remained fairly steady through mid-1971, and then peaked in the 1972 El Niño. The 1983 El Niño produced a strong peak in the series. A slight upward trend in SST is noticeable from 1971 onward.

Oceanic transport (Fig. 2) has been fairly steady, with noticeable increases during the El Niño periods of 1957-58, 1972 and 1983. The 1960s appeared to have been a decade of decreased variance in the transport, and the mean level during the 70s and 80s appears to be somewhat higher.

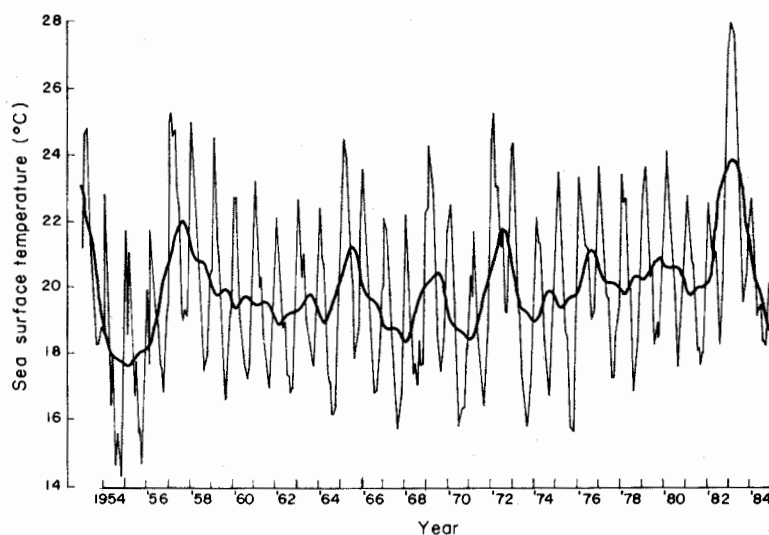


Fig. 1. SST off Peru with estimated local trend line.

Fig. 1. TSM frente a Perú con línea de la tendencia local estimada.

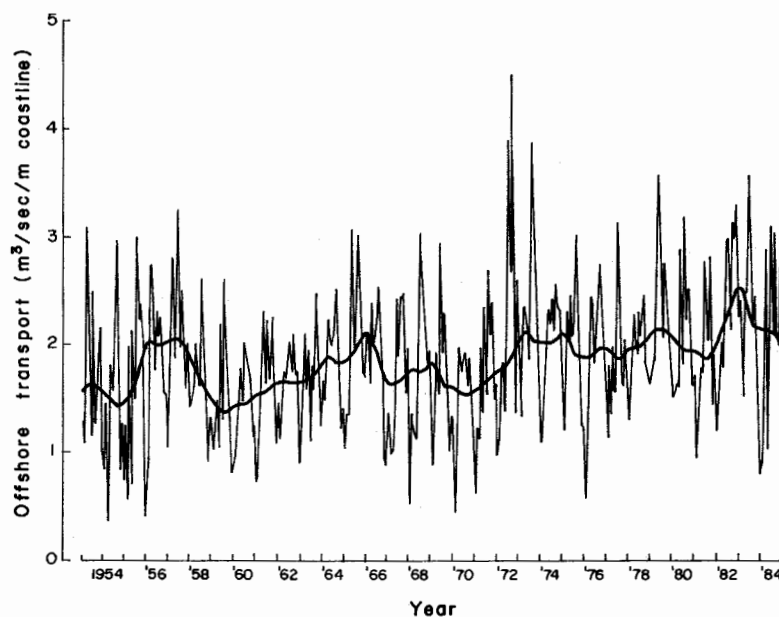


Fig. 2. Oceanic transport off Peru with estimated local trend line.

Fig. 2. Transporte oceánico frente a Perú con línea de la tendencia local estimada.

Transport at Trujillo (Fig. 3) shows the strongest trends among the data series. Transport increased through the El Niño of 1958, and then decreased and stayed relatively constant through the early 1960s. Starting around 1968, transport at Trujillo increased, staying at a higher level through 1972. Transport then dropped sharply till 1974, rose again till 1976, and then declined very sharply until 1982. Coincident with the El Niño of 1983, transport at Trujillo increased to a more normal level. Transport at Callao (Fig. 3) displays similar behavior, except that the drop in 1974 is not as precipitous, and the sharp decline from 1976-1983 is not noticeable.

None of the subsurface series in Brainard and McLain (1987) are used in this paper, even though Bohle-Carbonell (this vol.) suggests that the subsurface has the strongest relationship with the earlier recruitment estimates. I note that, as mentioned in the article, only 20% of the subsurface data are from actual observations; the rest are from an interpolation scheme of unknown statistical properties. It would be difficult to ascertain to what degree any fit using these data was due to the actual physical process or due to the interpolator.

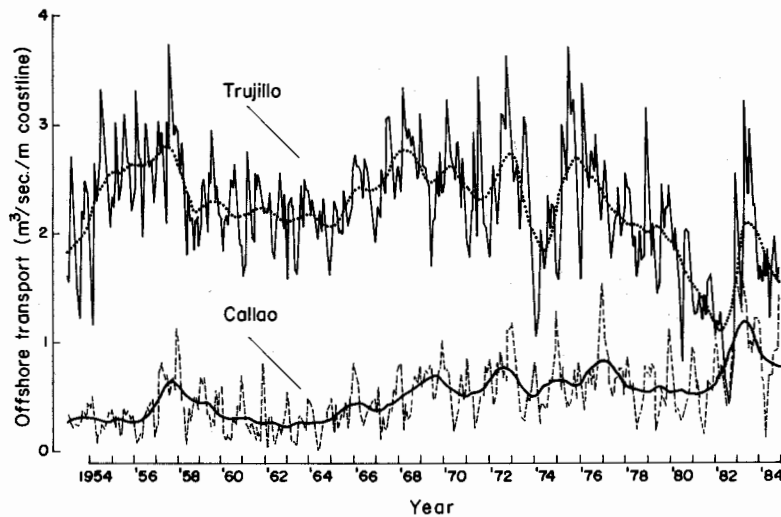


Fig. 3. Transport at Trujillo and Callao, with estimated local trend lines.

Fig. 3. Transporte en Trujillo y Callao, con líneas de las tendencias locales estimadas.

SST also is not used as a predictor. There are good *a priori* reasons for believing that SST would influence anchoveta recruitment. Unfortunately, several of the estimates of anchoveta consumption by other species (Muck and Pauly 1987; Pauly et al. 1987; Muck and Sanchez 1987) make explicit use of SST to modify the amount consumed. In the model of Muck and Sanchez (1987) for mackerel and horse mackerel, the offshore biomass of these fish are assumed at equilibrium sizes, but the relative number of mackerel close to shore varies with SST. Estimated consumption by these species are thus proxy variables for SST. Using SST in any further analysis leads to an obvious, direct bias. SST is also correlated with many of the other environmental variables, which may lead to indirect biases which cannot be totally avoided.

If the environmental variables are viewed as surrogates for a physical process in the ocean, one method for selecting which environmental variables to use in modeling is to see what unique information (in the statistical sense) each of the series contains. If each of the series contains essentially the same information, then there is little matter which is used. If the variables differ greatly in the information contained, then variables should be selected a priori based on knowledge of the fish and of the oceanographic processes likely to affect them.

Bakun and Parrish (1982) and Parrish et al. (1984) give cogent arguments as to why wind-induced transport should be an important factor in recruitment. Lasker (1978) has argued that turbulence affects early survival of larvae by affecting the concentration of available food. Based on these arguments, the transport and turbulence indexes discussed above are natural starting points for the analysis. The SOI will also be examined in relationship to these variables to see if it is reflected in any of these series.

Bakun's estimate of transport and wind is based on averaging a broad area off the coast of Peru, and is dominated by offshore observations. The series of Mendo et al. (1987) are from airports by the coast in Trujillo and Callao, and these authors present anecdotal evidence that these series accurately reflect the nearshore surface winds over the water. If these series differ in their information, then a basis for choosing a series is which area (nearshore or offshore, north or south) most likely influences the areas where the anchoveta are spawning.

The oceanic transport has the expected red noise spectrum at low frequencies, with a strong peak at a yearly frequency and small peaks at the harmonics of the yearly frequency (Fig. 4). Transport at Trujillo and Callao have a weak seasonal signal, and are dominated by the red noise spectrum (Fig. 4). The coherences between the oceanic transport and the transport at Trujillo and Callao are relatively low except at a few frequencies (Fig. 4) and the series are significantly out of phase. This implies that the inshore measures of wind and the oceanic measures contain quite different information about the environment.

Similarly, transport at Trujillo has significantly different dynamics than transport at Callao (Fig. 5). The spectrum of Trujillo transport has a more dominant red noise component, while the

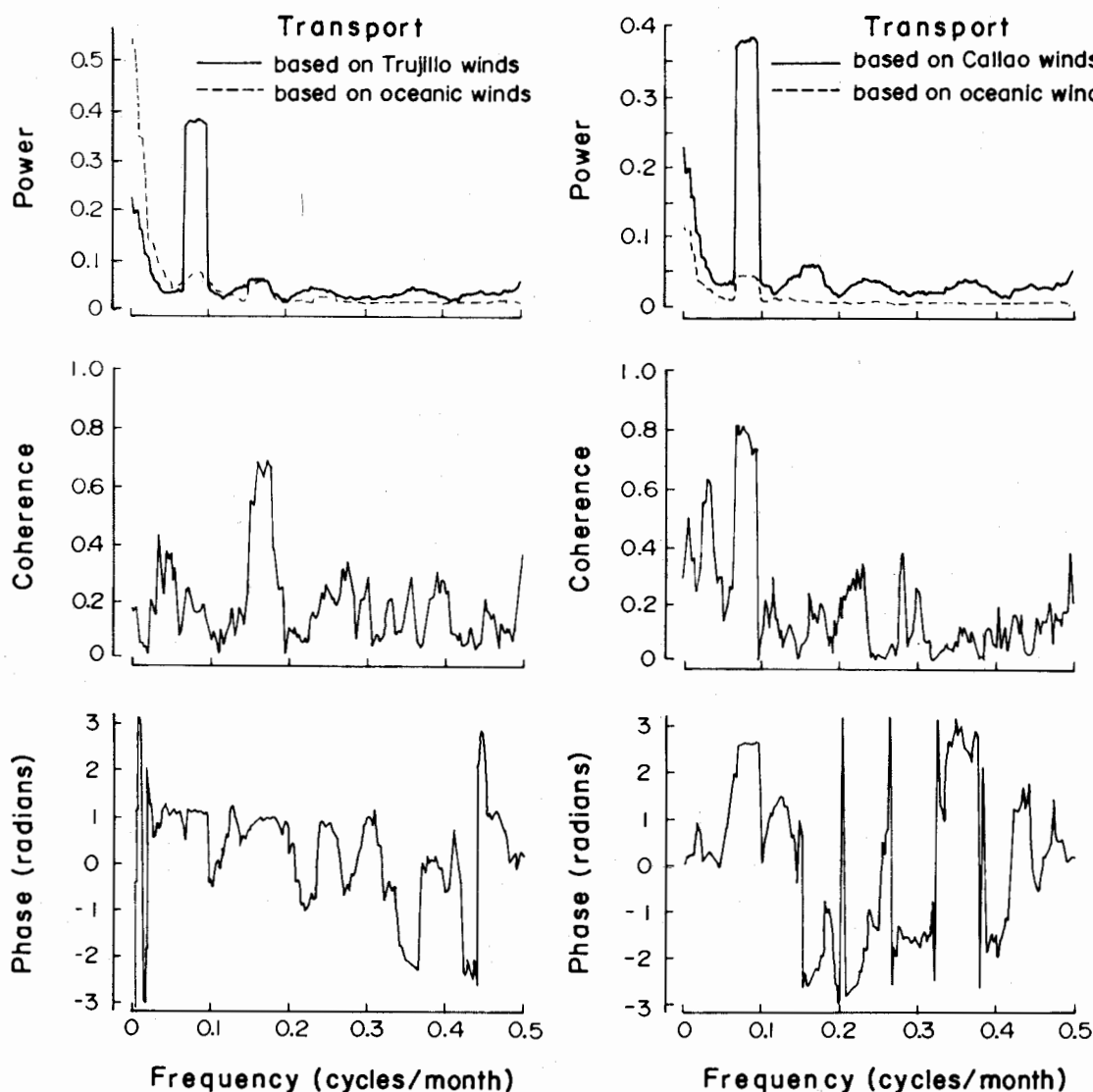


Fig. 4. Spectral analysis of transport off Peru (oceanic winds), Trujillo and Callao (local winds) transport.

Fig. 4. Análisis espectral del transporte frente a Perú (vientos oceánicos), transporte de Trujillo y Callao (vientos locales).

Callao transport has a relatively stronger seasonal cycle. The coherences are not particularly large, and the two series are significantly out of phase. A similar result is valid for the turbulence index at Trujillo and Callao (not shown). Thus, none of the three transport series closely reflects what is occurring in the other two series.

The SOI and oceanic transport have similar spectra, particularly at the yearly frequency and at a peak that would correspond roughly to the occurrence of El Niño (Fig. 5). The two series are highly coherent at these frequencies, and almost 180° out of phase. The same is not true of the SOI and Trujillo transport (Fig. 6), where the main coherence is at the half-yearly frequency. The SOI appears to be a significant advance indicator of what will happen offshore at the longer frequencies, but not of the more inshore behavior.

Long-term memory, if it exists in the ocean, has implications for forecasting too far ahead any process that depends on variables that exhibit this property. The more oceanic series, such as SOI and transport and turbulence calculated over the broad area, exhibit a similar, weak degree of long-term memory (Table 1). The more inshore measures exhibit a stronger long-term memory, approaching infinite variance. As I will be arguing that the more inshore environmental series are the most appropriate, the models involved will be using variables of limited predictability.

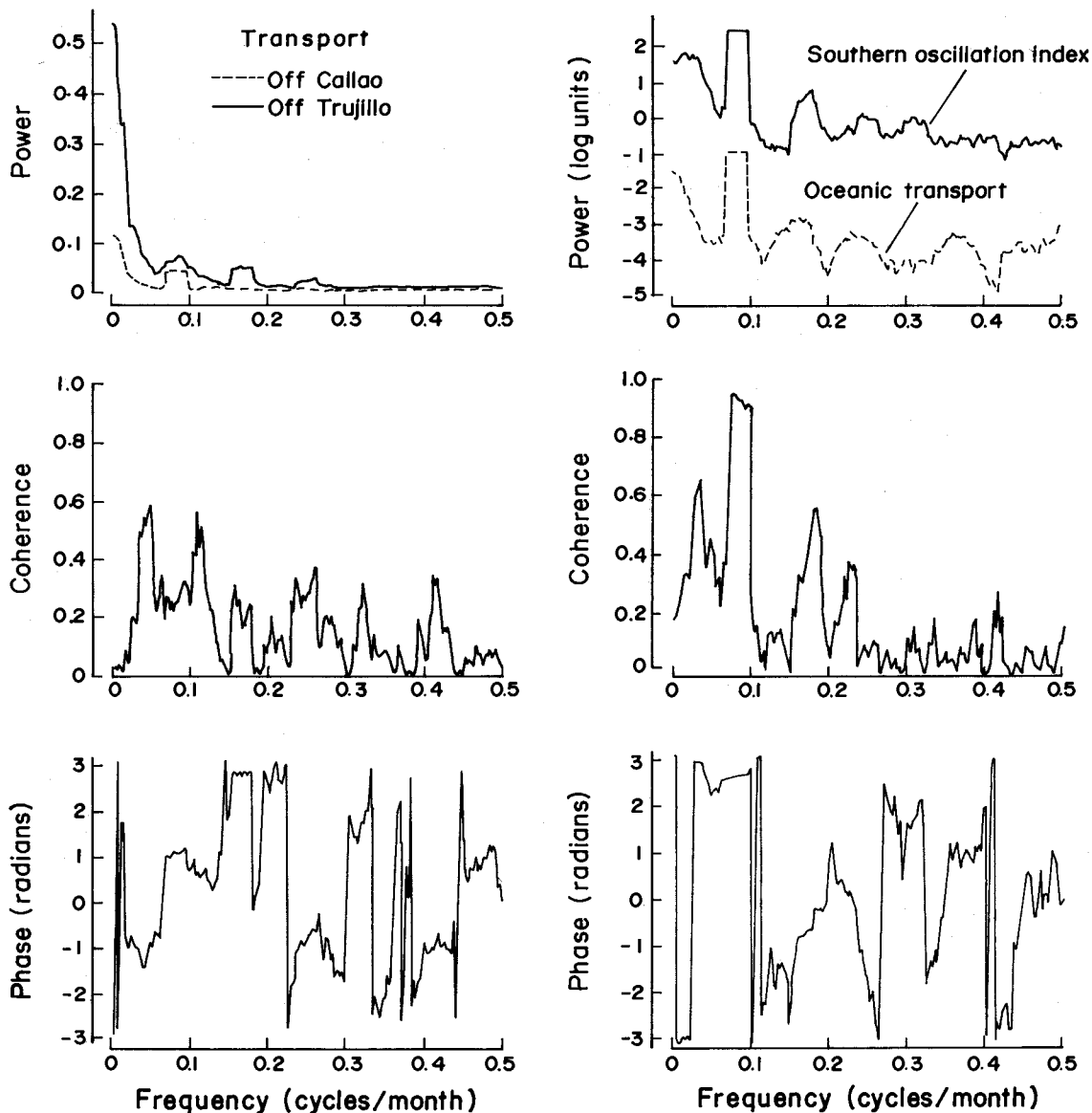


Fig. 5. Spectral analysis of local transport at Trujillo and Callao, of transport off Peru and of SOI.

Fig. 5. Análisis espectral del transporte local en Trujillo y Callao, del transporte frente a Perú y del Índice de Oscilación Sur (SOI).

Turbulence and transport, though both wind-induced, measure very different processes in terms of the anchoveta. If the wind does affect anchoveta recruitment, resolving if it is mainly through transport (most likely transporting larvae offshore) or mainly through turbulence (by affecting food availability to larvae) is an important issue. At Trujillo, transport and turbulence are highly coherent except at very high frequencies, and in phase at all frequencies (Fig. 6). As mentioned in M&M, the wind at Trujillo is predominantly from one direction, so that transport is close to wind speed squared, while turbulence is wind speed cubed. The difference in behavior at higher frequencies appears to be one of scale, where turbulence is more variable since it is the cube of the observed speed. As I will be using mostly non-linear techniques to model the data, this difference becomes negligible. (For example, on a log scale, the two series will differ by a multiplicative constant, which can be factored into the parameter on the series. This would not be the case if the wind varied greatly in its direction, so that the alongshore stress differed greatly from the wind speed squared). A similar result was found for Callao. Thus, though biologically there are significant differences between transport and turbulence, statistically for the inshore wind series, it will not be possible to discriminate if an effect is due to transport or turbulence.

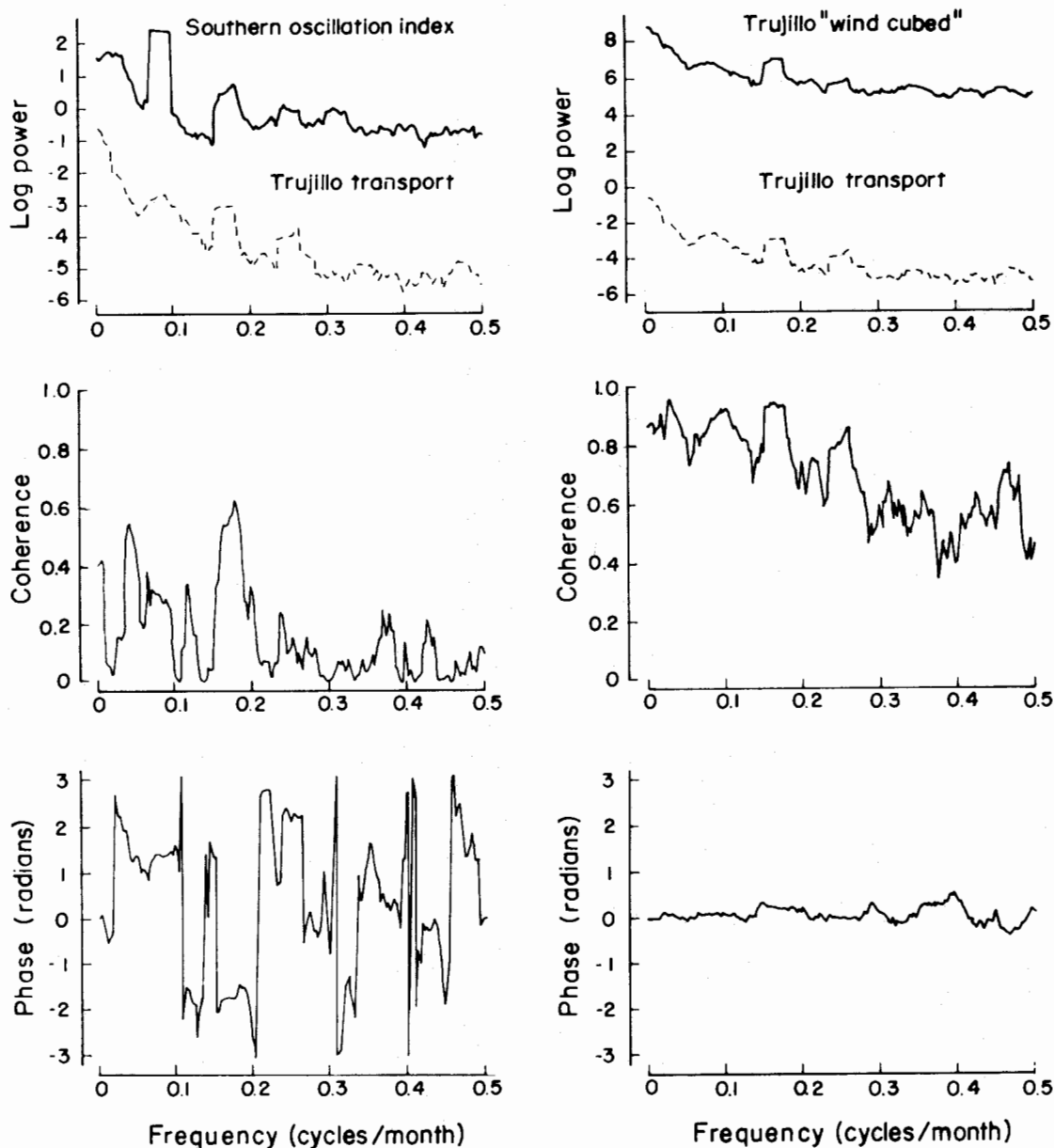


Fig. 6. Spectral analysis of SOI and transport off Trujillo, and of Trujillo transport and turbulence ("wind cubed").

Fig. 6. Análisis espectral del Índice de Oscilación Sur (SOI) y transporte de Trujillo, y del transporte y turbulencia ("viento al cubo") de Trujillo.

Table 1. Estimates of d , the fractional differencing parameter, in some environmental series off Peru.

Tabla 1. Estimaciones de d , parámetro fraccionario diferencial, en algunas series ambientales frente al Perú.

Series	Method	
	Geweke and Porter-Hudak (1983)	Kashypa and Eom (1988)
Callao wind cubed	.554	.600
Callao transport	.592	.637
Trujillo wind cubed	.470	.509
Trujillo transport	.603	.652
Oceanic transport	.286	.310
Oceanic wind cubed	.210	.229
SOI	.340	.387

Biological Series

One of the obvious but major problems in studying fisheries is that it is rarely possible to obtain a reliable direct census of the fish population. Instead, "sampling" is used to obtain estimates. Usually the sampling scheme is of no statistical design, but instead depends on uncontrollable factors such as fishermen's behavior. The actual data, or the observables, are things like catch and effort statistics, length distributions, etc. While a variety of schemes have been devised to use this information to estimate characteristics of the population, the inescapable fact is that only the catch, effort, length distribution measurements, etc. are data, while the rest are estimates.

A property of calculating estimates from data is that degrees of freedom are used. In most cohort-analysis schemes, many degrees of freedom are used in calculating population and recruitment estimates. As the schemes are operating on autocorrelated data, they also act as filters on the observed data, changing the importance of different frequencies. When the same algorithm is used to jointly estimate many series, it is likely that just due to the estimation scheme, there will be a certain amount of cross-correlation in the resultant estimates.

It has been common to treat estimates of recruitments and of parents as data with the usual degrees of freedom. (Ultimately I will be forced to do the same (it is all there is to work with), but not without some careful checks on artificially-induced correlation.) In effect, when I use the recruitment estimates to estimate a relationship with another variable, I am fitting a composite function $f(g(x))$ of the original catch, effort and length data, where x is the original data, $g()$ is the operation performed by the cohort analysis, and $f()$ is the final relationship. If two intermediate estimates of this composite process exhibit a strong relationship, it cannot be said for certain that this relationship is real, or is just a product of the estimation scheme. Thus if parents and recruits are strongly related, it may be an artifice of cohort analysis. This will make it difficult to interpret many of the results to follow.

As mentioned previously, in attempting to correct for mortality other than from fishing, the resulting consumption estimates are functions of SST, and this feeds into the recruitment and parent estimates. Thus SST, and any variable highly correlated with SST, will have an unknown degree of spurious correlation with the population estimates. Most of the transport series display a reasonable degree of correlation with SST.

The new estimates of recruitment are shown on Fig. 7, along with the old ones. The new estimates exhibit less relative variation than do the original estimates, as was anticipated by Pauly (1987) who wrote that "it can be hypothesized that the [new] recruitment and biomass [...] will be somewhat smoother". Both series show an increase from 1957 to 1958, during El Niño, but in the original estimates this increase produced a change in mean level in both parent biomass and in recruitment, while in the new estimates the recruitment level drops right after the end of the El Niño. The new estimates start increasing from about 1963 to 1969-1970, after which both the new and old estimates show a similar decrease. The old estimates then show a more significant relative increase than do the new estimates. The parent biomass follows a similar pattern (Fig. 8).

The estimated AR component of the new recruitment estimates (Fig. 9) is relatively less variable than the AR component of the old estimates, particularly during the 1960s. The log of the ratio of recruits to parent biomass three months earlier (Fig. 10) is relatively constant except for the El Niño years of 1972 and 1982-1983. The ratio with the number of eggs shows a similar pattern (not shown), though the decrease during the 1972 El Niño is not as sharp. The spectrum of both the recruit series and the log of the recruits (Fig. 11), is dominated by a red noise component with a weak yearly signal.

The picture presented by these graphs is of a highly persistent, stable series where the only significant change occurred during a one or two year period around 1969. In fact, the trend in the new recruitment estimates mirrors closely what would be expected from the smoothed (5-year averaged) trends in catch and effort in Agüero (1987). After all the corrections, except for questions of scale, the recruitment estimates tend to mirror catch-per-unit-effort (C/f).

Some of the smoothness in the new recruitment estimates are due to mackerel consumption being a surrogate for SST (Pauly 1987). During El Niño years, for example, the catch rate tended to decrease. In the previous models, this results in variability in the recruitment estimate. In the

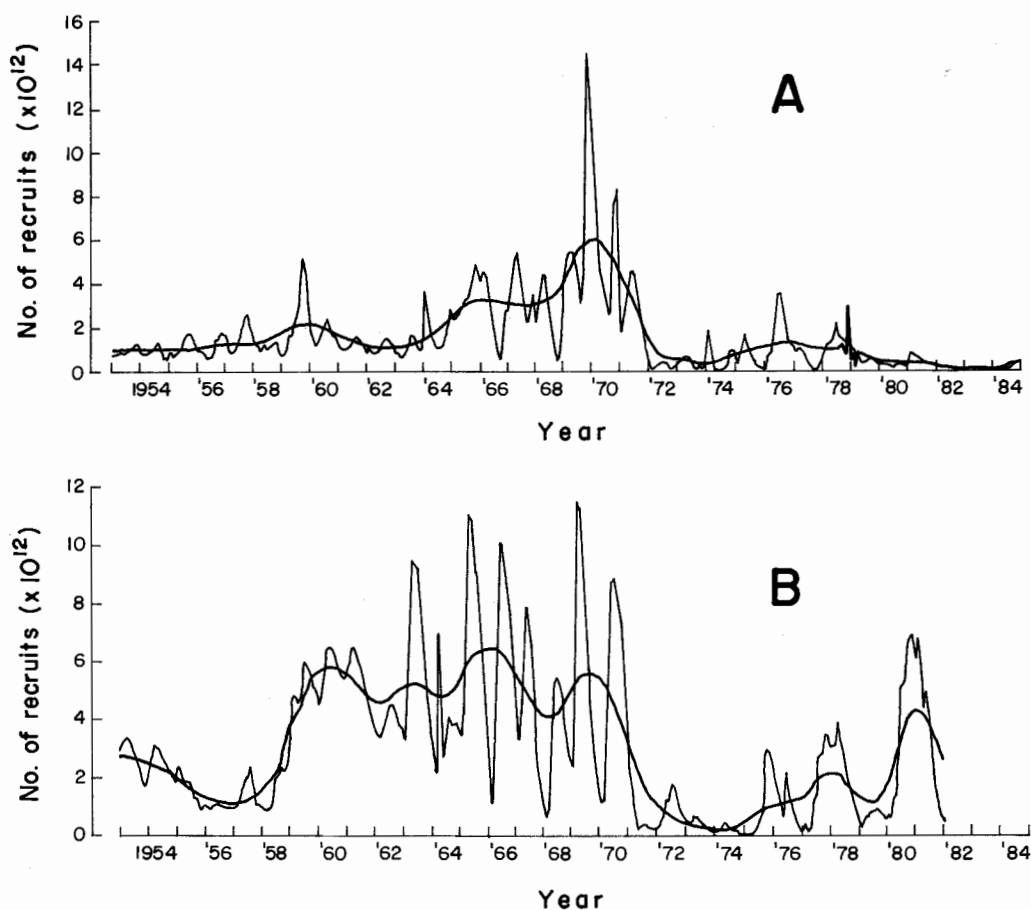


Fig. 7. Comparison of new (A) and old (B) recruitment estimates for the anchoveta, with estimated local trend lines.
 Fig. 7. Comparación de las nuevas (A) estimaciones del reclutamiento de la anchoveta y los antiguos (B), con líneas de las tendencias locales estimadas.

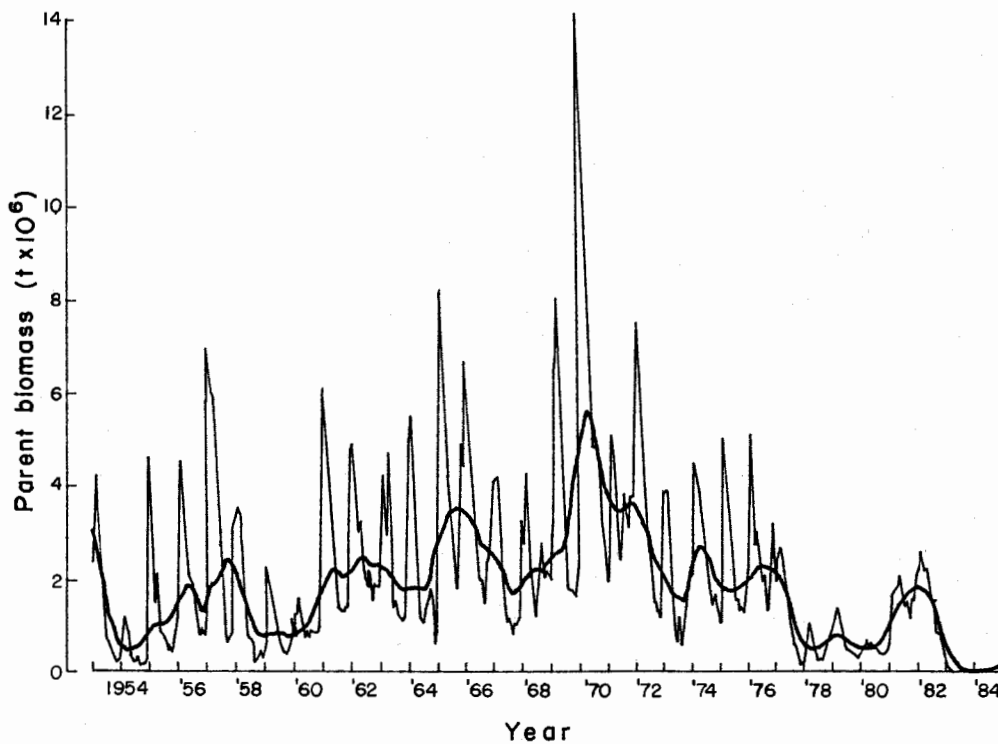


Fig. 8. New estimates of anchoveta parent biomass with estimated local trend.
 Fig. 8. Nuevas estimaciones de la biomasa parental de anchoveta con estimación de la tendencia local.

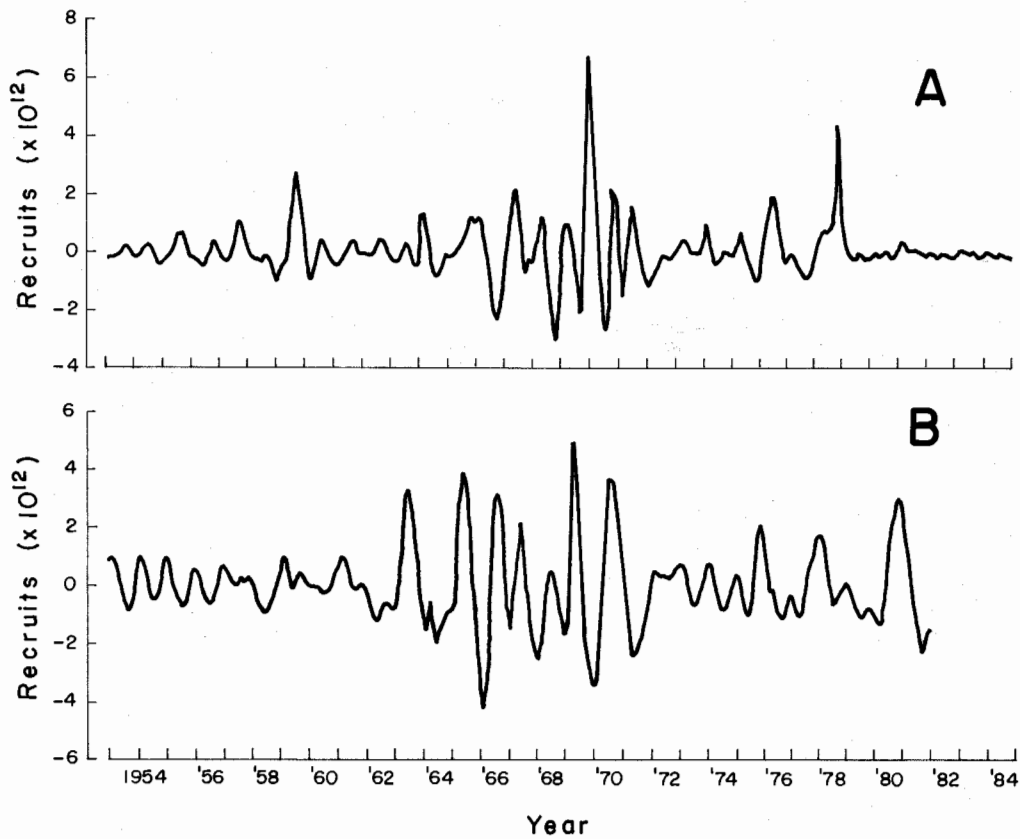


Fig. 9. Stationary (autoregressive) components of the new (A) and old (B) estimates of anchoveta recruitment.
 Fig. 9. Componentes estacionarios (autoregresivo) de las nuevas (A) y antiguas (B) estimaciones del reclutamiento de anchoveta.

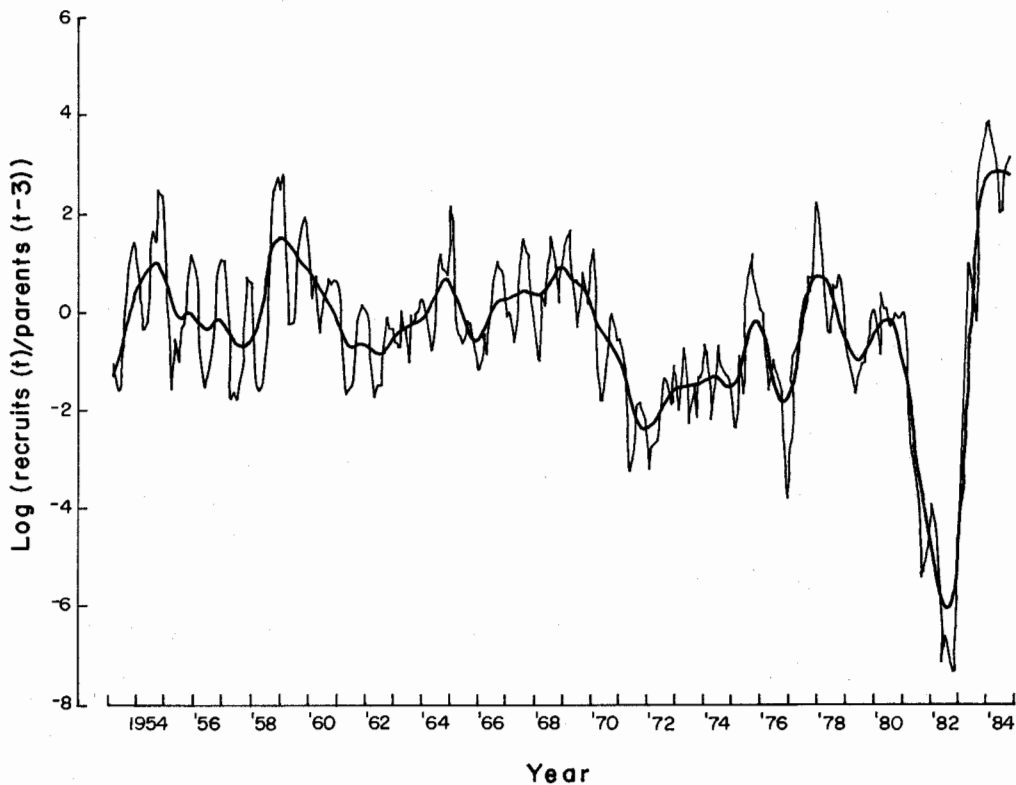


Fig. 10. The log of the ratio of the new recruitment estimates and parent biomass 3 months earlier, the estimated month of hatching.
 Fig. 10. Logaritmo de la razón entre la nueva estimación de reclutamiento y biomasa de padres 3 meses antes (mes estimado de eclosión).

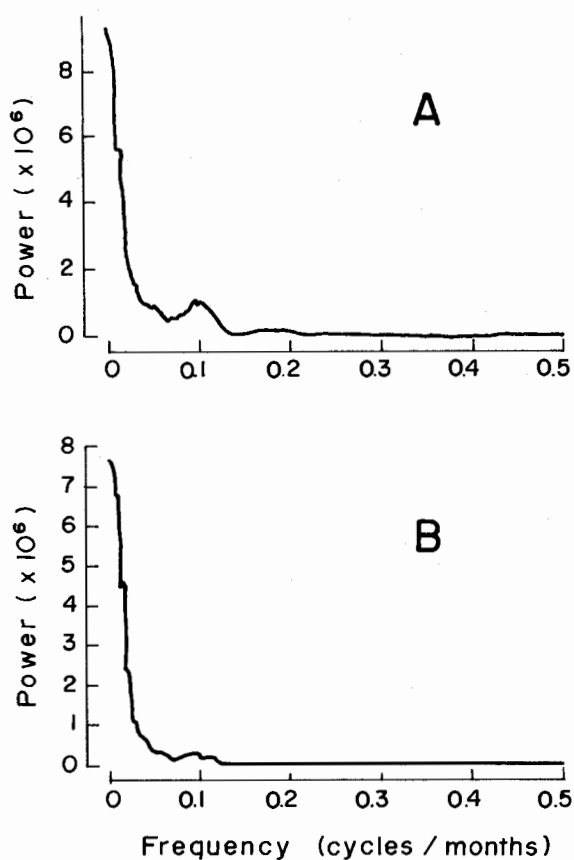


Fig. 11. Estimated power spectra for the new recruitment estimates (A) and for the log of the new recruitment estimates (B).

Fig. 11. Poder espectral estimado para las nuevas estimaciones de reclutamiento (A) y para el log de las nuevas estimaciones de reclutamiento (B).

new series, the mackerel are assumed to come closer to shore as SST warms, increasing mackerel consumption and thereby increasing the estimated population sizes. Mackerel consumption has prewhitened the inputs into the estimation algorithm based on the variation in SST. This does not necessarily mean that prewhitening the inputs is incorrect, but it does explain why there are such differences in the two sets of recruitment estimates.

Comparing the parent series (Fig. 8) with the ratio of recruits to parent biomass (Fig. 10), it is clear that the trend in the log of the ratio is largely explained by changes in the parent biomass, particularly if a mild density dependence is assumed. In the next section I will return to this point more formally, but it brings me back to the initial discussion of this section. If the estimated parent biomass and the estimated recruitment appear to be closely related, is it truly a feature of the population dynamics or a feature of the method that jointly estimates both series?

Data Analysis

In M&M it was found that the monthly recruitment estimates were so highly autocorrelated that it was necessary to examine the monthly series, mildly smoothed (two month nonoverlapping averages), across years. This allowed estimation of the interyear variability as well as to obtain some idea of the intrayear variability. The new recruitment estimates have an autocorrelation of .99 at a lag of 1 month. Even after first differencing, the series is still nonstationary, with the autocorrelations positive and significant at a lag of well over 20 months. This behavior in the autocorrelation function is expected, given the estimated spectrum of the series. Nonoverlapping averages can be formed to try to find a scale at which the series decorrelates and has a more stationary autocorrelation function. However, it is necessary to average almost on a yearly basis to achieve a reasonable degree of stationarity, at which point there is no reason to use anything except the yearly averages.

Following M&M, I have formed 2-month averages of recruitment and parent biomass, as December-January, February-March, etc. The value for December 1952-January 1953 is just the January value, as average, not total values, are used. Each of these series will be examined across

years. Senocak et al. (this vol.), based on the egg survey data in Santander (1987), show that the bulk of the egg distribution throughout the year is inshore rather than offshore. From 1961-1972, for most months the center of the egg distribution is more northerly, around Trujillo rather than Callao. From 1972 onward, the center shifts, being at many times evenly distributed along the coast from Trujillo to Callao, or in some months, clearly centered at Callao. Given the differences in the dynamics of the wind data series analyzed above, this argues for using either the Trujillo or Callao series. As Trujillo is more of a center of the egg distribution in these charts than is Callao, transport at Trujillo, as in M&M, will be used as the environmental variable. As mentioned previously, when a nonlinear analysis is used, this cannot readily be resolved from turbulence at the same location.

Additive models were estimated for the log of recruitment as the response variable, with parent biomass 2 averaged time periods prior (June-July parent biomass predicts October-November recruitment etc.) and Trujillo transport in the previous September and November as the predictor variables. The results in M&M, in Cury and Roy (1989), and the graphical results above all suggest that recruitment should be modeled on a log scale. The span for the transformations of the parent biomass were chosen using cross-validation, which explicitly calculates a tradeoff between the degrees of freedom and the variance of the fit. The estimated transformations of parent biomass (Fig. 12) are approximately that of a log transformation in each case. Thus on a log-log scale, for the period April through November, over 90% of the variance of the recruitment is explained by the parent biomass at the time of birth (Table 2).

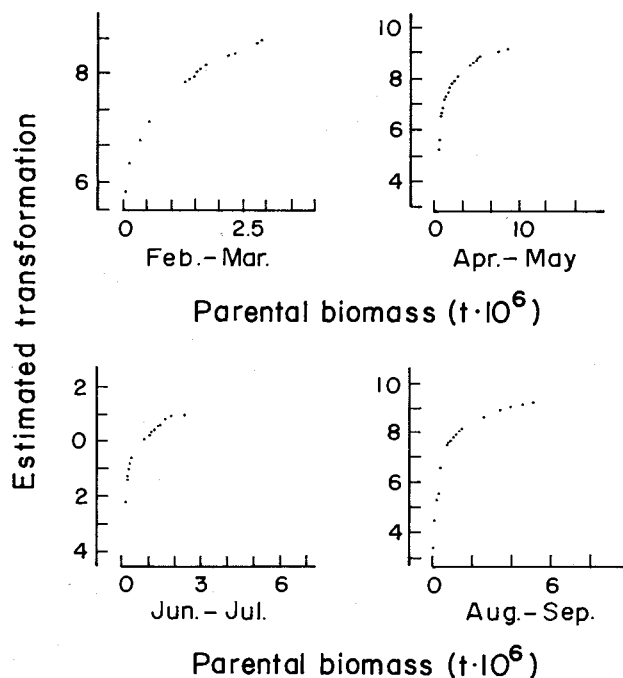


Fig. 12. Estimated transformations of the parent biomass when predicting anchoveta recruitment in a generalized additive model. All four transformations are close to a log transformation. *Fig. 12. Transformaciones estimadas de la biomasa parental cuando se pronostica el reclutamiento de anchoveta en un modelo aditivo generalizado. Las cuatro transformaciones son próximas a la transformación logarítmica.*

For the period from December through March, the estimated r^2 is around .60 (Table 3). The period from December through March is the period of lowest recruitment (Fig. 13A). Therefore the additive models work best during the most important periods of recruitment. On a log scale (Fig. 13B), the monthly recruitment values underline what I have said previously. Recruitment was fairly constant until 1969, with a big peak in 1969, followed by a drop to a new equilibrium

It is entirely possible that recruitment is tightly coupled to parent biomass as these models suggest. That then leaves open the question of why there was such a large parent biomass in 1969. Certainly the recruitment feeding into that year was nothing special compared to previous years; and graphs of the possible environmental factors by month (not shown), do not reveal anything unusual at this time period. The other possibility, of course, is that this is a feature of jointly estimating parents and recruits on such a fine time scale. The added degrees of freedom seemingly brought about from monthly recruitment estimates, at least for the purposes of this

Table 2. Analysis of Deviance for Recruitment-Parent Biomass Models, April-November.
 Tabla 2. Análisis de desviaciones para el modelo de Reclutamiento-Biomasa parental, Abril-Noviembre.

response variable April-May Recruits			
deviance = 10.577 # iterations = 1 #smooths/variable =, 1			
average deviance = .353			
dof of deviance 26.77 scale estimate .395			
r square = 84.01% of a null deviance of 66.169			
span	dof	slope	name
----	----	-----	-----
--	1	7.3602	s0---the intercept term
.60	2.234	smooth	cv: Dec-Jan Parent Biomass
response variable June-July Recruits			
deviance = 2.966 # iterations = 1			
#smooths/variable =, 1			
average deviance = .099			
dof of deviance 24.83 scale estimate .119			
r square = 95.67% of a null deviance of 68.493			
span	dof	slope	name
----	----	-----	-----
--	1	7.4202	s0---the intercept term
.30	4.166	smooth	cv: Feb-Mar Parent Biomass
response variable August-September Recruits			
deviance = 1.569 # iterations = 1			
#smooths/variable =, 1			
average deviance = .052			
dof of deviance 24.67 scale estimate .064			
r square = 97.73% of a null deviance of 69.229			
span	dof	slope	name
----	----	-----	-----
--	1	7.4654	s0---the intercept term
.30	4.331	smooth	cv: Apr-May parent Biomass
response variable October-November Recruits			
deviance = 5.830 # iterations = 1			
#smooths/variable =, 1			
average deviance = .194			
dof of deviance 24.78 scale estimate .235			
r square = 92.62% of a null deviance of 79.032			
span	dof	slope	name
----	----	-----	-----
--	1	7.3894	s0---the intercept term
.30	4.220	smooth	cv: Jun-Jul Parent Biomass

Table 3. Analysis of Deviance for Recruitment-Parent Biomass Models, December-March.

Tabla 3. Análisis de desviaciones para el modelo de Reclutamiento-Biomasa parental, Diciembre-Marzo.

response variable December-January Recruits			
deviance = 28.488 # iterations = 1			
#smooths/variable =, 1			
average deviance = .950			
dof of deviance 26.74 scale estimate 1.065			
r square = 60.05% of a null deviance of 71.343			
span	dof	slope	name
----	----	-----	-----
--	1	7.2947	s0---the intercept term
.70	2.257	smooth	cv: Aug-Sep Parent Biomass
response variable February-March Recruits			
deviance = 26.553 # iterations = 1			
#smooths/variable =, 1			
average deviance = .885			
dof of deviance 26.90 scale estimate .987			
r square = 59.44% of a null deviance of 65.465			
span	dof	slope	name
----	----	-----	-----
--	1	7.3055	s0---the intercept term
.60	2.097	smooth	cv: October-November Parent Biomass

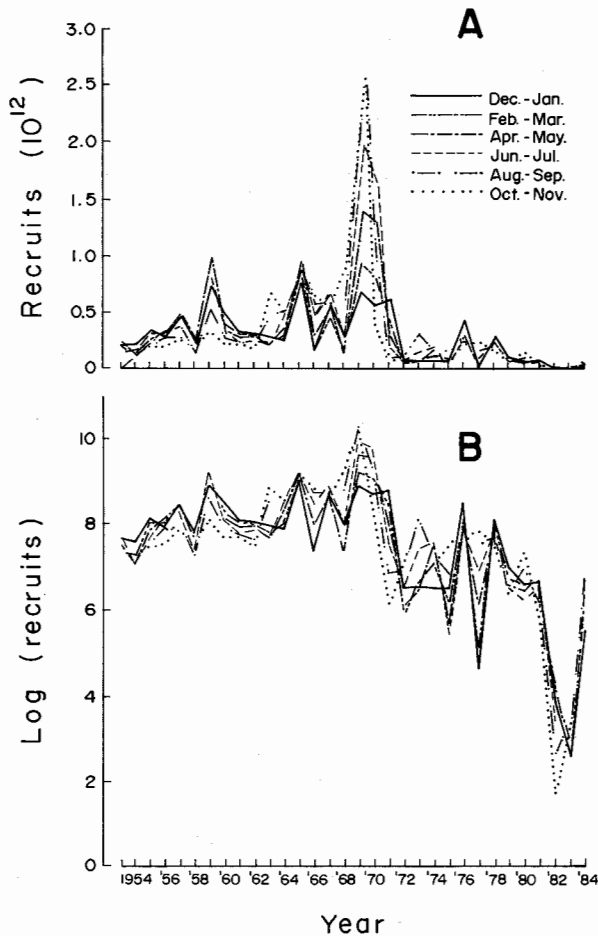


Fig. 13. Time series of bimonthly anchoveta recruitment and the log of bimonthly anchoveta recruitment.

Fig. 13. Serie de tiempo de reclutamiento bimensual de la anchoveta y el logaritmo del reclutamiento bimensual.

paper, do not seem to be there. It appears that all the adjustments in the estimates, while perhaps revealing interesting features in the dynamics of anchoveta recruitment, have also limited the amount of independence in the data.

Cury and Roy (1989) estimate transformations for the yearly averages for the old estimates using the ACE algorithm of Breiman and Friedman (1985). For completeness, I have redone this for the new recruitment estimates (Fig. 14A). Cury and Roy's basic conclusions remain unchanged. The ACE algorithm does not provide an analysis of variance, and given the correlation between transport and turbulence at Trujillo, starting with the variable of lower dimension appears wise. For this reason I refit this model using generalized additive models.

The analysis of deviance for a span of .20 (Table 4) shows that the single best predictor is transport, which for this choice of span explains 60% of the variance. With so few data points, the fit does vary with the choice of span, from roughly 50% to 60%. In all cases, however, the fit due to transport was much higher than that due to parent biomass. When both variables are included, the r^2 increases to .78, which suggests that there is also strong intercorrelation between the parent biomass estimate and turbulence. The range of r^2 for different values of the span was .68 to .78.

The estimated transformations (Figs. 14B and 14C) for both variables resemble a log transformation, and the 95% confidence intervals (Hastie and Tibshirani 1985) are reasonably tight around the mean and preserve the same shape. While the choice of span affects the estimated degrees of freedom, the shape of the transformation is unaffected by the choice of span.

The effect of the transformations can also be viewed by fitting a smoothed surface to the 3-dimensional data (Fig. 15). (This is also a phase plot of recruitment for both datasets). The transformed surface is unimodal and smoother. It is clear that the relationships on the raw scale are nonlinear, while those on the transformed scale are linear in each dimension. While the model is only an additive approximation, it has caught the essence of what information is contained in the data.

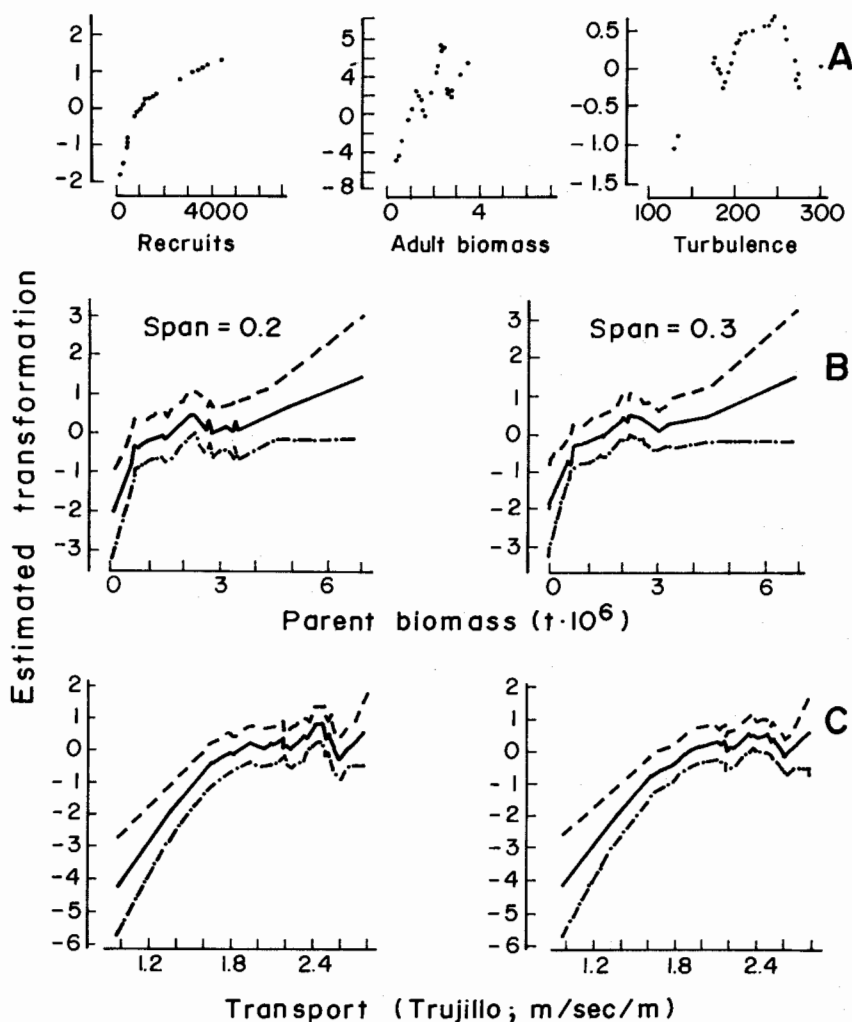


Fig. 14. Estimated transformations (A) from the ACE algorithm, redoing the analysis of Cury and Roy (1989) for the new recruitment estimates. (B) Parent biomass in a generalized additive model for predicting yearly anchoveta recruitment. Dashed lines are 95% confidence intervals for the transformations. (C) Trujillo transport in a generalized additive model for predicting yearly anchoveta recruitment. Dashed lines are 95% confidence intervals for the transformations.

Fig. 14. Transformaciones estimadas (A) del algoritmo ACE, rehaciendo el análisis de Cury y Roy (1989) para las nuevas estimaciones del reclutamiento. (B) Biomasa parental en un modelo aditivo generalizado para predecir el reclutamiento anual de la anchoveta. Las líneas punteadas representan el intervalo de confianza del 95% para las transformaciones. (C) Transporte de Trujillo en un modelo aditivo generalizado para predecir el reclutamiento anual de la anchoveta. Las líneas punteadas representan el intervalo de confianza del 95% para las transformaciones.

Discussion

I have shown that the new estimates of recruitment are much smoother than the previous estimates, with different trends, except for the sharp decrease following 1969 evident in both sets of estimates. Part of the difference between the two sets of recruitment estimates appears to be due to the fact that several estimates of anchoveta consumption, particularly that for mackerel, are surrogates for SST and tend to cause the recruitment estimates to be filtered (smoothed) based on the variation in the SST series.

The new recruitment estimates, even more so than the previous estimates, are highly autocorrelated, even after differencing. Essentially all of the variance in the monthly recruitment series can be modeled by a simple AR(1) model. It is questionable that this represents the true dynamics of recruitment, and certainly would follow, rather than predict, any sudden changes in the population dynamics. Nonoverlapping time averaging requires forming yearly averages to achieve a satisfactory level of stationarity.

Table 4. Analysis of Deviance for Recruit-Parents-Transport Model, Yearly Data.
 Tabla 4. Análisis de desviaciones para el modelo de Reclutamiento-Padres-Transporte, datos anuales.

response variable LOG (RECRUITS)			
deviance = 32.239 # iterations = 1			
#smooths/variable =, 1			
average deviance = 1.007			
dof of deviance	25.27	scale estimate	1.276
r square	= 45.37% of a null deviance of 59.017		
span	dof	slope	name
---	---	---	-----
--	1	6.8277	s0---the intercept term
.20	5.729	smooth	PARENT BIOMASS
response variable LOG (RECRUITS)			
deviance = 22.121 # iterations = 1			
#smooths/variable =, 1			
average deviance = .691			
dof of deviance	25.57	scale estimate	.865
r square	= 62.52% of a null deviance of 59.017		
span	dof	slope	name
---	---	---	-----
--	1	6.8277	s0---the intercept term
.20	5.435	smooth	TRANSPORT
response variable LOG (RECRUITS)			
deviance = 12.714 # iterations= 1			
#smooths/variable =, 6			
average deviance = .397			
dof of deviance	19.84	scale estimate	.641
r square	= 78.46% of a null deviance of 59.017		
span	dof	slope	name
---	---	---	-----
--	1	6.8277	s0---the intercept term
.20	5.729	smooth	PARENT BIOMASS
.20	5.435	smooth	TRANSPORT

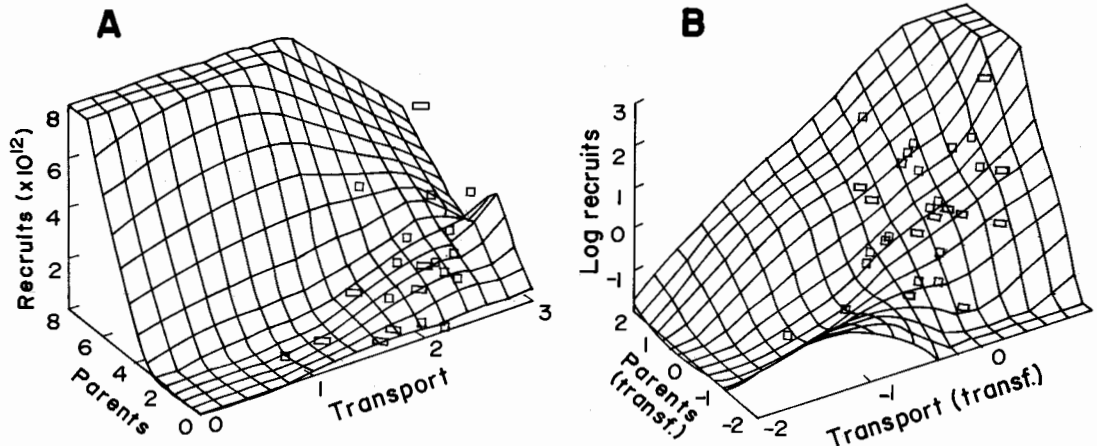


Fig. 15. Estimated smoothed surfaces for (A) yearly anchoveta recruitment, yearly parent biomass and Trujillo transport and (B) the estimated transformed data for the same variables. The small rectangles are the observed points. The effective linearization brought about by the transformations is immediate.

Fig. 15. Superficies suavizadas estimadas para (A) reclutamiento anual de la anchoveta, biomasa parental anual y transporte en Trujillo y (B) estimado de los datos transformados para las mismas variables. Los rectángulos pequeños son los puntos observados. La linealización efectiva producida por las transformaciones es inmediata.

Bimonthly averages of recruitment, viewed across years, are extremely correlated with the log of parent biomass when the recruits were born. The high degree of fit is suspicious, and may be due to the fact that both series were jointly estimated. This left little choice but to analyze yearly averages.

A generalized additive model was then estimated for the yearly averages, using the average parent biomass over the year, and the average transport at Trujillo. The resulting estimates suggest that on a nonlinear scale, about 75% of the variance in the recruitment estimates can be explained by these two series. The analysis suggests that large parent biomass, and a reasonable level of transport produce the best recruitment. Evidence is presented that these nonlinear estimates are relatively stable.

Parrish et al. (1984) argue that transport should be an important variable in the Peruvian system, but due to the dominance of wind in a single direction, it is not possible to resolve whether it is transport, turbulence or some combination of the two (as argued by Cury and Roy 1989) affecting the fish. Even at the yearly scale it is not possible to say what part of the relationship between the parent biomass and the recruitment estimates are due to correlation from their joint estimation. This is compounded by the fact that transport is correlated with SST, and all the population estimates have been influenced by changes in SST.

Unlike in M&M, the present model, if valid, has much explanatory power but little predictive use since all terms are contemporaneous and are averaged over a year. It may well be possible to construct models that will forecast using lagged terms to approximate the proper model, but it would be premature to do so at this time. More important at the moment is to study the various methods of cohort analysis to obtain either theoretical or empirical estimates of the expected cross-correlation functions between recruits and parents due to the fact that they are being jointly estimated in a model that uses up most of the degrees of freedom in the data. (Simulations based on model-generated data with recruitment a random variable, possibly autocorrelated, could give estimates of the expected level of correlation when none is present.) Further, some estimates of the likely base level of correlation with any environmental variable correlated with SST should also be ascertained.

With these results, more valid estimates of significance of a model would be possible. The yearly model in this paper, on the surface, has an intuitive biological interpretation, but this does not guarantee its validity. If all the new population estimates are valid, the existing interpretations of what has occurred in the anchoveta fishery would have to be greatly modified. The new estimates suggest a population that essentially stays in equilibrium until some single event changes the mean level. A new mean level is then found, until another shock comes to the system. The most likely cause of these shocks are environmental changes, but as examined here and in Bohle-Carbonell (this vol.), the environment around Peru exhibits long-term memory, so that monitoring of the environment would have to become an important part of the predictive process.

This implies that once local mechanistic models can be validated, then the use of surrogate variables, such as SOI, that may "monitor" the ocean further ahead, could be useful in forming a predictive model. I have not examined this possibility in detail, but I have presented evidence based on the interrelationship between the SOI and oceanic transport, that this longer lead prediction is at least physically plausible.

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Cover: False color satellite images of the Peruvian upwelling system taken during a 4-day period (5-8 May 1985) with a well developed area of cold waters along the Peruvian coast (front cover) and during a 3-day period (2-4 March 1986) when warm oceanic waters invaded the nearshore habitat of anchoveta (back cover). (Images: courtesy of the US National Oceanic and Atmospheric Administration).

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