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The Remote Sensing of Ocean Primary Productivity: Use of a New Data Compilation to Test Satellite Algorithms

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We tested global pigment and primary productivity algorithms based on a new data compilation of over 12,000 stations occupied mostly in the northern hemisphere, from the late 1950's to 1988. The results showed high variability of the fraction of total pigment contributed by chlorophyll *a* (*p*), which is required for subsequent predictions of primary productivity. Two models, which predict pigment concentration normalized to attenuation length or euphotic depth, were checked against 2,800 vertical profiles of pigments (chlorophyll *a*, phaeopigment and total pigment). Phaeopigments consistently showed maxima at about one optical depth below the chlorophyll maxima. We also checked the global Coastal Zone Color Scanner (CZCS; daily 20km resolution) archive for data coincident with the sea truth data. A regression of satellite-derived pigment versus ship-derived pigment had a coefficient of determination (r^2) of 0.40 ($n=731$ stations). The satellite underestimated the true pigment concentration in mesotrophic and oligotrophic waters (< 1 mg pigment m^{-3}) and overestimated the pigment concentration in eutrophic waters (> 1 mg pigment m^{-3}). The error in the satellite estimate showed no trends with time between 1978 and 1985. In general the variability of the satellite retrievals increased with pigment concentration. Several productivity algorithms were tested which utilize information on the photoadaptive parameters, biomass and optical parameters for predicting integral production. The most reliable algorithm which explained 67% of the variance in integral production for 1676 stations suggested that future success in deriving primary productivity from remotely sensed data will rely on accurate retrievals of "living" biomass from satellite data, as well as the prediction of at least one photoadaptive parameter such as maximum photosynthesis.

1. INTRODUCTION

A major goal of current international oceanographic endeavors has been "to understand the cycles of carbon and other biogenic elements in the upper ocean" [Ducklow *et al.*, 1988]. The International North Atlantic Bloom study of 1989 was designed to understand the large scale dynamics behind the spring bloom and its subsequent fate in one of the better understood ocean basins. Focus is now directed towards the Equatorial Pacific study as well as to the anthropogenic fertilization of the southern oceans with iron to "draw down" the atmospheric CO₂ presumably by stimulating surface productivity [see Banse, 1990; Martin *et al.*, 1990; Sarmiento, 1991]. Clearly, there is a need to understand the large scale patterns of global productivity in space and time. In regards to the iron issue, very significant decisions will rest on our ability to synoptically estimate global productivity as well as understand the global impact of proposed remedies to the CO₂ problem.

The best method for deriving large-scale information about phytoplankton is with the aid of satellites. Certainly, our understanding of the horizontal distribution of phytoplankton biomass was significantly improved during the lifetime of the Coastal Zone Color Scanner. This began with the refinement of satellite-pigment algorithms [e.g. Clarke *et al.*, 1970; Gordon and Clark, 1980; *a & b*, 1981], which gave us an overall accuracy of about ± 0.3 log units in the detection of phytoplankton pigment (chlorophyll *a* plus phaeopigment) [Gordon *et al.*, 1983]. The algorithms now also include the effects of backscattering and absorption by yellow substance and coccolithophores

[Gordon *et al.*, 1988]. The evolution of these efforts has gone through considerable refinement from empirical algorithms to semi-analytical models.

Error in the Derivation of Subsurface Information from Satellite-Derived Pigment

The step of converting surface pigment data to integral production data has admittedly been difficult due to several factors such as limited depth of the phytoplankton visible to the satellite, variable fraction of phaeopigments versus chlorophyll, variable phytoplankton species and varying physiology.

Ninety percent of the signal detected by the satellite originates from the top optical depth of the euphotic zone [Gordon and McCluney, 1975]. The euphotic zone is defined as being 4.6 optical depths [1% light level] thus most of the phytoplankton cannot be detected by the satellite. Another source of error is the amount of "active" chlorophyll *a* relative to the total pigment observed by the satellite. This parameter, *p*, varies from 0.6 to 0.9 with average values of about 0.75 in the top optical depth [Morel and Berton, 1989]. Therefore, maximum relative error in assuming a constant value of *p* of 0.75 is about $\pm 20\%$ (the difference between the estimated value and the real value, divided by the real value; the likely maximum error represents 2 standard deviations away from the mean).

The presence of subsurface chlorophyll maxima represents another source of error but it does not make the calculation of subsurface biomass intractable; it requires models to take its effects into account. Typically, the biomass observed by the satellite only accounts for about 20% of the total biomass in a well-mixed water column and 2-15% in a typical stratified water column [Platt and Herman, 1983; Balch *et al.*, 1989a, 1989b]. One possible solution to this problem [Platt, 1986] involves assuming a uniform chlorophyll profile. Subsequent error analysis showed that the maximum error incurred by this assumption was about

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90% or less of the estimate of integral biomass [Sathyendranath and Platt, 1989].

Another convenient way to model the vertical distribution of chlorophyll, phaeopigments and total pigment was presented in Balch et al. [1989b]. This technique involved integrating pigments over each optical depth and plotting this versus optical depth. This collapses the variance of pigments onto a scale which is more relevant to phytoplankton, namely the optical attenuation scale. It was observed that the subsurface chlorophyll maximum usually occurred between the second and third optical depths and chlorophyll concentrations varied between about 4 and 10 mg chlorophyll $a\ m^{-2}$ per optical depth. Analogous patterns have also been observed by Mueller and Lange [1989] for normalized chlorophyll a fluorescence for data from the NE Pacific Ocean. Morel and Berton [1989] have used a similar procedure (normalizing the depth profiles of chlorophyll to the depth of the euphotic zone) to reduce the depth-dependent variance in pigments.

Another recent observation [Morel and Berton, 1989] is that simulated satellite-derived pigment is well correlated to the integrated pigment concentration. Morel and Berton checked their relationship for about 3500 stations in the West African upwelling region, the Mediterranean, South Indian/Antarctic, and Sargasso Sea and found a correlation coefficient of 0.87. They suggest that although surface pigments may not always be correlated to integral pigment, the average relationship is well defined and highly significant. The error limits on their relationship are not given, but it can be seen that at a surface pigment level of 0.5 mg m^{-3} , integrated pigment can be calculated to plus or minus approximately 10 mg m^{-2} or a maximum relative error of about $\pm 30\%$. This maximum error increases slightly to $\pm 40\%$ at the lower pigment concentration of 0.1 mg m^{-3} .

The above errors are quasi-independent and propagate multiplicatively. Using standard error expansion techniques [Leibelt, 1967] with knowledge of the 95% confidence limits at each step of the calculation, the final error in the estimate of integral chlorophyll can be calculated. It is expected that if 1) surface pigment concentration can be calculated to $\pm 35\%$ relative error [95% confidence limits] from satellite observations, 2) the integral pigment can be derived from surface pigment within $\pm 35\%$, and 3) the actual active biomass can be estimated to $\pm 20\%$ from total pigment, then the overall relative error in calculating integral pigments from satellite data is about $\pm 60\text{--}80\%$. Thus, even before any calculations of productivity, the initial error in determination of integrated, photosynthesizing plant biomass is substantial.

It is interesting to compare the above results of Morel and Berton [1989] with the analysis of Hayward and Venrick [1982] in which they examined integral pigment and surface pigments from the Central North Pacific Ocean. Although they observed no significant relationship between surface and integrated chlorophyll concentrations, almost two thirds of their data ($n=33$ stations) fall within $\pm 35\%$ of the relationship proposed by Morel and Berton [1989], and the deviation of the outliers is greatest at the very lowest pigment concentration, 0.04 mg m^{-3} , close to the limit of detection of the fluorometric technique for measuring chlorophyll a [Holm-Hansen et al., 1965]. Clearly, the oligotrophic regions present the biggest challenge in calculating integral pigment concentrations using satellite data.

Productivity Algorithms

The precision of the carbon 14 technique sets the lower limit on the precision of our productivity estimate

using remotely sensed data, (the accuracy of the carbon 14 technique will not be addressed here). The coefficient of variation for the standard carbon 14 technique (Steemann Nielsen, [1952] as given in Parsons et al. [1984]) is 40% for open ocean samples and 17% for coastal samples [Fitzwater et al., 1982]. Thus, as long as we base algorithms on carbon 14 measurements, then the error in satellite-derived productivity estimates must be greater than or equal to the error of the carbon 14 technique. Given that the error in our estimates of the "producing biomass" is $\pm 60\text{--}80\%$ (see above) then our estimates of integral productivity can be no better than our estimates of the integral euphotic zone biomass.

In Balch et al. [1989a], we examined the error in deriving integral productivity from surface pigments using a suite of empirical algorithms. These simple algorithms explained 28%–38% of the variance of integral productivity, with a maximum relative error of 200–300% using either shipboard or satellite-derived pigment as input. Subsequent trials with semi-analytical approaches explained more variance, provided field calibration data were available from one station within 1° latitude squares over a 10–14 day time period ($r^2=0.58$). The "PTL algorithm" (based on pigments, temperature, and light) used a model of quantum efficiency to derive photosynthesis as a function of light, and constrained maximum photosynthesis based on temperature. The algorithm was good to about 100–200% relative error. The largest source of error was intercruise variance. Because of this, calibration data could be applied over mesoscale features having length scales of 500 km and time scales of 2 weeks. This is critical if we are to estimate global production from remotely sensed data, aided by mooring data.

Another more complex semi-analytical model was recently proposed by Platt and Sathyendranath [1988] (see also Sathyendranath and Platt, [1989]). Their approach basically involved using the model of Paltridge and Platt [1976] to calculate solar angles at a given geographical position and time. The solar angles were then coupled to Bird's [1984] clear-sky model for computation of surface irradiance over visible wavelengths throughout the day. Cloud cover was simulated using a nonspectral approach [Paltridge and Platt, 1976]. Platt and Sathyendranath [1988] modeled the vertical pigment distribution using 11 generic "water types" each characterized by a unique vertical depth profile and defined according to the latitude and depth to the seafloor. Vertical irradiance profiles were simulated throughout the day by dividing the light field into diffuse and direct components, and spectrally attenuating (via absorption and scatter) due to water and pigments. Using irradiance calculated from the Paltridge and Platt [1976] model and the Bird [1984] model, productivity was calculated based on generic values of α , the light-limited slope of the photosynthesis irradiance curve, and generic values of P_m^b , the maximum photosynthesis per unit chlorophyll. (As stated above, "generic" refers to parameters defined according to the 11 generic "water types". Note also that generic values of α were given spectral dependence.) Their model performance looks quite encouraging when measurements of integral primary production are compared to model runs using ship-derived photoadaptive parameters and ship-derived chlorophyll profiles as input [Platt and Sathyendranath, 1988; their Figure 1). Although the model has been applied on regional basin scales, it has yet to be tested using generic pigment profiles, photoadaptive parameters associated with the 11 regional watertypes, and large amounts of shipboard data.

One family of algorithms has been used with considerable success for predicting integrated productivity from knowledge of maximum photosynthesis per unit chlorophyll in the top optical depth, divided by the downward

diffuse attenuation coefficient for wavelengths from 400 to 700 nm (K) (hereafter referred to as " P_m^b/K " models). The first model of this sort appeared in *Ryther* [1956] and *Ryther and Yentsch* [1957]. We rearranged equation (1) of *Ryther and Yentsch* [1957] by replacing their saturated production per unit volume with the product of P_m^b ($\text{gC g Chl}^{-1} \text{h}^{-1}$) and chlorophyll concentration of a homogeneously distributed population (B ; $\text{g chlorophyll a m}^{-3}$). Integral production (P ; $\text{gC m}^{-2} \text{d}^{-1}$) was calculated by normalizing this product by the diffuse attenuation coefficient, K (m^{-1}) and multiplying by P (a unitless parameter which describes the curvilinear relation between light and relative photosynthesis; see figure 1 from *Ryther and Yentsch*, [1957]).

$$P = R * (P_m^b * B) / K \quad (1)$$

This equation was further rearranged to:

$$P/B = R * P_m^b / K \quad (2)$$

Equation (2) has appeared in the literature at least seven times in various forms over the last 33 years: a tribute to its effectiveness.

Talling [1957] scaled the maximum photosynthesis in Lake Windermere according to the minimum diffuse attenuation, K_{\min} (in the green wavelengths). We rearranged his equations (2) and (3) to give the following:

$$P/B = [\ln(I_0/(0.5I_k))] * (1/1.33) * P_m^b / K_{\min} \quad (3)$$

The dimensionless coefficient, R , from *Ryther and Yentsch* [1957] was essentially replaced by an I_0/I_k parameter with added constants. Where I_k was the light intensity at which photosynthesis saturated.

Bannister [1974, his equation (28)], *Smith and Baker* [1978, their equation (16)] and *Eppley et al.* [1985, their equation (2)] used the simple relation:

$$P/C_k = 2.3 P_m^b / K \quad (4)$$

where C_k was the chlorophyll concentration in the top optical depth. The factor 2.3 is the optical depth at which the maximum production was observed and corresponded to the slope of a plot of P_m^b/K versus P/C_k [*Eppley et al.*, 1985].

Lewis et al. [1987] derived an algorithm for the estimation of integral production, which was similar to *Talling* [1957]:

$$P/C_k = [I_0/I_k] P_m^b / K \quad (5)$$

Finally, *Banase and Yong* [1990] published another variation in which the value P_m^b was replaced by $P/\text{Chl}_{\text{opt}}$, the maximum photosynthesis per unit chlorophyll observed between the 20% and 50% light level (this eliminated data where P_m^b was at the base of the euphotic zone or at the very surface). This is given in equation (6):

$$P/C_k = 2.3 [P/\text{Chl}_{\text{opt}}] / K \quad (6)$$

In the remainder of this paper, we will describe a recently compiled data set of pigments and productivity data and compare them to data retrieved with the CZCS. Then we will use these data to validate the above primary productivity algorithms. We will show that much of the variance in global primary production can be explained with a small amount of

physiological information such as that required by the P_m^b/K algorithms. The challenge still remains to estimate these physiological parameters remotely.

2. METHODS

Assembly of global data set and description of data base

Software was written to allow entry of station data, integrated parameters, and discrete data for productivity, pigment, nutrient, dissolved and particulate organic matter, photosynthesis-light curves, and hydrographic parameters. The software performed a preliminary level of quality control during input by questioning unreasonably high or low values of various parameters. Subsequent quality control was performed at the analysis stage, specifically by setting criteria for data flagging (for example, the maximum possible assimilation number [*Falkowski*, 1981] was used as the criterion to flag exceedingly high productivity values).

Data were compiled into 15 record types according to the parameters given above during 1988 and 1989. Major aspects of the productivity protocol (length of incubation, type of bottles used, cleaning techniques, etc.) were also included to aid in quality control. The data sets that were assembled are given in Table 1. The total data set consists of 159,000 records, and over 12,000 stations.

Data manipulation

Diffuse attenuation, K , was calculated using a hierarchical procedure. If percent light (as a percent of surface photosynthetically available radiation, PAR) and depth were available, K was calculated between each sample depth using Beer's law. If only Secchi depth data were available, then K was calculated according to *Idso and Gilbert*, [1974] ($1.7/(\text{Secchi depth}) = K$). Simulated-satellite pigment values were calculated by using equation (7) of *Gordon and Clark* [1980 a & b] which weights pigment concentration by e^{-2KZ} .

All productivity data were converted to mg carbon per m^3 per day. To convert measurements in units of "per hour" to "per day", daylength was calculated using equation 7:

$$DL = [-1 * \cos(J) * (\sin(L))^3] + 1 * 12 \quad (7)$$

where daylength, DL , was in hours, J was the annual cycle (calendar day converted to radians by dividing by 58.09), and L was latitude in radians. This simple algorithm was useable up to about 75° latitude with minimal error. All data used in this study were equatorward of 75° latitude.

Pigment and productivity integrations were performed using a standard trapezoidal routine. If surface samples were at a depth of 1 m or less, the surface depth was reset to 0 m before doing the integration. If the surface bottle was at a depth exceeding 1 m, then it was assumed that the water column above was completely mixed. No integration was performed if fewer than four depths were sampled at a given station.

The second level of quality control was done during the analysis phase. Our format used 280 different variables that were encoded (unit codes, protocol codes, and actual values). Quality control of all of these parameters was logistically impossible. Instead, our software flagged data during analysis after which we decided on whether the data were useable. The only caveat about quality control of the productivity data concern the NODC data, filetype 029. There is a typographical error in the NODC Users Guide (*United States Department of Commerce-National Oceanographic*

TABLE 1. Description of Pigment and Productivity Data Used in This Study

Data Set	Date	Location	No. of Recordings
Biowatt-Marra	4/84	N. Atlantic	27
CalCOFI-Hayward	5/81-11/86	Calif. Current	10,163
Fronts Cruise-Marine Life Res Grp	7/85	Calif. Current	464
Marmap Data Set-NOAA	8/78-6/80	NW Atlantic Shelf	26,236
Mediterranean Data-Lorentz	5/86	W. Mediterranean	173
NODC File 029-NOAA	1958-88	Sub Arctic Pacific	52,823
NODC File 049-NOAA	1973-78	NY Bight	27,626
North Sea Data Set-Holligan	4/80-7/86	N. Sea and NE Atlantic	3,856
PRPOOS Study-Eppley/Marra	8/85	Bermuda.-Sargasso	162
TOGA Data Set-Barber	1/86-2/86	E. Equatorial Pacific	4,568
SCOR/Discoverer Expedition-SIO VisLab	5/70-6/70	W. Pacific/Carib.	1,037
Southern California Bight Study-Food Chain Research Group,SIO	9/74-1/87	S. Calif. Bight	14,904
Warm Core Rings-Wiebe	4/82-10/82	NW Atlantic	842
Yentsch Chlorophyll Data Set	1956-82	Global	15,887
Total			158,868

One observation is equivalent to one sample at one depth and time.

Data Center [1986] section 4.1.12, page 3) in which carbon assimilation was given as milligrams per m^3 per hour with no decimal. The value should have been given to tenths (*E. Collins*, personal communication, 1990) so we divided by 10 before our analyses.

Statistical manipulations

All data subsets were checked for normality before analysis (or, when appropriate, log normality). Standard least squares regression and curve fitting routines were used during all data manipulation.

3. RESULTS

Description of the data

The spatial distribution of the data was quite patchy (Figure 1). It can be seen that the station density was highest along the east and west coast of the United States, as well as the North Pacific. Most of the data extend to $10^\circ S$ latitude (Figure 2); thus the foregoing analysis is considered to represent mostly the northern hemisphere.

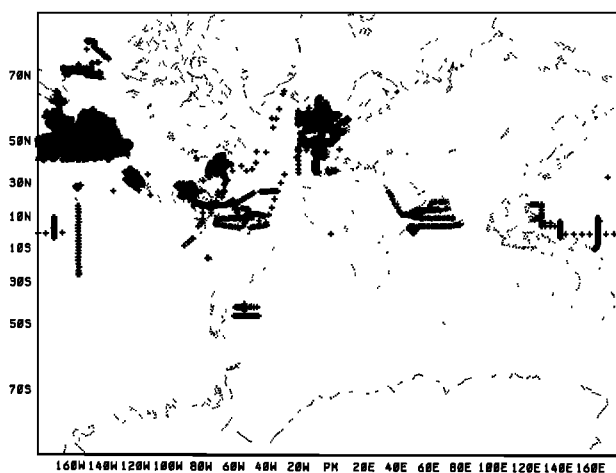


Fig. 1. Station locations for pigment and productivity data.

Figure 3 shows a histogram of the chlorophyll data (>41,000 observations). Showing that pigment data extended from the late 1950's through 1988, mostly focussing on the duration of the CZCS. The seasonality of the pigment data coverage (Figure 4); shows that the winter period between late December and early January had the lowest coverage of 200-400 observations per 10 day increment. The productivity data (>20,000 observations) show a similar latitudinal and seasonal distribution to the pigment data.

Analysis of ρ

Figure 5 shows a scattergram of chlorophyll *a* versus phaeopigment where isopleths of the percent chlorophyll *a*, ρ , were superimposed. It appears that there may have been two groups of data with different slopes. The average value of ρ was about 0.76 with a range of about 0.28

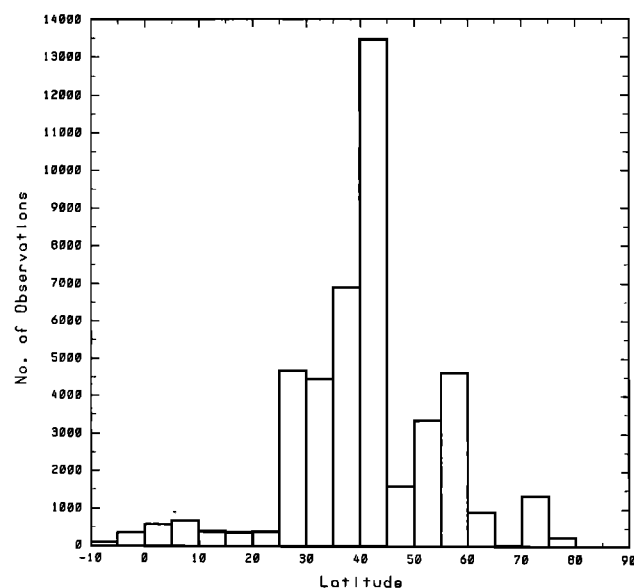


Fig. 2. Histogram showing 41,204 chlorophyll observations as a function of latitude.

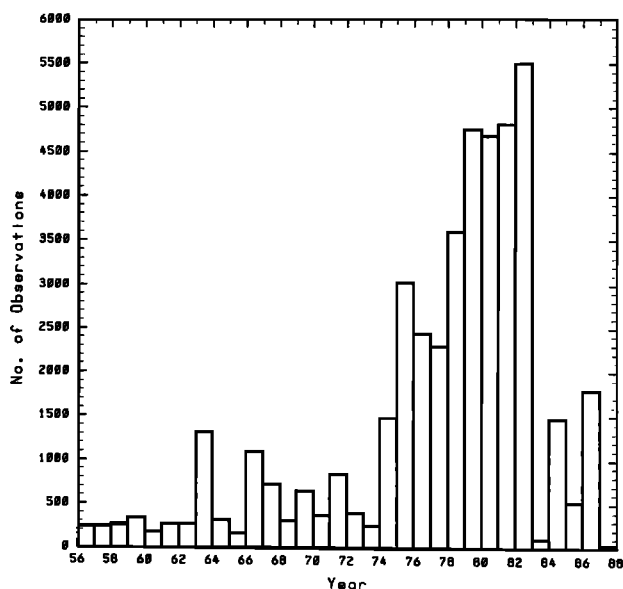


Fig. 3. Histogram of chlorophyll observations versus year ($n=41,204$).

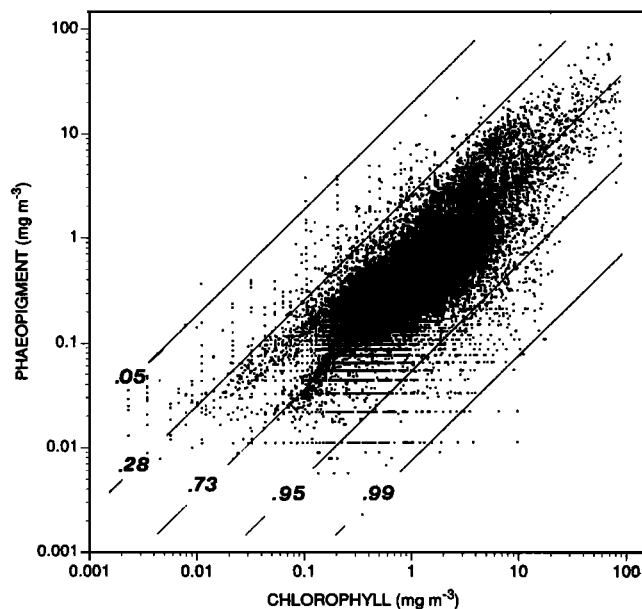


Fig. 5. Scatterplot of chlorophyll *a* versus phaeopigment ($n=23,000$). Least squares fit line to these data: $\text{Log Phaeo} = \text{Log Chl} * 0.76 - 0.46$ ($r^2=0.68$). Isopleths of r (fraction of total pigment as chlorophyll *a*) are superimposed to illustrate the variance in this parameter.

and 0.95 ($r^2=0.68$). This demonstrates the large uncertainty in p in our data set, greater than that described by *Morel and Berthon* [1989]. It is impossible to know whether this difference is real or due to a difference in data quality.

Given the limitations of our data set, integral pigment per square meter per optical depth ($1/K$) could be calculated at about 2800 of the 12,000 stations. The mean pigment concentrations along with 95% confidence limits of the mean (± 2 standard error) are shown in Fig. 6. It is interesting to note that the absolute phaeopigment concentration did not increase dramatically at the base of the euphotic zone. However, as a percentage of the total pigment,

the phaeopigment concentration increased by 10% at 5.5 optical depths compared to the surface.

Since the derivation of this type of profile by *Balch et al.* [1989b] for the Southern California Bight, addition of about 2000 more stations to the data set has resulted in a rounder profile of chlorophyll per m^2 per optical depth. The least squares polynomial curve fit between optical depth (Z_{od}) and pigment concentration (Pod ; $\text{mg pigment m}^{-2} (\text{optical depth})^{-1}$) is

$$\text{Pod} = 9.242 - 3.900 * Z_{\text{od}} + 3.914 * (Z_{\text{od}})^2 - 1.018 * (Z_{\text{od}})^3 + 0.077 * (Z_{\text{od}})^4 \quad (8)$$

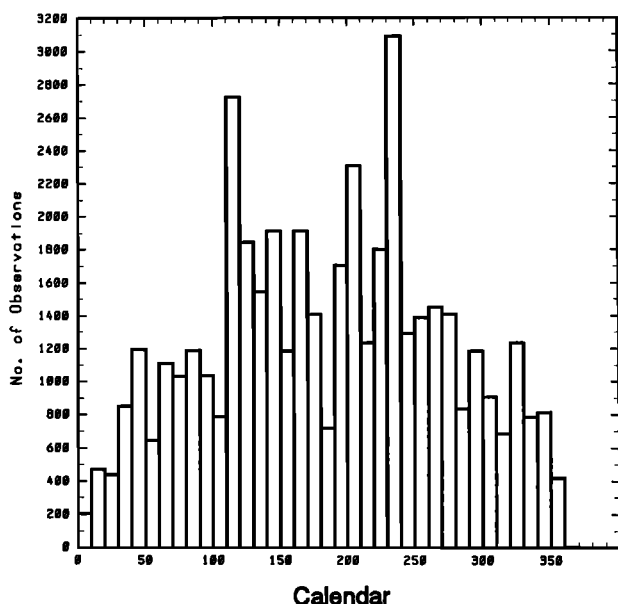


Fig. 4. Histogram of pooled chlorophyll observations versus calendar day.

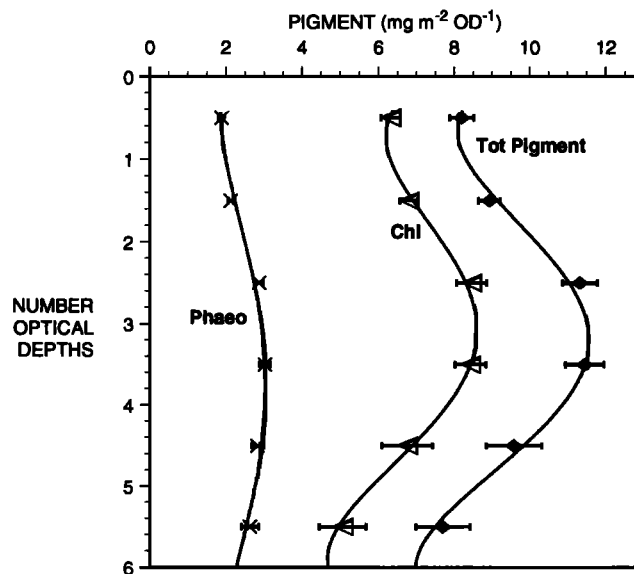
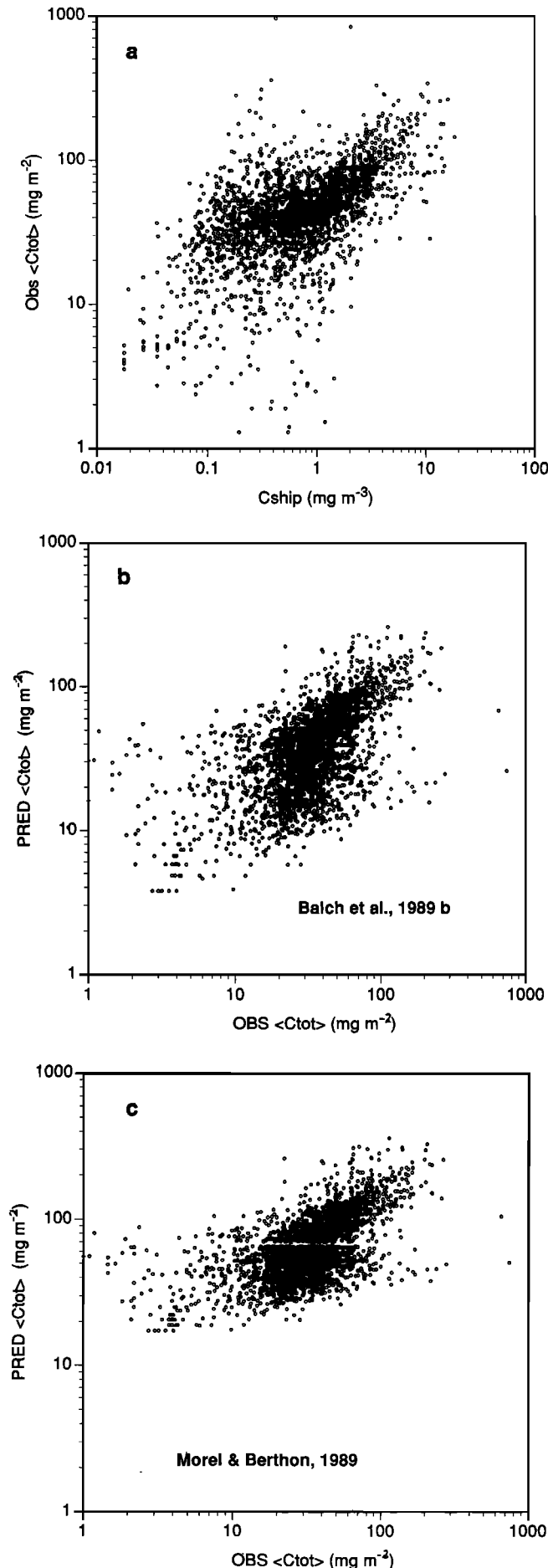


Fig. 6. Plot of integral pigment per square meter per optical depth versus optical depth in the water column. Solid diamonds signify total pigment, triangles signify chlorophyll *a*, and crosses signify phaeopigments. Error bars represent ± 2 times the standard error.



The comparable relationship for chlorophyll (Cod) and phaeopigment (Phod) per square meter per optical depth is given in equations (9) and (10).

$$\text{Cod} = 7.365 - 3.638 * \text{Zod} + 3.412 * (\text{Zod})^2 - 0.895 * (\text{Zod})^3 + 0.069 * (\text{Zod})^4 \quad (9)$$

$$\text{Phod} = 1.882 - 0.279 * \text{Zod} + 0.511 * (\text{Zod})^2 - 0.125 * (\text{Zod})^3 + 0.008 * (\text{Zod})^4 \quad (10)$$

Note that the curves in Figure 6 are only useable to six optical depths, below which their accuracy declines markedly. To estimate subsurface pigment from satellite data, first the above curves were normalized so the surface values (in the top optical depth) were 1.0. The normalized depth profiles were then multiplied by the surface pigment (chlorophyll, phaeopigment, or total pigment) to obtain a profile of pigment concentration per m^2 per optical depth. These curves were used to predict mean pigment in the euphotic zone at all stations, which clearly spanned a wide range of pelagic environments. Obviously, they did not apply to a totally mixed water column (but this is where prediction of subsurface pigments from a surface value would be easiest, provided one can recognize a mixed water column from space). Fig. 7a shows a scattergram of ship-derived surface pigment and shipboard-integrated pigment for 2177 stations. The least squares fit to these data had an r^2 value of 0.34. The integral euphotic zone pigment predicted with equation (8) (originally derived by Balch *et al.* [1989b]) and surface pigment data are plotted against the ship-derived integral pigment in figure 7b (same stations as in Figure 7a). This equation also explained 34% of the variance in integral pigment concentrations, providing no improvement over the empirical model.

Integral pigment predicted by the model of Morel and Berthon [1989] was plotted against sea truth integral pigment in figure 7c. This model basically predicts the vertical distribution of pigments assuming nine "trophic categories" (i.e., various degrees of eutrophication). Pigment variance is reduced by normalizing pigment concentrations by the integrated euphotic pigment concentration, and depth variance is reduced by normalizing to the euphotic depth. Note, this model is identical in concept to that of Balch *et al.* [1989b], where pigments are normalized by optical depth (as opposed to the euphotic zone or 4.6 optical depths) and depth was given in optical depths (instead of fractions of the euphotic zone). However, the model of Morel and Berthon would be expected to account for more variance in the vertical pigment distributions, since it contains information about different trophic categories. Their model was run here (1)

Fig. 7. (a) Empirical relationship between surface discrete pigment weighted according to Gordon and Clark [1980a] (Cship) and integrated pigment (<Ctot>obs). ($n=2177$; least squares fit: $\log <Ctot>_{\text{obs}} = 0.38 * \log \text{Cship} + 1.59$; $r^2=0.34$) (b) Shipboard-derived integrated pigment (<Ctot>obs) versus predicted integrated pigment (<Ctot>pred) using the algorithm of Balch *et al.* (1989b), substituting equation (8) and the curve shown in Figure 6 of this paper; 2177 measurements were used in this analysis. The least squares fit line to this data set was: $\log <Ctot>_{\text{pred}} = 0.64 * \log <Ctot>_{\text{obs}} + 0.64$ ($r^2=0.34$) (c) Observed integrated pigment versus predicted integrated pigment using the algorithm of Morel and Berthon [1989]. The least-squares fit line to these data was $\log <Ctot>_{\text{pred}} = 0.38 * \log <Ctot>_{\text{obs}} + 1.14$ ($r^2=0.34$).

using the two-equation formulation of $\langle C_{tot} \rangle$ based on a satellite-simulated surface pigment value (their equations (3b) and (3c), (2) using their equations (1a) and (1b) to calculate the depth of the euphotic zone, (3) with no separate calculations of $\langle C_{tot} \rangle$ for deep mixed layers (their equations (4) and (5), and (4) calculation of $C(z)$ based on satellite simulated pigment concentrations (C_{sat}), rather than mean pigment concentration within the surface layer (C_{pd}). Note that C_{pd} and C_{sat} are essentially the same as defined in their model. Despite the added trophic information included in this model, the model of Morel and Berthon [1989] explained the same amount of variance in integral pigment concentrations as equation (8) (Figure 7b), or the empirical relation (Figure 7a), 34%.

Comparison of Sea-truth and Satellite Values

Stations in our data set between October 1978 and May 1986 were checked for matches to the daily 20 km CZCS data set, archived by NASA Goddard Space Flight Center [Esaias *et al.*, 1986]. If no data were located for a given station date, the day before and the day after were checked for CZCS data. If data were located, the value at the appropriate pixel was extracted along with its accompanying standard deviation. Ship pigments were calculated as the sum of chlorophyll *a* and phaeopigment, weighted as described previously. For each ship or satellite match, the relative deviation was calculated as $(sat-ship)/ship$.

A plot of log ship-derived pigment versus log satellite-derived pigment is shown in Figure 8a. We limited the analysis to pigment concentrations less than 10 mg m^{-3} . The coefficient of correlation, r^2 , was 0.40. The equation relating the 731 ship and satellite values was $C_{sat} = 0.60 \cdot C_{ship} - 0.14$. This equation implies that satellite estimates of pigment were consistently underestimated. Figure 8b shows a plot of satellite-derived pigment versus the relative deviation of the satellite data from the sea-truth data. The error in the satellite measurement was a function of the total pigment in the water column. That is, at satellite derived pigment values less than 1 mg m^{-3} , the average deviation was 21% lower than the ship value (standard error $\pm 4\%$; $n=387$), while above 1 mg m^{-3} , the satellite estimate averaged 150% higher than the ship value (and considerably more variable, standard error = $\pm 24\%$; $n=160$). Given the large scatter in the data, we could not discern any significant change in the average deviation from 1978 through 1985 (Figure 8c).

The time lag between ship and satellite observations made a small difference in the correlation between the two variables. When the ship and satellite data were taken on the same day (Figure 9a) an r^2 value of 0.44 was observed for 322 stations. If the ship and satellite data were one day apart, the coefficient of determination was 0.38 for 411 stations (Figure 9b). The coefficient of variation of the satellite retrievals was calculated as the standard deviation (of the individual 4 km pixel values used in making the 20 km pixel) divided by their mean value; this value was generally about 0.2 but showed no trend with absolute pigment concentration (data not shown).

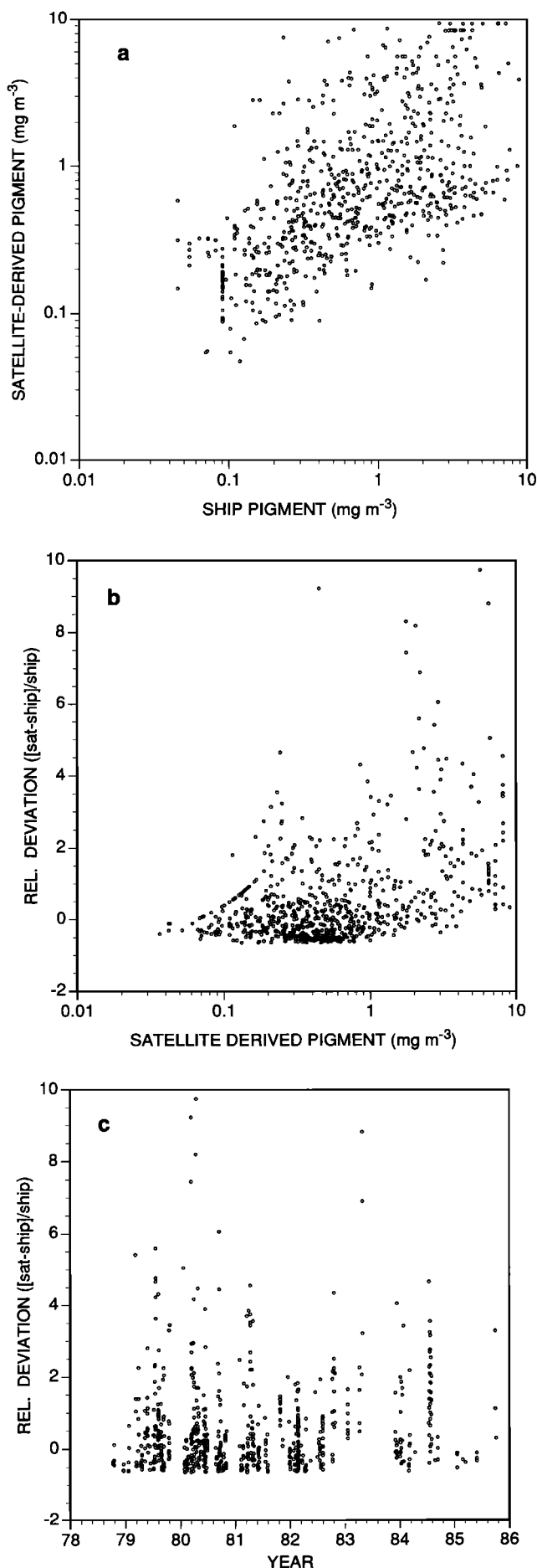


Fig. 8. (a) Plot of ship-derived pigment versus satellite-derived pigment for all stations where the satellite estimate was within ± 1 day of the ship station. These data represent CZCS retrievals from the 20-km resolution global data set ($n=731$). Only shipboard stations having pigment values between 0.01 and 10 mg m^{-3} were used in this analysis. (b) Normalized deviation of satellite pigment value from ship value versus satellite-derived pigment concentration. (c) Normalized deviation of satellite pigment value from ship value versus year of CZCS operation.

Analysis of Empirical and " P_m^b/K " Models

Empirical relations between surface pigments and integrated production were examined as in *Balch et al.* [1989a]. Surface chlorophyll explained about 6% of the variability in integral productivity ($n=2595$), pointing out the need for a more accurate semi-analytical productivity algorithm.

The productivity data compilation was used to test the P_m^b/K models, in which P_m^b was scaled by the diffuse attenuation coefficient. Figure 10a illustrates the results of the Ryther and Yentsch [1957] algorithm. It can be seen that with basic knowledge of the photoadaptive parameter, P_m^b , the plot of observed versus predicted integral productivity had an r^2 of 0.60 for 1206 stations where there were sufficient data to apply the model. The plot of observed versus

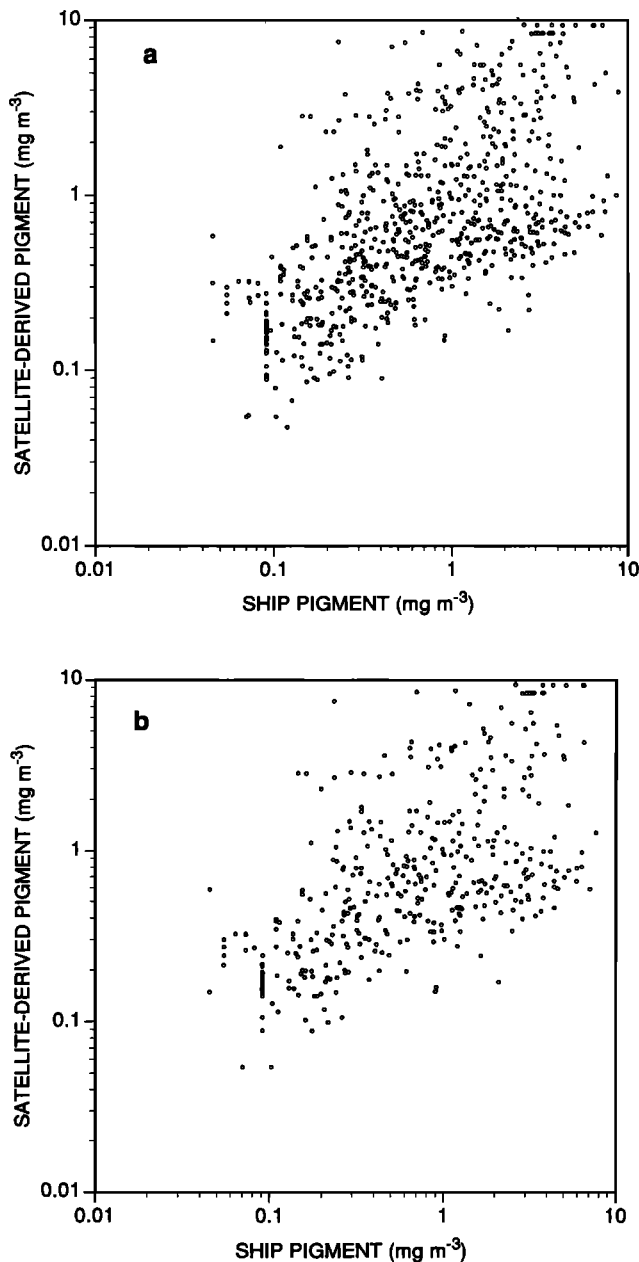


Fig. 9. (a) Error of satellite pigment estimate for data taken on same day as ship measurement. (b) error of satellite pigment estimate for data taken one day before or after ship pigment measurement.

predicted production had a slope of 1.17 (standard error = ± 0.028). An ideal algorithm would give a slope of 1.0. The Ryther and Yentsch model explained 10 times more of the variance than the simple chlorophyll versus production empirical relation.

Figure 10b shows the performance of the *Talling* [1957] algorithm. It explained only 27% of the variance in integral productivity for the 1178 stations where it could be applied. The plot of observed versus predicted production had a slope of 0.62 (standard error = ± 0.029).

The performance of the formulation of *Bannister* [1974] (see also *Smith and Baker* [1978] and *Eppeley et al.* [1985]) explained 65% of the variance for the 1754 stations of data for which it could be applied (Figure 10c). The slope of the line in this figure was 0.88 (95% confidence limits on the slope were 0.85 to 0.91), quite close to 1.0.

The performance of the *Lewis et al.* [1987] algorithm was quite similar to that of *Talling* [1957]. It explained 30% of the variance for the 1171 stations for which it could be applied (Figure 10d). The slope of the least squares fit to the data is 0.66 (standard error ± 0.029). This model required input for the slope of the light-limited portion of the photosynthesis-light relation (α) at each station. As few such data were available in our data compilation, we used a constant value of $0.01 \text{ mg C (mg Chl)}^{-1} (\mu\text{E m}^{-2} \text{ s}^{-1})^{-1}$. (It could be argued that the algorithm would have performed better had values of α from each station been used.

The algorithm of *Banase and Yong* [1990] explained 67% of the variance for 1676 stations where it could be applied (Figure 10e). The slope of the plot of log observed versus log predicted production is 0.91 (95% confidence limits on the mean slope are 0.88 to 0.95), closest of all the above algorithms to the ideal value of 1.0.

The above tests of the P_m^b/K algorithms involved using ship-derived pigment, K and P_m^b as input. We performed a more stringent test of the algorithm using just the satellite-simulated pigment to calculate K and sea surface temperature (SST) to derive maximum photosynthesis, P_m^b . The P_m^b/K algorithm of *Bannister* [1974]; (see also *Smith and Baker*, [1978]; *Eppeley et al.*, [1985]) was chosen as an example due to its high explained variance and the ease with which satellite-simulated data could be applied. Equation 11 shows derivation of K from satellite-simulated pigment, C_{sat} (this was derived from a separate analysis of all of the optical and pigment data):

$$K = 1 / (10^{(-0.39 * (\log(C_{sat})) + 0.80)}) \quad (11)$$

The value of ρ , the fraction of pigment consisting of chlorophyll a , was calculated using the following relation based on the data of figure 5 (see also discussion section):

$$\rho = 0.706 + (8.87 \times 10^{-1} * \log(C_{sat})) - (7.48 \times 10^{-3} * \log(C_{sat}^2)) \quad (12)$$

The value of C_k to be used in equation (4) was calculated as the product of C_{sat} and ρ . P_m^b for the water column (in units of $\text{mg C mg Chl}^{-1} \text{ d}^{-1}$) was assumed to be P_b at the surface, assuming no photoinhibition. In our data compilation, P_b was approximated from temperature using the following relation:

$$P_b = 10^{[(-0.054 * SST) + 2.21]} \quad (13)$$

where SST is the sea surface temperature. This equation is based on a plot of $\log P_b$ versus SST for our entire data

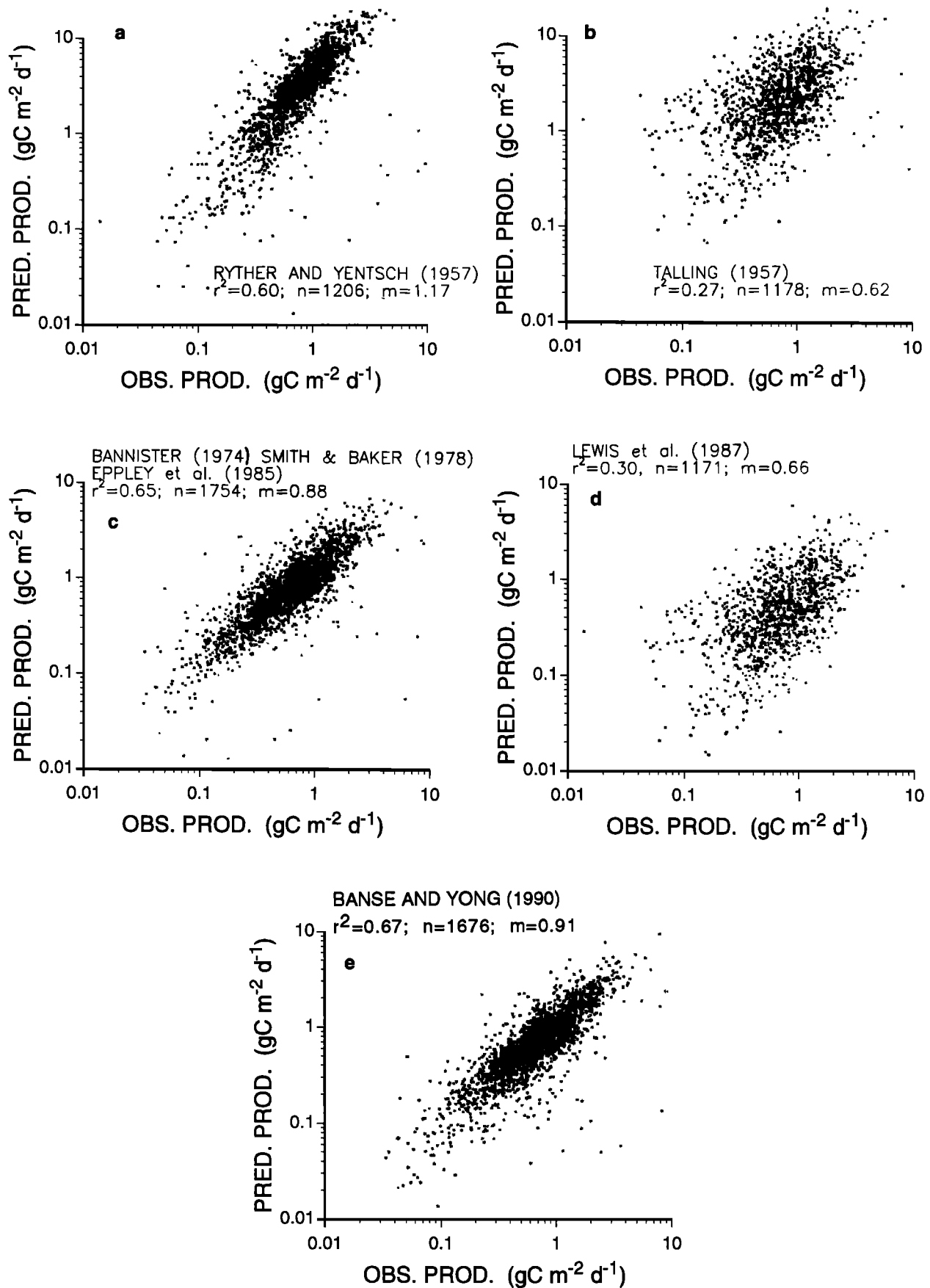


Fig. 10. Predicted versus observed integral production for family of five " P_m^b/K " models described in text: (a) model of *Ryther and Yentsch* [1957 equation (1)], (b) model of *Talling* [1957, equations (2) and (3)], (c) model of *Bannister* [1974, equation (28)], *Smith and Baker* [1978, equation (16)], and *Eppley et al.* [1985, equation (2)], (d) model of *Lewis et al.* [1987, equation (6)], and (e) *Banse* [1990, equation (2)]. Statistical parameters are given on each figure as well as number of stations having necessary data to apply to the model.

compilation, which had a significant *negative* slope ($r^2=0.22, n=4179; P<0.001$). This negative slope was likely the net result of several opposing processes: (1) a positive relation between temperature and the dark reactions of photosynthesis [Eppey, 1972], (2) a positive relation between nitrate and growth [Eppey *et al.*, 1969], and (3) a strong negative relation between temperature and nitrate [e.g., Jackson, 1983]. The value of P in equation (4) was calculated with the above values of C_k , P_b (assumed to be equal to P_m^b at the surface), and K . when using satellite-simulated data with this P_m^b/K algorithm, a plot of predicted integral production versus observed integral production gave an r^2 of 0.13 ($n=478$), considerably less than the r^2 value of 0.65 when ship-derived data for C_k , P_m^b and K were used (Figure 11a). The lower r^2 was attributed to the predictions of P_b using SST in equation (13). Note also that the requirement for satellite-simulated data restricted the number of stations in this test to 25% of the stations used in the first test (Figure 10).

The model of Platt and Sathyendranath [1988] was

also tested against our data compilation using satellite-simulated data. Each subroutine of their model (e.g., planetary angle calculations, clear-sky irradiance calculations, subsurface irradiance propagation, pigment profiles, and productivity calculations) was tested and validated independently before integration into the main model. Running of the model required input variables for surface pigments, latitude, and water depth. Water types were defined (based on latitude and depth), which then determine generic pigment profiles, water absorption coefficients, chlorophyll absorption coefficients, and generic values of α and P_m^b . Tables of these input parameters were provided by the authors (note that water types were defined between 20°S latitude and 50°N latitude thus the model was only run within these latitude ranges). The individual subroutines of the model provided reasonable results, but a plot of predicted production (based on satellite-simulated measurements) versus observed production showed that the model of Platt and Sathyendranath [1988] explained 0.04% of the variance in integral primary production (Figure 11b; $r^2=0.0004$, $n=1329$ stations).

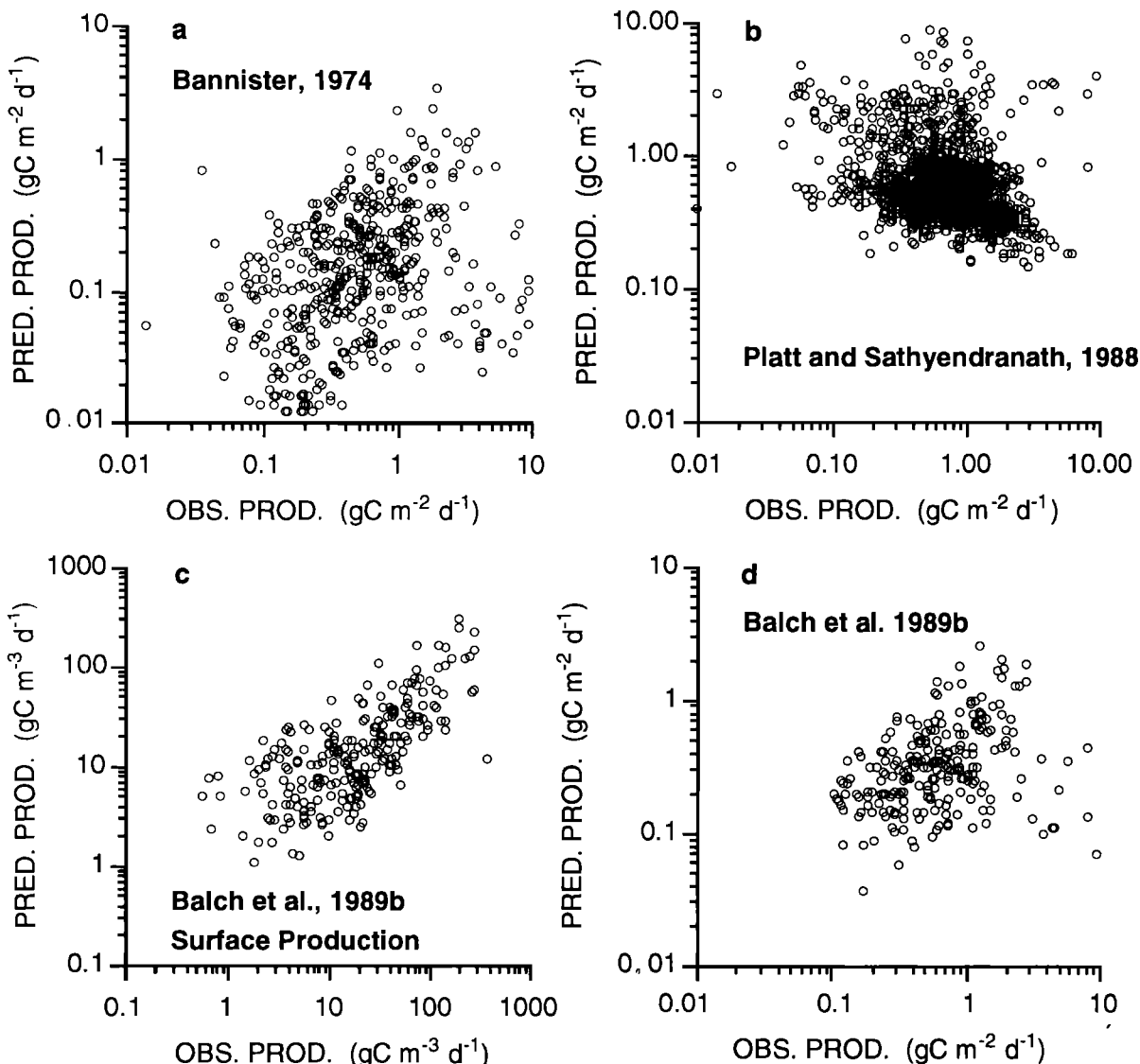


Fig. 11. Performance of three semi-analytical models in predicting integral primary production using satellite-simulated data as input (statistics and least squares fit line given below in parentheses) (a) Bannister [1974] ($r^2=0.12$; $n=478$; $\text{Log(Pred Prod)}=0.37*\text{Log(Obs Prod)}-0.82$) (b) Sathyendranath and Platt [1988] ($r^2=0.0004$; $n=1329$; $\text{Log(Pred Prod)}=.01*\text{Log(Obs Prod)}-0.26$). (c) Balch *et al.* [1989b] for surface production only; $r^2=0.48$; $n=249$; $\text{Log(Pred Surf Prod)}=0.58*\text{Log(Obs Surf Prod)}+0.34$). (d) Balch *et al.* [1989b] for integral production ($r^2=0.12$; $n=249$; $\text{Log(Pred Prod)}=0.28*\text{Log(Obs Prod)}-0.50$).

The results of the semi-analytical model based on pigments temperature and light (PTL) of *Balch et al.* [1989b], using only satellite-simulated data as input, are shown in Figures 11c and 11d. Due to the requirement for surface pigment, temperature and light data as input to test the model, there were 240 stations available to check its performance. Note, only measured light values were used in the test (no climatological light data were used as in *Balch et al.* [1989b]). Moreover, the PTL algorithm requires information on the mixed layer depth (MLD) from each station, for construction of temperature profiles. The MLD was defined as the depth above the maximum temperature gradient or, if no temperature data were available, the depth above the maximum nitrate gradient. It was derived using an empirical, multiple linear regression approach from SST, latitude (LAT), and surface pigment (C_{sat}) as shown below.

$$\text{LogMLD} = -0.34 \cdot \text{SST} - 0.50 \cdot \text{Log}(\text{C}_{\text{sat}}) - 0.036 \cdot \text{LAT} + 2.92 \quad (14)$$

This equation was based on 505 stations of available data and the r^2 value was 0.67 (Figure 12). The next step was to produce a temperature profile for the euphotic zone based on surface temperature for input to equation (13). For the depths above the mixed layer depth, the temperatures were set equal to the SST. For 30 m below the mixed layer depth, the temperature gradient was 0.13° per m (assuming a 4° thermocline). From 30 m below the MLD to the base of the euphotic zone, the temperature gradient was set at 0.019°C per meter (based on data from the Atlantic, Pacific and Indian Oceans (see *Emery and Dewar*, [1982] and *Pickard and Emery*, [1982])).

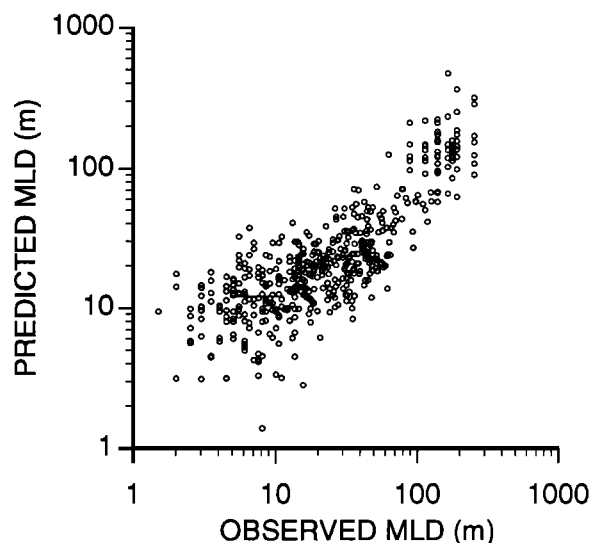


Fig. 12. Plot of empirical multiple linear regression for predicting mixed layer depth (equation (14)) versus observed mixed layer depth ($n=505$ stations).

The performance of the PTL algorithm was tested for surface and integrated production. A plot of predicted surface production gave an r^2 value of 0.48 (Figure 11c; $n=240$) but as observed by *Balch et al.* [1989b], prediction of integral productivity was less accurate (Figure 11d; plot of observed integral production versus predicted integral production; $r^2=0.12$). Both the P_m^b/K model and PTL model explained about twice the variance explained by the purely empirical relation between surface pigment concentration and integral production ($r^2=0.06$), but the r^2 values are still unacceptably low.

4. DISCUSSION

Analysis

It is apparent that we are still far from explaining all of the variance in phytoplankton pigments and primary productivity using satellite-derived data coupled to a variety of empirical or P_m^b/K models. Nevertheless, some important points can be made from the above results.

For pigment estimates, the satellite data accounted for 40% of the ship-derived pigment variance. The deviation of the satellite data from ground truth estimates can be attributed to several error terms: ship/satellite co-location error, shipboard error in the pigment determination, error due to the calculation of C_{sat} from satellite-derived water-leaving radiances, error due to different sampling times of the ship and satellite sensor, error due to the presence of different phytoplankton taxa (containing various pigment complements), and error due to absorption by non-chlorophyllous compounds (e.g., detritus, dissolved organic matter, sediments). It is important to remember in the following discussion that the smallest error that could be encountered in a spectral estimate of chlorophyll, using cultures, averages about $\pm 15\%$ [*Yentsch and Phinney*, 1982].

Co-location of ship and satellite data is particularly difficult, especially with the data we have compiled here. Typically, errors in co-location are much less when using continuous transect data because one can make slight geographic corrections to minimize the covariance between the two data sets (essentially matching the peaks and troughs). In our compilation, most of the data are individual stations, and no such corrections can be made. The size of this co-location error cannot be defined with our data set. There was also error due to the fact we used 20 km averaged CZCS data and the variance associated with this length scale can be large, especially in coastal waters [see power spectra of chlorophyll transects in *Platt and Denman*, [1980]]. The separation of satellite data into those images taken on the same day as the sea truth or those which lagged by ± 1 day made only a slight difference in their correlation. This was probably due to the fact that advective velocities were rarely fast enough to move a water parcel more than 20 km in a day. Moreover, as there was little difference in the correlation, with or without the 1 day lag, then it can be concluded that growth and grazing over a 1 day time period also had indistinguishable effects on the correlation.

The precision of the shipboard determination of chlorophyll at the 0.5 mg m^{-3} concentration varies from $\pm 15\%$ [*Yentsch and Menzel*, 1963] to less than $\pm 10\%$ [*Parsons et al.*, 1984]. The overall accuracy of the fluorometric technique for chlorophyll *a* concentrations has been cited as $\pm 20\%$ [*Holm-Hanson et al.*, 1965], but more recent comparisons of fluorometric and HPLC determinations showed the accuracy of the fluorometric determinations to be approximately $\pm 30\%$, depending on the water mass, presence of chlorophyll *b*, chlorophyll *c*, or phaeopigments [*Trees et al.*, 1985]. Error due to various taxa such as dinoflagellates and coccolithophores can be as high as 200-300%, due to various scattering and behavioral properties of phytoplankton [*Balch et al.*, 1989c]. The combined relative error (as calculated above) was most predictable for the lower pigment concentrations, below 1 mg m^{-3} , where satellite-derived pigment concentrations averaged about 80% low. Fortunately, this pigment range applies to the bulk of the world ocean, but the results do raise important questions about how to interpret the remotely sensed pigment data in shelf waters.

Variance in satellite-derived pigments was highest in the eutrophic shelf waters. The deviation of the satellite retrievals from the ship data in these waters was typically

from -50% to 400%. Higher error in case II, coastal waters is not a new observation; see work of *Morel* [1980], *Clark* [1981], *Yentsch and Phinney* [1982], and *Gordon and Morel* [1983], who discuss the importance of yellow substance and suspended particulate material in modulating the water-leaving radiance in coastal waters and thus increasing the potential for error in pigment retrievals. Moreover, *Gordon and Clark* [1980b] predicted that satellite-derived pigments would be very inaccurate at concentrations $\geq 10 \text{ mg m}^{-3}$ due to poor knowledge of the aerosol optical thickness at various wavelengths. Our work, however, provides new insight into the sign and magnitude of this error (Figure 8). In respect to primary productivity, coastal waters play a disproportionately large role in terms of the amount of primary productivity that they foster. Productivity algorithms that use satellite-derived pigments as input will be limited by the accuracy of the surface pigment retrievals. It is essential for the interpretation of coastal pigments and productivity that case II pigment algorithms be more accurate.

Another factor which is essential for improving the accuracy of primary productivity algorithms is the ability to predict p (the fraction of total pigment which is made up of chlorophyll a), because this represents essentially the "living" component of the total satellite-derived pigment. It is clear from our Figure 5 as well as the data of *Morel and Berthon* [1989] that one cannot assume a constant value of p . Some variability can be accounted for by the trends shown in Figure 6, in which p increased 10% at the bottom of the euphotic zone. A model of p should involve factors such as grazing, photodegradation, degree of eutrophication, and other physiological effects [*Welschmeyer and Lorenzen*, 1985; *Downs and Lorenzen*, 1985; *Nelson*, 1989].

Equally important in interpreting these data is the method by which phaeopigments were calculated. Perhaps the two distinct populations shown in Figure 5 were due to use of two different pigment determination protocols such as the fluorometric techniques of *Yentsch and Menzel* [1963] and *Holm-Hansen et al.* [1965]. It also should be noted that *Gordon and Clark* [1980a] saw values of p widely ranging from 0.03 to 0.96 that generally increased in magnitude and variance with chlorophyll concentration (using their Figure 1). Their equation relating chlorophyll a and phaeopigment was approximately

$$\log \text{ phaeopigment} = \log \text{ chlorophyll} * 1.075 - 3.6$$

The average relationship for our data compilation was

$$\log \text{ phaeopigment} = \log \text{ chlorophyll} * 0.76 - 0.45$$

while the two individual data clouds in Figure 5 fell approximately along the following lines:

$$\log \text{ phaeopigment} = \log \text{ chlorophyll} * 0.71 - 0.22$$

$$\log \text{ phaeopigment} = \log \text{ chlorophyll} * 1.26 - 0.22$$

The actual value of the slope in these linear regressions is an important issue; it can be shown after expansion that, if the least squares fit slope to a plot of p versus chlorophyll is < 1 , then p increases with increasing chlorophyll. If the slope is > 1 , then p decreases with increasing chlorophyll (and if the slope equals 1, then p is about 0.62 for all chlorophyll concentrations; see Figure 13). If we take the high chlorophyll values as representing eutrophic green water environments and low chlorophyll values as representing oligotrophic blue water environments, then our data support the view that phaeopigments are a more important part of the total pigment complement in oligotrophic waters.

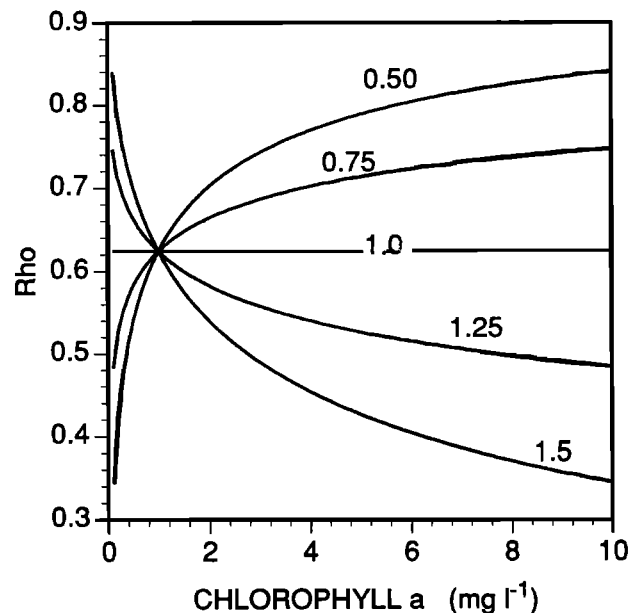


Fig. 13. Parameter p versus chlorophyll concentration extrapolated from plots of log chlorophyll versus log phaeopigment. A linear fit to a plot of log chlorophyll and log phaeopigment (e.g., Figure 5) yields a slope (M) and intercept (I). If M is different from 1.0 then r will vary as a function of chlorophyll. To estimate r from knowledge of M and I at various pigment combinations, the following equation can be algebraically derived: $\log \text{ phaeo} = \log \text{ chl} * M + I$, which can be transformed to $\text{phaeo} = 10^{(\log \text{ chl} * M + I)}$, and since, $r = \text{chl} / (\text{chl} + \text{phaeo})$, then one can substitute to get $r = \text{chl} / [\text{chl} + (10^{(\log \text{ chl} * M + I)})]$. The figure shows how r would vary between oligotrophic regions (low chlorophyll) and eutrophic regions (high chlorophyll) for various statistically derived slope values as discussed in the text (intercepts were assumed to be zero in this example). The data of Figure 5 have a least squares slope of 0.76, which shows, in a general sense, that phaeopigments are a larger portion of the total pigment concentration in oligotrophic regions.

Productivity Algorithms

Our results suggest that if we can accurately derive chlorophyll a concentrations and values of K_{par} from satellite data, and either model or calculate P_m^b , then subsequent calculation of primary productivity will be considerably easier. Using the simple " P_m^b/K " formulation, we have explained 10 times more variance in integral primary productivity than was explained by the purely empirical relations. The P_m^b/K models are successful because they combine the inverse effects of optical transparency (K_{par}) and maximum photosynthesis per unit volume ($P_m^b \times C_k$) towards determination of integral production. Those models which did not incorporate light [Bannister, 1974; Smith and Baker, 1978; Eppley et al., 1985; Banse and Yong, 1990] or only incorporated light effects on relative photosynthesis [Ryther and Yentsch, 1957], did the best in predicting primary production. Those models which relied on absolute irradiance plus the photoadaptive term, I_k [Talling, 1957; Lewis et al., 1987] did not perform as well, even though they had essentially the same " P_m^b/K " format. The introduction of I_k and I_0 terms lessened the model accuracy probably due to the way in which we arbitrarily used constant photoadaptive terms (I_k, α).

It is important to point out that model performance was evaluated at two levels in this work, using ship-derived data available from either (1) complete euphotic zone casts or

(2) surface data, mimicking measurements only available to satellites. As the P_m^b/K algorithm has never been applied to large data sets, we tested it first using complete euphotic zone data. This is how *Platt and Sathyendranath* [1988] tested their semi-analytical model (see their Figure 1) in which the predicted production was based on ship-derived pigment profiles and ship-derived photoadaptive constants. A comparison at this level shows that a simple, one equation algorithm like the P_m^b/K algorithm performs extremely well, even in comparison to a more complex, wavelength-, time-, and depth-dependent algorithm such as *Platt and Sathyendranath* [1988] (compare their Figure 1 and our Figure 10c, noting the differences in the axes). An advantage of the P_m^b/K models though is that they are computationally faster on mainframe computers. Nonetheless the major problem is that satellites do not have direct access to ship-derived photoadaptive parameters such as P_m^b .

Evaluation of models at the second level (using only satellite-simulated data as input) is a much more stringent test of any algorithm. We have tested the algorithms of *Bannister* [1974], (representative of a P_m^b/K algorithm), *Balch et al.* [1989b] and *Platt and Sathyendranath* [1988] in this fashion. The results show that algorithm complexity is not necessarily correlated to performance. The model of *Bannister* [1974] accounted for 13% of the variance in integral production, the algorithm of *Platt and Sathyendranath* [1988] accounted for 0.04% of the variance and the PTL algorithm [*Balch et al.*, 1989b] accounted for 12% of the variance, in integral primary production.

The fundamental issue is that if we use semi-analytical algorithms to predict integral primary productivity, their performance should exceed the simple empirical relation between surface pigment and integral primary production ($r^2=0.06$; see also Figure 3 of *Campbell and O'Reilly* [1988]). Moreover, all of the semi-analytical models examined here perform well when using ship data as input, but this performance degrades substantially when satellite-simulated data are applied. Therefore, the question remains, for semianalytical algorithms, how do we derive the photoadaptive parameters from space to use as input to the models. Intuitively, remote estimation of P_m^b should be more direct than estimation of α or I_k because surface populations which the satellite "sees" are most likely to be photosaturated (at maximal or near-maximal rates), whereas α and I_k are terms which relate to the light limited portions of the water column, well below the depth of satellite visibility. The work of *Balch et al.* [1989a, Figure 7] and this paper (Figure 11c) showed that surface production could be predicted quite well with a simple algorithm involving temperature and pigments. Another factor which makes P_m^b attractive for derivation by satellite is that P_m^b , which is limited by the dark reactions of photosynthesis, is temperature dependent [*Eppley*, 1972]. Thus, satellite infrared data might allow derivation of P_m^b in surface waters. Unfortunately, better mixed layer models are needed to calculate subsurface temperature from surface temperatures, and better models are needed for the P_m^b /temperature relationship which contains variability due to nutrient stress and photoinhibition [*Eppley*, 1972; *Yentsch et al.*, 1973; *Falkowski*, 1981; *Balch et al.*, 1989b]. This is one of the major challenges for estimating ocean productivity remotely.

Considerable progress has been made in recent years in designing productivity algorithms for application to remote sensing methods as well as understanding the complexity and inherent limitations of such an approach. Some might argue that the complexity of the problem has

been understood since the early photosynthesis experiments of Warburg, Rabinowitch, Emerson and Duysens and that this is why a model developed 34 years ago (like *Ryther and Yentsch* [1957]) performs just as well as some of the most complex models that are generated today. We agree with this statement. However, now in situ ocean data sets of productivity and pigments have become sufficiently large to test these models at global scales, not isolated seas. Since we know that productivity does not equal biomass, then if images of productivity simply mirror maps of pigments, we will have learned nothing from these efforts. However, if productivity algorithms can be made more accurate by incorporating pigment-, temperature-, and light-dependent terms, then images of primary production will be invaluable for understanding carbon cycling in the world ocean.

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