QUANTIFYING WATER QUALITY CONDITIONS USING LANDSAT

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ABSTRACT

Investigations have indicated that the presence of specific water quality conditions, chlorophyll a and suspended solids, can be detected and quantified using Landsat data. A method to obtain accurate, synoptic information of the distribution and concentration of these conditions has been established and the results are presented.

INTRODUCTION

South African water resource managers and planners face the problem of a severe shortfall of water by the year 2 000 (Commission of Enquiry into Water Matters, 1970). The concern is directly related to South Africa's position in the drought belt of the globe and it socio-economic standing as a fast developing country.

The high population growth rate, increasing urbanization and industrialization, rising expectations and standards of living, present a grave picture when combined with the scarcity and variability of the rainfall, which is the major source of water in South Africa (Whitmore, 1978).

It is therefore of major importance that the water resources of South Africa be managed and developed with maximum efficiency and speed. This entails maintaining the quality of established and new water supplies, developing new sources of water, and being able to quantify the water resources available at any one time. It is at this point that the lack of accurate, up to date data impedes efficient management.

"Water systems can no longer be analysed from data acquired by statistical measurements at a single point, rather, data which allow evaluation of an entire region as it applies to the control of water supply are required" (Skibitzke, 1976).

Researchers have suggested that the answer to the problem lies in the use of satellite imagery with its continuously recorded, accurate, synoptic data, available at low cost and in quantifiable terms (Kendrick, 1976; Malan, 1976; Skibitzke, 1976; Reed, 1978; Croteau, 1979).

In an attempt to throw further light on the subject it was decided that Landsat's potential for monitoring the possible deterioration of a South African impoundment by pollution in the form of sediment and nutrient containing effluent from urban, industrial and farming sources should be investigated.

A Landsat water quality project was initiated, two water quality conditions being chosen for examination i,e. chlorophyll a (algal pigment) and turbidity (suspended solids).

OBJECTIVE

The major objective of the project was to determine the potential and limitations for quantitative measurement of the distribution of turbidity (suspensoids) and chlorophyll a (algae) in a specific water body using Landsat data.

This meant that the relationship between the two water quality conditions and the satellites reflectance data had to be established, the aim being to provide reasonable estimates of chlorophyll a and turbidity for engineers, limnologists and hydrologists, using satellite derived data.

CHLOROPHYLL a

Chlorophyll a is generally considered to be the most reliable measure of an impoundment's response to eutrophication (Lambou et al, 1982; Sartory, 1982). It is the primary green photosynthetic pigment present in algae and in all oxygen-evolving photosynthetic organisms (Wetzel, 1983). It is the algal plant pigment, chlorophyll a that the satellite detects and not algae, the numbers of algae or biomass per se. The presence of chlorophyll elicits the red pseudo colouring seen on satellite images.

Algae are microscopic aquatic organisms that grow rapidly in the presence of plant nutrients such as phosphorus and nitrogen. Excessive algal growth is considered to be a major water quality problem (Toerien, 1975, 1977). The clogging of filters, flow meters, valves and irrigation canals may occur. Tastes and odours can be unpleasant and foul smelling scums on water surfaces are not conducive to recreational activities. Certain algae, under specific conditions, release toxins that can poison livestock (Powling, 1977).

It is therefore important to try and quantify chlorophyll a in an impoundment. Previously, estimations of chlorophyll a have been carried out using point source information and it has been recognised that satellite derived data, with a synoptic and quantifiable view, can be an invaluable aid in determining the distribution of chlorophyll a with greater efficiency (Bukata and Bruton, 1974; Sydor et al, 1978; Welby et al, 1980; Canfield, 1983).

TURBIDITY

Turbidity is determined by the concentration, size, shape and refractive index of suspended particles (including chlorophyll a) which increase the amount of energy backscattered in water bodies (Moore, 1980). The presence of suspensoids is determined by the turbidity of the water, which is recognised as bluish-white on satellite images.

Suspensoids transported into or disturbed by turbulence in impoundments present many problems. Impoundments can become silt laden thereby reducing the water holding capacity. Decreased light penetration can occur, therefore decreasing light in the photic zone which inhibits rooted plant growth and algal productivity. Fauna too, especially the filter feeders and food capturing predators, are affected by sediment laden water. Nutrients attach themselves to sediments and depending on the availability of the nutrients, eutrophication can result.

Sediment laden waters affect the treatability of water, sometimes blocking filters, pipelines and tunnels, while attempts to floculate certain types of sediment can be expensive and difficult.

Investigations into sediment transport are important in understanding the hydro-dynamics of a water body and for the purposes of modelling the system.

Satellite imagery's synoptic and quantifiable data could be extremely advantageous in assessing the turbidity in an impoundment.

THE RELATIONSHIP BETWEEN ALGAE AND TURBIDITY

The remote sensing researcher should be aware of the fact that sunlight as well as nutrients such as nitrogen and phosphorus, is required for algae to grow. The presence therefore of suspended sediments can have two conflicting effects on algal growth. Firstly, the prevention of light penetration by sediments in suspension inhibits algal productivity. Secondly, "phosphate adsorbed onto sediments can make up a large proportion of the total phosphate available for algal growth in an impoundment" (Grobler and Davies, 1981)

In addition turbidity is a measure of light penetration and absorbance and therefore inorganic as well as organic suspended solids will be included in the turbidity measured by nephelometry.

It becomes apparent that the relationship between turbidity and algae is complex and highly interrelated.

REPRESENTATIVENESS

The poor fit sometimes achieved between water quality variables and satellite reflectance data in regression equations has been of vital concern to many researchers. This problem has been attributed to an inadequate range of water quality data used to obtain the regression equations (Boland *et al*, 1979; Carpenter, 1982). A requirement of regression analysis if it is to provide useful predictive models, is that the parameters cover a representative range of values (Carpenter, 1982). The greater the range of data obtained covering the full complement of conditions, the more successful the equation or model will be.

For example, the situation may arise whereby, only one or two sampling points represent a large area of a particular chlorophyll *a* range, and conversely a large number of points may represent a smaller area of another chlorophyll *a* range. Therefore when analysing the data, the larger number of points will weight the equation incorrectly, a spuriously high value of r might result and while true for the sample set, there may be no physical reality or meaning for the parent population (Kenney *et al*, 1954; Witzig and Whitehurst, 1981; Whitlock *et al*, 1982). An analogy may be seen in the situation when investigating land use types using Landsat data. It is considered necessary to sample a number of fields of each land use type in order to classify the image. Therefore it is conventional to plan the position and number of sampling points prior to sampling in order to obtain representative sampling. If one land use type is sampled intensively to the exclusion of the others, then an inaccurate classification of the image will result (Prof. C. Haan* pers. comm.).

It is, therefore, imperative that information on the full range of values present in the water body at the time of sampling, be included in the statistical analysis in order to ensure statistical representativeness of the relevant conditions (Boland et al, 1979; LeCroy, 1982).

MULTICOLLINEARITY OF THE REFLECTANCE BANDS

A very important feature of Landsat's MSS, with respect to examining water quality conditions, is the multicollinearity of the reflectance data (Shih and Gervin, 1980). An inspection of images indicates that water quality conditions are usually visible in at least three of the four bands depending on the concentrations. Bands 4, 5 and 6 are often correlated to turbidity while Band 7 usually correlates with high concentrations of chlorophyll (Bukata et al, 1975; Harris et al, 1976; Holmquist, 1977; Boland et al, 1979; Munday et al, 1979; Muraliskrishna and Rao, 1982).

It has been established that information from more than one band width is required to predict water quality conditions with any reasonable degree of accuracy (Grimshaw et al, 1980).

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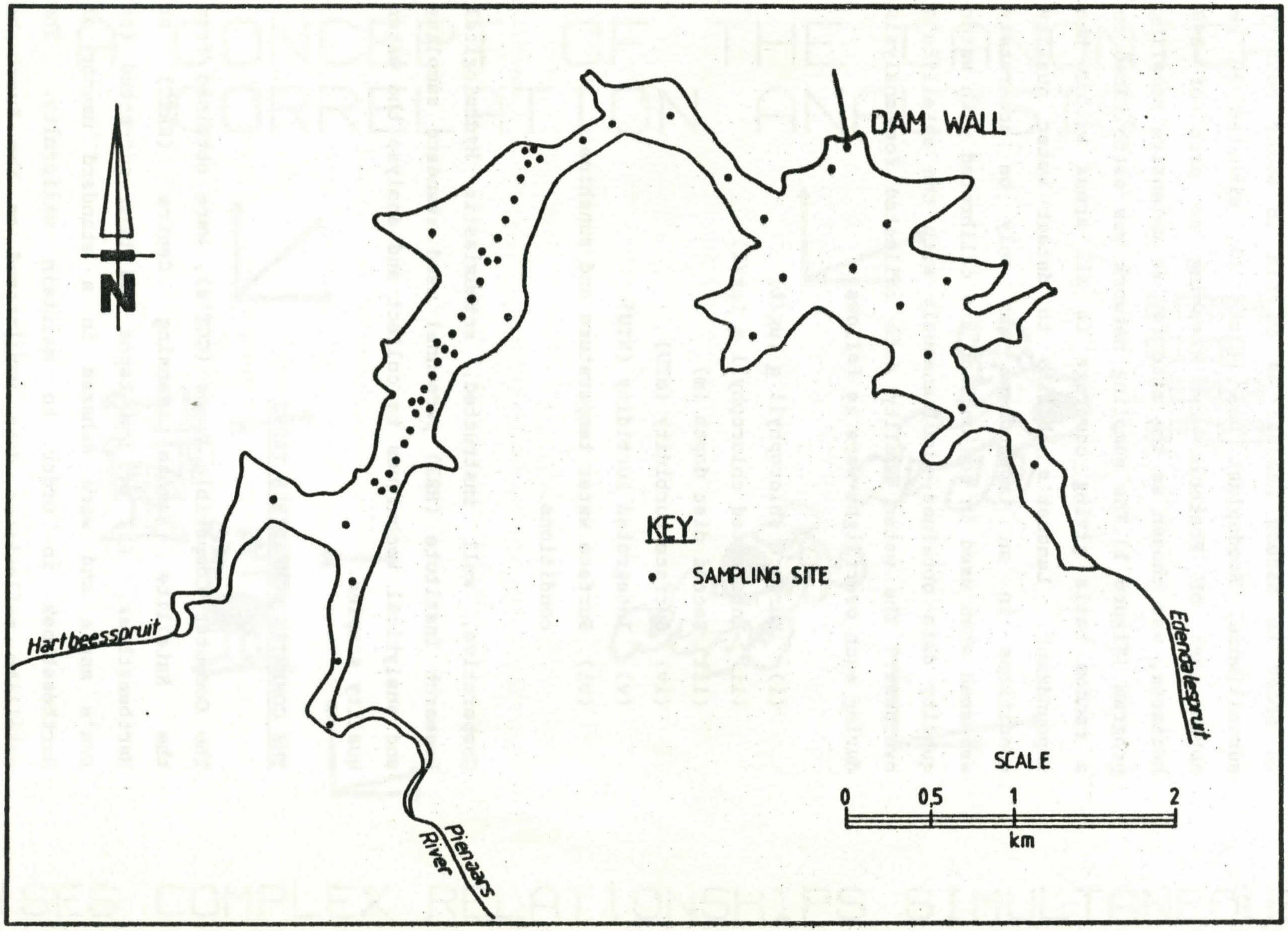


FIGURE 1: ROODEPLAAT DAM SHOWING SAMPLING SITES: 55 POINTS

THE SAMPLING NETWORK

In order to assess Landsat as an aid to water quality surveillance, Roodeplaat Dam (Plate 1), situated 30 km north east of Pretoria and covering an area of 398 hectares, was chosen as the site for an extensive sampling program (Figure 1).The sampling network was established on a random basis giving coverage to all areas within the impoundment. Landsat's ability to detect water quality conditions in an impoundment can only be accurately assessed when used in conjunction and calibrated with water quality data obtained simultaneously with the satellite's overpass. The water quality data collected for analysis during each overflight were as follows:

(i) Surface chlorophyll a (µg/ℓ)
(ii) Integrated chlorophyll a (µg/ℓ)
(iii) Secchi disc depth (m)
(iv) Surface turbidity (NTU)
(v) Integrated turbidity (NTU)
(vi) Surface water temperature and sunshine conditions.

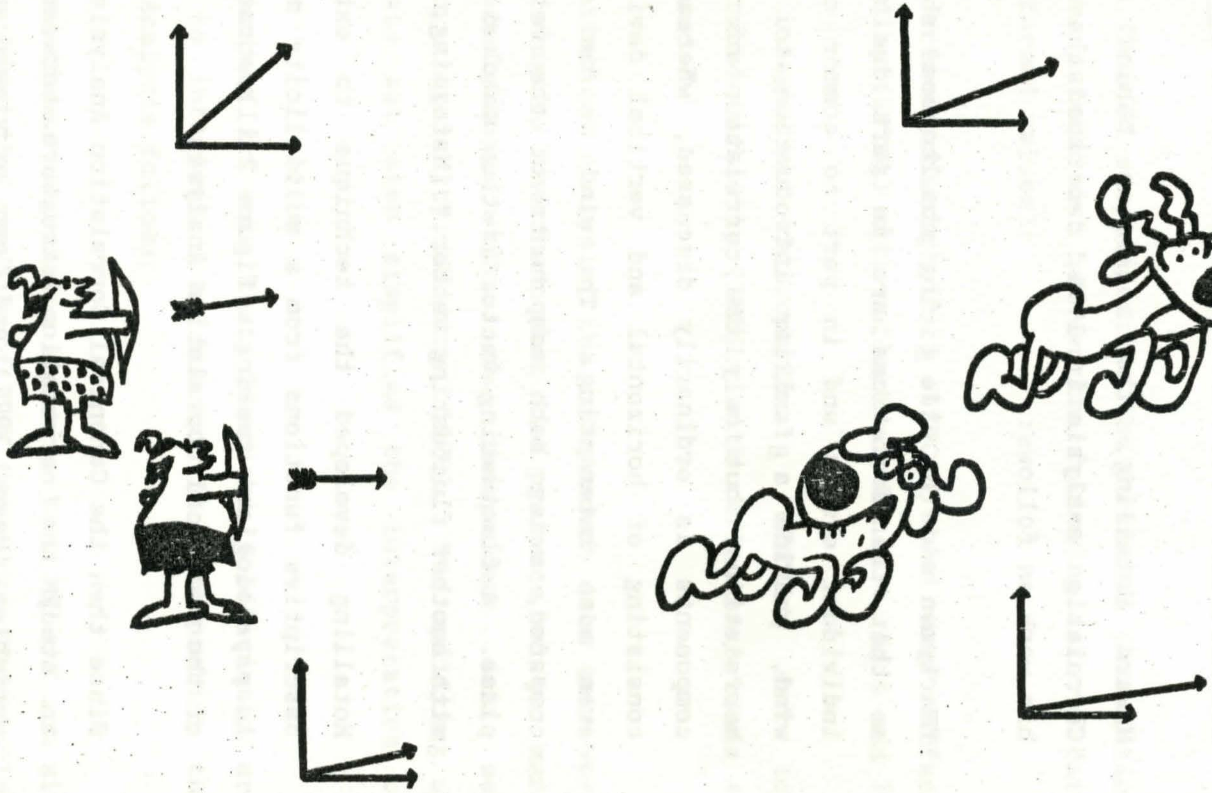
Cooperative, well instructed, enthusiastic Hydrological Research Institute (HRI) personnel used standard sampling and analytical techniques to collect and analyse the water quality samples.

THE COMPUTER COMPATIBLE TAPES

The Computer Compatible Tapes (CCT's), were obtained from the Satellite Remote Sensing Centre (SRSC) at Hartbeesthoek. All of the tapes had been corrected for sun's angle and were dehazed in a standard manner at Hartbeesthoek in order to maintain uniformity. The satellite reflectance data was stored on the Burroughs computer and was accessed by an image processing system originally called CATNIPS (Cape Town Image Processing Suite) and modified for use on the Burroughs system (Maaren, 1981).

A CONCEPT OF THE CANONICAL CORRELATION ANALYSIS

STRENGTH
ARROW SIZE
WIND
VELOCITY
SPIN
DISTANCE



STRENGTH
SIZE
TERRAIN
SPEED

OPTIMISES COMPLEX RELATIONSHIPS SIMULTANEOUSLY INTO A SINGLE FUNCTION IN N DIMENSIONAL SPACE.

THE CANONICAL CORRELATION ANALYSIS

The interdependency between the water quality conditions (chlorophyll a and turbidity) and the four reflectance bands, meant that a statistical test was required that would take into account the interrelatedness.
A multi-variate multiple regression analysis technique was required and the use of Canonical Correlation Analysis was recommended.

Howard Hotelling, the motivator behind the Canonical Correlation analysis in 1936, described the concept behind his work as follows:

"Marksmen side by side firing simultaneous shots at targets so that the deviations are in part due to independent individual errors and in part to common causes such as wind, provide a familiar introduction to the theory of correlation; but only the correlation of the horizontal components is ordinarily discussed, whereas the complex consisting of horizontal and vertical deviations may be even more interesting. The wind at two places may be compared, using both components of the velocity in each place. A fluctuating vector is thus matched at each moment with another fluctuating vector." (Hotelling, 1936).

Hotelling developed the technique to extract suitable descriptive functions from a multiplicity of correlations in psychological testing. Figure 2 illustrates the concept of the Canonical Correlation Analysis.

Since then the Canonical Correlation Analysis has been used to study the correlation structure between two sets of variables (Haan, 1977) and "can be viewed as extension of multiple regression analysis" (Dixon et al, 1979). There are usually sets of dependent Y variables (in this instance reflectance bands 4, 5, 6 and 7) as well as sets of independent X variables (surface and integrated chlorophyll *a* and surface and integrated turbidity). "The problem is to find a linear combination of the X variables that has maximum correlation with a linear combination of the Y variables" (Dixon *et al*, 1979).

The computerised Canonical Correlation Analysis used is part of the BMDP Biomedical Computer Program P-series (Dixon *et al*, 1979).

Using data from 32 sampling sites the Canonical Correlation analysis was carried out between the following sets of data (log-transformed values):

(1) Log surface chlorophyll *a* (SUCOL) and log surface turbidity (SUTUL) with reflectance bands 4, 5, 6 and 7.

(2) Log integrated chlorophyll *a* (INCOL) and log integrated turbidity (INTUL) with reflectance bands 4, 5, 6 and 7.

In the statistical analysis, the independent data sets were split up owing to the fact that the presence of too many mutual correlations within the independent data set resulted in singularity (Gittins, 1979). The splitting up of the data set also simplified the interpretation of results.

It is important to note that Canonical Coefficients are difficult to interpret. An attempt at interpreting the Canonical Analysis follows:

The standard linear regression equation Y = MX + K can aid in understanding the results of the Canonical Correlation Analysis.

If Y represents the dependent variables, in this instance reflectance bands 4, 5, 6 and 7,

X represents the independent variables, surface and integrated chlorophyll a and surface and integrated turbidity,

then a possible interpretation of the results for surface chlorophyll a and turbidity data for the day 81.10.14, shown in Table 1 could be as follows:

BAND 4 (0,39) + BAND 5 (0,08) + BAND 6 (0,03) + BAND 7 (0,06) = M (SUCOL (0,91) + SUTUL (6,43) + K.

The major points to be noted are:

(1) Surface chlorophyll a with a coefficient of 0,91 contributes 23% to the independent variable.

(2) Surface turbidity is the major independent variable representing 77%.

(3) Band 4 with a coefficient of 0,39 is seen to be the most important dependent variable (64%).

(4) Bands 6 + 7 jointly represent 21% of the relationship contributed by the dependent variables.

(5) The highest independent coefficient may be directly related to the highest dependent coefficient, thereby connecting surface turbidity with Band 4. The Canonical Correlation mainly represents a relationship between surface turbidity and band 4 since the contribution of surface chlorophyll a to the relationship is only 23%.

A possible interpretation of Table 2 for integrated chlorophyll a and turbidity is:

BAND 4 (0,32) + BAND 5 (0,18) + BAND 6 (0,02) + BAND 7 (0,01) = M (INCOL (-0,99) + INTUL (7,15)) + K

This equation suggests the following:

1. Integrated turbidity is the prime independent variable contributing 79% of the relationship.

2. Band 4 is the prime dependent variable (56%).

3. Band 4 is linked to integrated turbidity.

4. Bands 6 and 7 have less significance (8%)

The results for the day 81.10.14 indicate that Landsat detects suspended solids (turbidity) in Roodeplaat Dam. Both surface and integrated turbidity results are highly correlated with band 4 and to a lesser extent with band 5: this supports the established theory that bands 4 and 5 shows up suspended solids (Bukata et al, 1974; Moore, 1980; Lindell, 1981). A low band 7 contribution suggests that there are no high concentrations of algae.

TABLE 1: RESULTS OF THE CANONICAL CORRELATION ANALYSIS FOR SURFACE CHLOROPHYLL a AND SURFACE TURBIDITY AND SATELLITE REFLECTANCE BANDS.

DATE: 81.10.14	N 32	CC	Mean	%
INDEPENDENT X VARIABLES	SUCOL	0,91	1,46	23
	SUTUL	6,43	0,7	77
DEPENDENT Y VARIABLES	BAND 4	0,39	5,59	64
	BAND 5	0,08	6,41	15
	BAND 6	0,03	8,81	8
	BAND 7	0,06	7,25	13
CANONICAL CORRELATION	r	0,88		
TAIL PROBABILITY		0,0000		

N = NUMBER OF SAMPLING POINTS
CC = CANONICAL COEFFICIENT
MEAN = MEAN OF DATA SET (LOG)
% = PERCENTAGE CONTRIBUTION
SUCOL = SURFACE CHLOROPHYLL a
SUTUL = SURFACE TURBIDITY

TABLE 2: RESULTS OF THE CANONICAL CORRELATION ANALYSIS FOR INTEGRATED CHLOROPHYLL a AND INTEGRATED TURBIDITY AND SATELLITE REFLECTANCE BANDS.

DATE: 81.10.14	N 32	CC	Mean	%
INDEPENDENT X VARIABLES	INCOL	-0,99	1,46	21
	INTUL	7,15	0,74	79
DEPENDENT Y VARIABLES	BAND 4	0,32	5,59	56
	BAND 5	0,18	6,41	36
	BAND 6	0,02	8,81	6
	BAND 7	-0,01	7,25	2
CANONICAL CORRELATION	r	0,89		
TAIL PROBABILITY		0,0000		

N = NUMBER OF SAMPLING POINTS
CC = CANONICAL COEFFICIENT
MEAN = MEAN OF DATA SET (LOG)
% = PERCENTAGE CONTRIBUTION
INCOL = INTEGRATED CHLOROPHYLL a
INTUL = INTEGRATED TURBIDITY

OBTAINING THE MODEL

The Canonical Correlation Analysis is an extension of linear regression analysis and a linear regression equation in the form of Y = MX + K can be obtained, for which Y and X are linear polynomial variables. The coefficients for each variable in the polynomials are determined in the analysis, the slope (M) of the regression line and the Y intercept (K) need to be established however. This was carried out by inserting the Canonical Coefficients, together with the respective surface reference and satellite reflectance data, into a linear regression program.

The Canonical Correlation analysis was calculated for four pairs of variables: surface chlorophyll a and surface turbidity with the four satellite reflectance bands; integrated chlorophyll a and integrated turbidity with the four satellite reflectance bands; surface and integrated chlorophyll a with the four satellite reflectance bands and surface and integrated turbidity with the four satellite reflectance bands. These provided four simultaneous equations relating the water quality variables to the satellite reflectance data. The solution of the four simultaneous equations enabled a model to be produced. The model was then used to obtain the calibration equation for each day.

By applying the respective Canonical Coefficients and M and K values, values could be calculated for the four water quality variables for each pixel of the impoundment, by entering the corresponding reflectance values of the four wavebands. This made possible the synoptic determination of chlorophyll a and turbidity concentrations in the impoundment.

TESTING THE ACCURACY OF THE CALIBRATION EQUATION

To determine the accuracy of the calibration equation obtained from the Canonical Correlation Analysis, the linear regression program and the solving of the four simultaneous equations, it was necessary to test the model with data that had not previously been used in the model development or the calibration thereof. 55 sampling points had originally been analysed and 32 of these points had been used for calibration purposes. Therefore 23 data points were available to test the accuracy of the models. These points were termed the validation data set.

Two indicators were used to assess the performance of the models and the calibration equations. A coefficient of efficiency of model performance was used to examine the accuracy of the calibration equations on the original calibrated data set. The Student t test and the percentage relative error, between the simulated and the observed mean values of the validation data were determined.

The coefficient of efficiency of model performance (Nash and Sutcliffe, 1970) is "an index of one to one correspondence that is sensitive to systematic errors in the model output" (Roberts, 1978) and essentially determines the closeness of the observed versus simulated data around the 45° line on a graph. The closer the regression line lies to the 45° line the higher the coefficient of efficiency. Used in conjunction with the coefficient of determination (R^2) "the value of the coefficient of efficiency will be lower than the coefficient of determination if the results from the model are highly correlated but biased" (Aitken, 1973). Ideally the coefficient of efficiency values approximate to 1,0 with intercept values of 0 and slope of 1,0.

The Student's t test from the SPSS Statistical Package for the Social Sciences (SPSS), (Nie <u>et al</u>, 1975), was used to test the similarity between the observed and the simulated data set means.

The t test gives an indication of the significance of the difference between the means. The closer the t value to zero, the better the fit, whereas the larger the value, (sign ignored) the poorer the simulation.

If the absolute value of t (the sign ignored) is greater than the critical value of t obtained from a table of the t distribution then there is a significant difference between the two means. The critical values for 44 degrees of freedom at the 5% two tailed level of significance is 2,02.

The percentage relative error between the simulated and the observed mean values were also calculated.

<u>RESULTS AND DISCUSSION OF RESULTS</u>

The results shown in Table 3 indicated good mean and standard deviation values between observed and simulated data, reasonable coefficients of determination all above 0,72 and an acceptable coefficient of efficiency for integrated turbidity of 0,78. The coefficients of efficiency for the remaining variables were between 0,59 and 0,62. The validation data, (Table 4) showed small t values and percent relative errors for all of the variables.

TABLE 3: COEFFICIENT OF EFFICIENCY ANALYSIS FOR THE CALIBRATION DATA SET

	SUCOL	INCOL	SUTUL	INTUL
Mean of observed data	22,55	24,49	4,75	5,06
Mean of simulated data	23,93	25,63	4,84	5,14
Std. dev. of observed data	12,79	12,15	1,58	1,60
Std. dev. of simulated data	16,65	15,15	1,86	1,91
Regression intercept	6,34	6,56	1,24	1,07
Regression slope	0,68	0,70	0,72	0,78
Coeff. of determination R^2	0,78	0,76	0,72	0,86
Coeff. of efficiency	0,59	0,61	0,61	0,78

TABLE 4: ANALYSIS OF ACCURACY OF THE VALIDATION DATA SET FOR 82.09.30:

Water Quality Variables 23 Cases		Mean	Std. Dev.	Diff. Mean	t Test	% Relative Error
Surface Chlorophyll a µg/ℓ	Observed	27,17	10,59	-1,43	-0,63	5
	Simulated	28,60	12,94			
Integrated Chlorophyll a	Observed	30,61	8,43	-1,21	-0,56	4
	Simulated	31.82	12.71			
Surface Turbidity NTU	Observed	5,67	1,69	0,16	0,71	3
	Simulated	5,51	1,42			
Integrated Turbidity	Observed	6,00	1,52	-0,14	-0,81	2
	Simulated	6,00	1,52			

These results indicated that the models calibrated with coefficients determined from the Canonical Correlation Analysis enabled acceptably accurate simulations to be made of concentrations of water quality variables for the overpass of the 82.09.30 using satellite reflectance data as the major input.

Utilizing the model to calculate chlorophyll a and turbidity values for the entire water body could therefore provide both synoptic and quantitative information of the distribution and concentration of the four water quality variables.

A model was developed which enabled the four water quality variables to be obtained from the reflectance values of each pixel in the impoundment. The concentration and the overall percentage distribution of surface and integrated chlorophyll a and surface and integrated turbidity was determined.

The results of the model for the overflight pass on 82.09.30 are presented in Table 5.

TABLE 5: SIMULATED CONCENTRATIONS AND DISTRIBUTION OF THE WATER QUALITY VARIABLES ON ROODEPLAAT DAM USING SATELLITE REFLECTANCE DATA.

Numbers of pixels in impoundment = 849

SURFACE CHLOROPHYLL RESULTS µg/ℓ

MEAN = 27,47
MAX = 430,09
MIN = 0,81

CLASS RANGE	PERCENTAGE AREA
0,00 - 10,00	21,44
10,00 - 20,00	36,16
20,00 - 30,00	18,96
30,00 - 40,00	7,66
40,00 - 50,00	2,83
50,00 - 60,00	2,59
60,00 - 70,00	1,88
70,00 - 80,00	1,53
80,00 - 90,00	2,12
90,00 - 100,00	1,06
100,00 - 110,00	1,41
110,00 - 440,00	2,37

SURFACE TURBIDITY RESULTS NTU

MEAN = 4,87
MAX = 22,52
MIN = 1,02

CLASS RANGE	PERCENTAGE AREA
0,00 - 2,00	6,60
2,00 - 4,00	38,28
4,00 - 6,00	35,10
6,00 - 8,00	7,89
8,00 - 10,00	6,83
10,00 - 12,00	3,06
12,00 - 14,00	1,41
14,00 - 16,00	0,35
20,00 - 22,00	0,24
22,00 - 24,00	0,24

INTEGRATED CHLOROPHYLL RESULTS µg/ℓ

MEAN = 28,41
MAX = 344,05
MIN = 1,42

CLASS RANGE	PERCENTAGE AREA
0,00 - 10,00	17,67
10,00 - 20,00	31,57
20,00 - 30,00	22,50
30,00 - 40,00	10,84
40,00 - 50,00	4,95
50,00 - 60,00	2,83
60,00 - 70,00	1,88
70,00 - 80,00	1,53
80,00 - 90,00	1,77
90,00 - 100,00	1,53
100,00 - 110,00	0,47
110,00 - 350,00	2,49

INTEGRATED TURBIDITY RESULTS NTU

MEAN = 5,14
MAX = 21,06
MIN = 1,84

CLASS RANGE	PERCENTAGE AREA
0,00 - 2,00	0,47
2,00 - 4,00	35,92
4,00 - 6,00	39,34
6,00 - 8,00	12,84
8,00 - 10,00	6,60
10,00 - 12,00	2,71
12,00 - 14,00	0,94
14,00 - 16,00	0,94
20,00 - 22,00	0,24

Table 5 presents mean, maximum and minimum values and distributional estimates of concentrations, as simulated by the model.

Surface chlorophyll a in the range between 1 and 30 µg/ℓ was found to cover 77% of the impoundment. An area of 20% was shown as having between 30 to 100 µg/ℓ and 3% of the area had over 100 µg/ℓ. The maximum simulated value of surface chlorophyll a was 430 µg/ℓ but it is highly likely that the high values over 100 µg/ℓ are due to mixels, mixed land and water pixels. An area of 72% of the impoundment was simulated as containing between 1 to 30 µg/ℓ in the water column (integrated chlorophyll a).

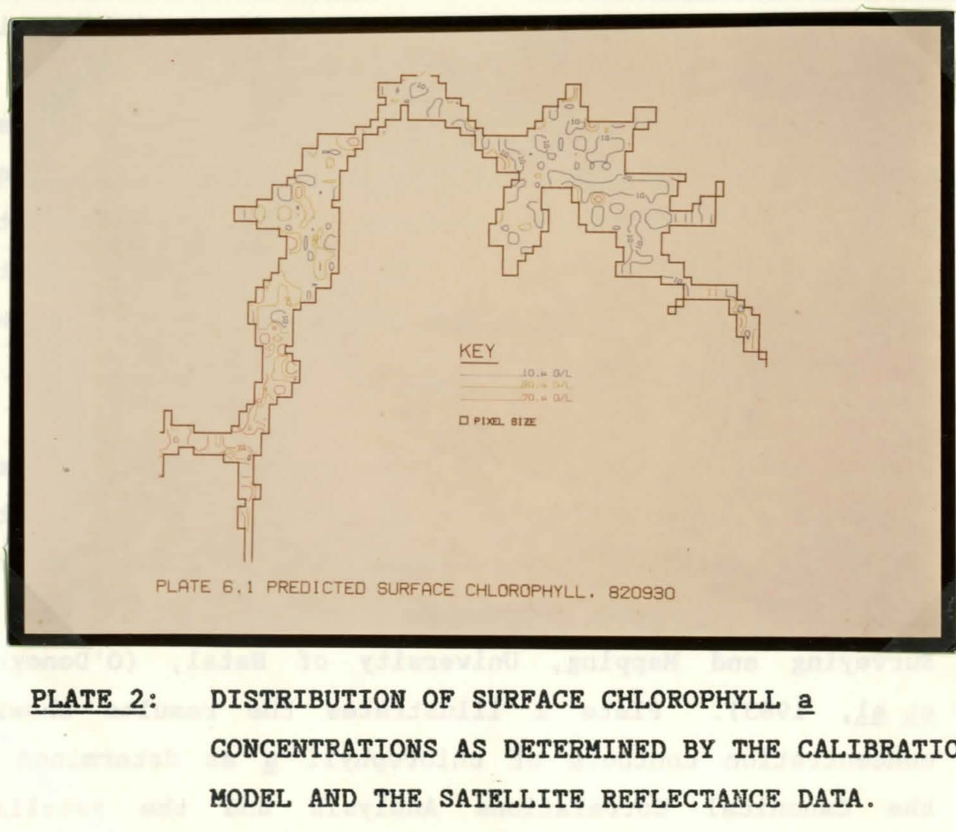
Turbidity values between 1 to 8 NTU were found to cover 88% of the impoundment whereas integrated turbidity for the same value range was found to cover 86% of the area.

A SYNOPTIC VIEW

The value of satellite reflectance data lies mainly in its synoptic view. Concentrations and areal estimates can be enhanced by the spatial characteristics of satellite data to provide researchers with data concerning the location, concentration and areal coverage of a specific water quality condition. Mapping the distribution of water quality conditions using values determined by the model was the next step.

Maps of simulated (predicted) water quality conditions were produced using the simulated data and PIPS, a portable image processing suite for remote sensing and geographic information systems, obtained from the Department of Surveying and Mapping, University of Natal, (O'Donoghue et al, 1983). Plate 2 illustrates the results showing concentration contours of chlorophyll a as determined by the Canonical Correlations Analysis and the satellite

<u>PLATE 1</u>: FALSE COLOUR COMPOSITE OF ROODEPLAAT DAM.



<u>PLATE 2</u>: DISTRIBUTION OF SURFACE CHLOROPHYLL <u>a</u> CONCENTRATIONS AS DETERMINED BY THE CALIBRATION MODEL AND THE SATELLITE REFLECTANCE DATA.

reflectance data. Plate 2 indicates that chlorophyll a concentrations are highest along the western arm where the Pienaars River and Hartbeespruit enter the impoundment. It is also evident that concentrations of chlorophyll a are found along the edge of the impoundment, where the greatest productivity can be expected, and along the northern shoreline perhaps due to wind action.

SUMMARY

It is evident that satellite reflectance data provides spatial and quantifiable information unlike any other data source yet available in the field of water resources. The extrapolation of point source data to that of synoptic data is a step forward for limnological and hydrological research. Quantitative, reasonably accurate information showing the position and concentration of specific water quality conditions may, for example, aid in monitoring levels of eutrophication of an impoundment, enable regions of greatest productivity to be assessed, detect water hyacinth and algal scums and help determine factors involved in the sedimentation process.

The method of analysis and the resulting model discussed in this paper can be applied to any impoundment visible to the satellite, providing that adequate care is taken to ensure representative surface reference data; and providing the basic relationship between the satellite reflectance data and the surface reference data in the impoundment can be approximated by a linear model.

Only when researchers, limnologists and hydrologists realise the potential of satellite imagery for aiding water resources management and serious attempts are made to utilize this vast source of information, will the value of satellite reflectance data really be appreciated.

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