CONCENTRATION (SSC) FROM REMOTELY SENSED DATA

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1. INTRODUCTION

Earth objects are not perfect diffusing surfaces. Their espectral response depends on sensing geometry (Kriebel,1978; Kimes et al., 1980; Kollenkark et al., 1982; Guyot, 1984; Ranson et al., 1985; Milton and Webb, 1987; Curran and Novo, 1987; Novo et al., 1987). Water remote sensing is particularly influenced by sensing geometry (Clarke and Ewing, 1974; Preisendorfer, 1976) which affects the sensitivity of water reflectance to changes in SSC. Laboratory experiments suggested that the asymptote of the reflectance/SSC relationship is reached at different points under different sensing geometries (Novo et al., 1987). Wadsworth and Piau (1987) suggested that off-nadir SPOT images enhance ocean features such as internal wave fields, ship wakes, oil slicks and other oceanographic phenomena.

Empirical models developed to estimate SSC (McCauley and Yarger, 1976; Ritchie at al., 1976; Munday and Alföldi, 1979; Khorram, 1981; Curran et al., 1987; Rimmer et al., 1987) are sometimes inconsistent from application to application owing to a wide range of sub optimal conditions, including sensing geometry (Curran and Novo, 1987) and atmospheric effects (Philpot,1987). Attempts have been made to suppress those environmental effects on empirical models (Goldman et al., 1974; Ritchie et al., 1975; Witte, 1975; Munday and Alföldi, 1979; Coney and Salzman, 1979; Mckim et al., 1984). No attempts however were made in combining vertical and oblique reflectance measurements to improve those models since the reflectance dependence on sensing geometry could improve target discrimination, (Guyot, 1984).

This paper presents preliminary results of an experiment carried out to assess the suitability of multiviewing linear models in SSC estimation.

2. THE EXPERIMENT

The experiment was performed in the laboratory and involved three stages: a) the simulation of SSC variation, b) the simulation of viewing geometry variation and c) the measurement of each SSC at different viewing geometry. The experimental set up is described elsewhere (Novo et al., 1987). Two sets of sediments (fine silt and mixed silt) provided 18 different SSC's ranging from 0 mgl⁻¹ to 400 mgl⁻¹ by adding increasing amounts of preweighed sediment into the water. A Milton Multiband Radiometer (Milton, 1980) was employed to measure the radiance in two selected bands (Novo et al., 1987) centerd at $0.55\mu m$ (green) and $0.65\mu m$ (red) respectively. Three viewing angles (θv) were used; nadir, + 20° looking into the light source; - 20° looking away from it. Light source zenith angle (-55°) and azimuth angle in relation to the sensor (-60°) were kept constant. The light source was provided by 650 Watt tungsten-halogen lamp, and the laboratory was kept dark to avoid any other light source interference. Reflectance data were derived from near sequential measurements of relative radiance from the water mixture and a calibrated reference panel for each SSC and viewing angle.

3. DATA ANALYSIS

Although non-linear models were thought to be more suitable to SSC estimation (Munday and Alföldi, 1979; Curran et al., 1987; Rimmer et al., 1987) laboratory and field experiments support the use of linear multiple regression techniques with remotely sensed reflectance as the independent variable (Whitlock et al., 1982). Based on this, water reflectance data were correlated to SSC using statistical stepwise multiple regression available in the Burroughs Advanced Statistical Inquiry System BASIS (Burroughs, 1975). Six independent variables were used to derive the equations: green reflectance at nadir (GØ); green reflectance at + 20° off-nadir (G2Ø); green reflectance at +20° off-nadir (RØ); red reflectance at +20° off-nadir (RØ); red reflectance at +20°.

The stepwise regression technique is a statistical procedure for selecting the best regression equation by choosing the smallest and best set of variables to produce a reliable model for predictive purposes (Chatterjee and Price, 1977; Celaschi, 1983). The BASIS package was used to produce the equations. The best equation is determined by examining at every stage of the regression the variables incorporated into the model in the previous stages. A variable which may have been the best single variable to enter at an early stage, can at a later stage, be superfluous because of the relationship between it and other variables now in the regression. To check on this aspect, a F test is performed at each stage. Any variable which provides a non significant contribution is removed (Chatterjee and Price, 1977).

To evaluate the consistency of the variables entering into the best equation, the stepwise regression was run for two sets of sediments with the same mineralogy but with varying grain size distribution. Since both sediments are subject to the same experimental errors, differences in the variables of importance to the best model can be related to sediment properties.

4. RESULTS AND DISCUSSION

Table 1 presents the partial correlation between SSC(dependent variable) and the 6 reflectance variables (GØ, G2Ø, GM2Ø, RØ, $R2\phi$; $RM2\phi$) for both sets of sediments (fine and mixed silt). A consistent trend of increasing correlation between SSC and water reflectance from green wavelengths towards red wavelengths is observed independent of viewing angle as far as fine silt is concerned. This trend is inverse for mixed silt. The correlation coefficient between SSC and green water reflectance also does not vary significantly with viewing angle for both sediments owing to the higher water scattering coefficient at that wavelength (Jerlov, 1976). However, both viewing geometry and type of sediment affect the correlation coefficient between SSC and red reflectance. For fine silt suspension, correlation increases from nadir in both directions (down and up light source); for mixed silt, however, there is an increase up light source $(R2\emptyset)$ and a decrese down light source $(RM2\emptyset)$ in the red range of the spectrum. The physical reasons for that are not persued here.

TABLE 1

CORRELATION COEFFICIENT BETWEEN SSC AND WATER REFLECTANCE AND RESPECTIVE D STATISTIC

TYPE OF SEDIMENT	FINE	SILT	MIXED SILT		
VARIABLES	CORRELATION COEFFICIENT	D STATISTICS	CORRELATION COEFFICIENT	D STATISTICS	
GØ	0.90	0.18	0.95	0.40	
G2Ø	0.90	0.30	0.96	0.27	
GM2Ø	0.92	0.29	0.94	0.15	
RØ	0.92	1.17*	0.91	1.01*	
R2Ø	0.93	1.92*	0.93	1.41*	
rm20⁄	0.96	0.83	0.81	0.72	

DL (5% s.l.; N=18) = 1.16 *No autocorrelation in the error terms.

The Durbin - Watson test (D statistics) indicates that only two variables are needed to produce accurate simple linear regression models. For both fine and mixed silt only RØ and R2Ø, inspite of lower correlation values, are explanatory variables fitting the requirements to produce an efficient equation (Chatterjee and Price, 1977). The remaining variables depict correlated errors suggesting that there is additional explanatory information in the data which has not been explored by the simple linear regression model.

Data in table 1 indicate that most of the simple variable

models do not fully explain the dependent variable variance. It also suggests that viewing angles off-nadir can provide better explanatory models. Table 2 presents the result from multiple stepwise regression for fine silt suspension which shows the following trends: a) from the 1st entry stage towards the 3rd, the standard error decreases only 3% and the r value increases only 0.7% while RM2Ø explains 92% of the SSC variation, the inclusion of 2 new variables explains only more 2% of the variation; b) D statistic for the "best equation" which includes 5 out of 6 variables indicates no-autocorrelated errors.

Results suggest that in a multiregression model the first variable to enter is red water reflectance measured at -20° off-nadir followed by the green water reflectance measured at $+20^{\circ}$. Both, spectral and viewing features contributed to improve the estimation of SSC, but the small improvement do not encourage, in this case, the use of multiple regression. On the contrary, it seems that the selected set of explanatory variables are not adequate to accurate prediction of SSC of fine silt owing to a degree of inter-correlation.

TABLE 2

RESULTS FROM MULTIPLE STEPWISE REGRESSION FINE SILT SUSPENSION

ENTRY STAGE	VARIABLES	STANDARD ERROR OF ESTIMATE		F RATIO	ρ
1st	rm2Ø	34	mg/l	216.20	0.964
2nd	G2Ø	3.3	mg/l	115.55	0.969
3rd	RØ	33	mg/l	78.94	0.971
4th	R2Ø	34	mg/l	55.82	0.972
5th	GM2Ø	35	mg/l	42.33	0.972

D statistic = 0.80

DL (5% S.1. N=18) = 0.71 j k≧5

Table 3 presents the results from stepwise regression for mixed silt concentration as the dependent variable. The following trends are shown: a) the standard error of estimate decreases 11.76% from a single independent variable model towards the tree independent variables. b) the two first variables to enter into the model are viewing variables; that is green water reflectance at 2 opposite angles. c) the inclusion of the fourth variable does not decrease the standard error of estimate; also the F ratio reduction is only 28%. d) D statistic for the "best equation" which includes the 6 independent variables indicates no-autocorrelated errors.

TABLE 3

ENTRY STAGE	INDEPENDENT VARIABLE	STANDARD ERROR OF ESTIMATE		F RATIO	r
1st	G2Ø	34.00	mg/l	223.61	0.96
2nd	GM2Ø	32.00	mg/l	127.45	0.97
3rd	R2Ø	30.00	mg/l	95.98	0.97
4th	GØ	30.00	mg/l	68.84	0.97
5th	RØ	31.00	mg/l	53.73	0.97
6th	rm2Ø	31.00	mg/l	44.91	0.98

RESULTS FROM MULTIPLE STEPWISE REGRESSION MIXED SILT SUSPENSION

D Statistic = 1.21

The results suggest that multiviewing independent variables have potential to improve the models used to estimate SSC. However the importance of multiviewing variables varies with grain size distribution. The physical reasons for the results are not clear. Fine silt, for instance, (-0,008mm in grain diameter) has dimensions larger than green and red wavelengths presenting а Mie scattering type (Sturm, 1980). This grain size however is sufficiently large to affect light flux with its specific absorption properties (Moore, 1977). The silt sediment used to derive SSC is characterized by low reflectance in the green range (Figure 1) that could explain lower correlation in that spectral band. As the dry sediment is more reflexive in the red range, the correlation is higher at 0.65µm. As this suspension in fine silt is homogeneous its scattering properties can be compared to diffuse scattering with lower viewing geometry dependence.



Fig. 1 - Spectral reflectance of the sediment used in the experiment.

Dry mixed silt also has a maximum reflectance in the red range. Inspite of that it depicted higher correlations in the green band, probably owing to large variance in the grain size distribution (Maul, 1985, Sturm, 1980; Moore, 1977). The variability in the size distribution can also explain the higher dependence of mixed silt suspension on viewing angle. Further research is needed to fully understand the interaction of eletromagnetic radiation with natural water since the theoretical understanding of how to determine several of the optical properties of natural waters by remote sensing is in its infancy (Maul, 1985).

5. CONCLUSIONS

- a. The efficiency of multiviewing regression models to estimate SSC varies with sediment type. Water reflectance for homogeneous grain size suspension seems to have lower dependence on the viewing angle than mixed grain size suspension.
- b. The selected sensing geometry with sensor and light source at 60° of azimuthal angle does not enhance reflectance changes as a function of viewing angle. The sensor head moves back and forth in a direction which is nearly perpendicular to the plane of maximum water reflectance changes. Most of the surface reflexion leaves water surface in a plane away from the sensor range of detection.

6. RECOMMENDATIONS

- a. Multiviewing variables should be tested for a variety of sensing geometry and sediment types to assess its role in the accuracy of suspended sediment estimation.
- b. Environmental variables such as water components, range of concentration and bottom effects should be also tested to assess their effects on multiviewing models.

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A B S T R A C T

MULTIVIEWING LINEAR MODELS FOR ESTIMATING SUSPENDED SEDIMENT CONCENTRATION (SSC) FROM REMOTELY SENSED DATA

Stepwise regression was applied to select the "best" set of independent variables to predict suspended sediment concentration from water reflectance. The independent variables consisted of reflectance measured at three different viewing angles in two wavebands. Reflectance measurement and simulation of two types of sediment suspension (fine silt and mixed silt) under laboratory conditions provided a controled environment to assess the suitability of multiviewing linear models to estimate sediment concentration. Water reflectance dependence on viewing angle varied with sediment type. As a consequence the efficiency of multiviewing regression models seems to be dependent on the type of sediment suspension. The standard error of estimate is reduced when multiviewing variables are applied to the estimation of sediment suspension. Fine sediment suspension estimation is not affected by the inclusion of multiviewing variables.