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ANALYSIS OF WATER QUALITY VARIATIONS IN RESERVOIRS: IMPLICATIONS FOR MONITORING AND MODELLING EFFORTS

by

William W. Walker, Jr.*

INTRODUCTION

One objective of the Environmental Water Quality and Operational Studies (EWQOS) Program being conducted by the Army Corps of Engineers is to develop and evaluate simplified methods for assessing eutrophication problems in impoundments. This task has grown out of concern for the fact that existing methods (employing the phosphorus loading/trophic response concept) have been developed using data almost exclusively from natural lakes and within a narrow geographic region (northern temperate zone). Due to the empirical nature of these models and to lake/reservoir differences in morphometry, hydrodynamics, sedimentation, and region, a systematic study is required in order to evaluate the influence of such factors on model performance. A data base for such a study has been compiled which describes the morphometry, hydrology, water quality, and sedimentation rates of over 300 active CE projects located throughout the U.S. (Walker, 1980).

The development and testing of empirical eutrophication models for reservoirs requires averaging of water quality measurements over spatial and temporal scales. If within-pool water quality variations are not random with respect to date, station, or depth, then summary statistics for a given reservoir will depend to some extent upon the particular data-reduction method employed. The choice of reduction method may, in turn, influence conclusions regarding the adequacy of existing models as well as the parameter estimates of any new models which may be developed.

There is no standard data reduction procedure which can be used prior to model development, testing, or application. Methods have included, for example, (1) taking the median or mean of all within-pool observations (EPA, 1975); (2) sequential averaging over depths, stations, and dates (Lambou et al, 1976); (3) seasonal averaging within specific depth ranges (Carlson, 1977); and (4) various weighted-averaging schemes which reflect morphometric characteristics. As compared with natural lakes, many reservoirs pose special data reduction problems due to extreme spatial and/or temporal variations in conditions.

In this paper, a subset of the current CE water quality data base is analyzed in order to describe spatial and temporal variations in trophic state indicators within a group of reservoirs. The analysis

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Fig. 1 White River System

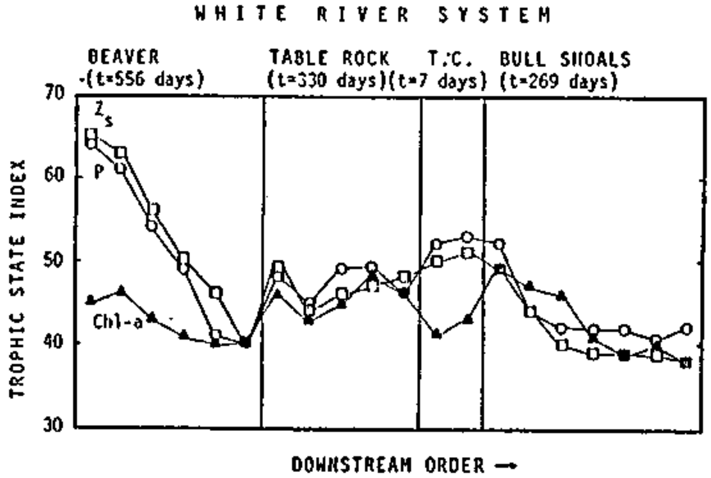


Fig. 2 Sakakawea

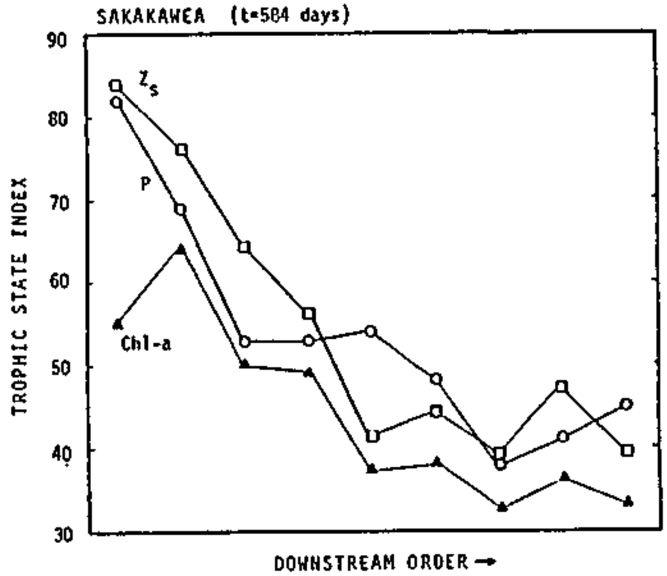


Fig. 3 Old Hickory

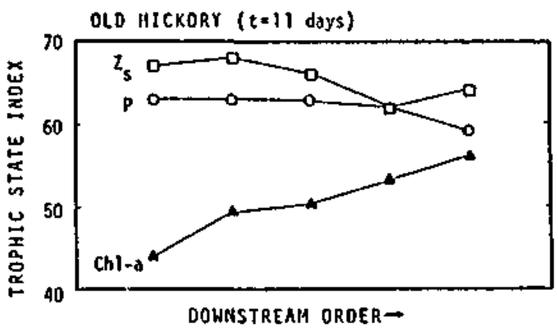
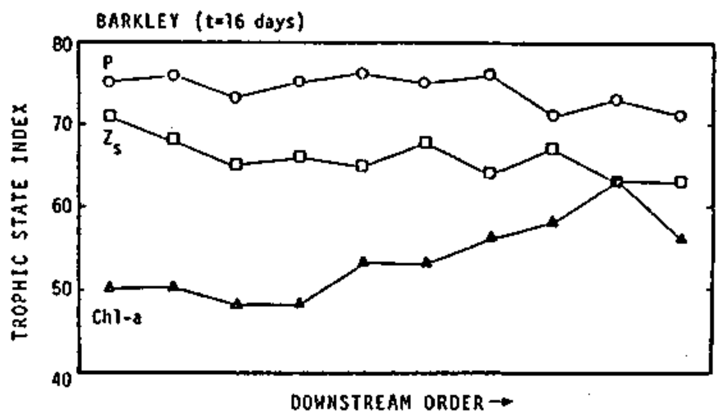


Fig. 4 Barkley



SEASONAL RELATIONSHIPS

Average seasonal variations in the index components are depicted in Figure 5. Station means have been computed and their effects removed from the data prior to calculating the mean and standard error for each month (March-November) and index component. Analyses of variance indicate that monthly effects are significant ($\rho < .0001$) for each component and strongest in the case of chlorophyll-a. The seasonal variations depicted in Figure 5 are characteristic of this collection of reservoirs but not necessarily of each reservoir individually.

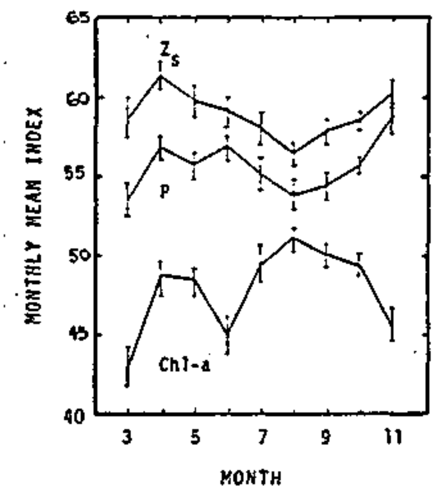


Fig. 5

Seasonal Variations* in Trophic State Indicators

*mean ± 2 standard errors

Average seasonal effects on phosphorus and transparency are similar: both tend to be lowest during March and midsummer and highest during April and November, possibly reflecting seasonal flow and turbidity variations and the influences of turnover periods. Monthly effects on chlorophyll-a suggest a spring maximum (April-May), followed by a June depression, a midsummer maximum, and lower values in November. Temperature and light effects may be responsible for the relatively low chlorophyll-a levels during March and November. The June depression may be due to seasonal succession of algal species. A more detailed examination of the data indicates that lower June chlorophyll-a levels are characteristic of about half of the stations sampled in June, while the rest have June levels more typical of May or July values. In testing seasonal aspects of TSI behavior, Carlson (1977) also noted a June depression in chlorophyll-a index relative to the phosphorus index in three natural lakes.

Differences among various versions of the index provide a measure of "lake-like" behavior, since the index system is calibrated so that I_B, I_T, and I_P values are equivalent, on the average, when applied to midsummer, epilimnetic data from northern, natural lakes. Figure 5 indicates that the range of index means is generally lowest during midsummer (approaching 5 during August) and highest during March, June, and November (approaching 15). Minor recalibration of the phosphorus and/or transparency index would bring I_P and I_T into agreement for all seasons, since the monthly effect curves in Figure 5 are roughly parallel. Since seasonal chlorophyll-a behavior is fundamentally different, however, recalibration alone would not eliminate biases (i.e., significant the error associated with model parameter estimates.

SAS (Statistical Analysis Institute, 1979) has been used to estimate the above variance components for each index separately and to estimate analogous covariance components for each pair of indices (I_B/I_T, I_B/I_P, I_T/I_P). Results are shown in Figure 6.

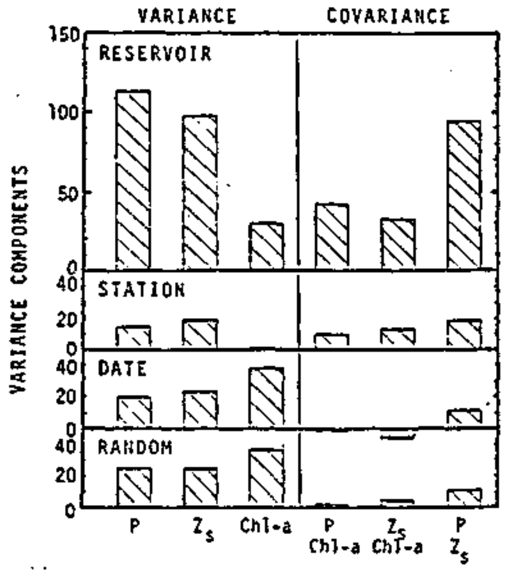


Fig. 6

Variance and Covariance Components of Trophic State Indices

The phosphorus and transparency index components exhibit similar patterns: between-reservoir differences account for 60-66% of the total index variance, as compared with 29% in the case of chlorophyll-a index. Between-reservoir variances indicate that differences in chlorophyll-a are considerably less marked than would be predicted based upon differences in the phosphorus or transparency indices. Conversely, there is greater temporal and random variance in chlorophyll-a than in phosphorus or in transparency.

The covariance components on the right-hand-side of Figure 6 provide some insights into relationships among the indices at different averaging levels. The between-reservoir and between-station covariance components are positive in all cases. Thus, the various versions of the index correlate positively both among reservoirs and among stations within reservoirs. Temporal components indicate a positive covariance for phosphorus/transparency but slightly negative covariances for the pairs involving chlorophyll-a. Thus, when temporal variations at a given station are analyzed, one would expect, on the average, to find a positive correlation only between the phosphorus and transparency indices. This correlation might be attributed, for example, to turbidity variations following seasonal or short-term (storm-event) flow variations. Despite its positive covariance between reservoirs and between stations, chlorophyll-a does not covary temporally with the other indices.

The EPA/NES data base includes measurements from one growing season within any reservoir and does not permit testing for between-year variance or covariance components. Thus, it is not possible with this data set to test for year-to-year covariance between chlorophyll-a and phosphorus or transparency. Distinguishing between seasonal and year-to-year variance components will be possible with an expanded data base including data from other agencies and monitoring programs.

Considering the effects of spatial and temporal variance components (equation (7)) increases mean error by about a factor of three over estimeates derived from equation (6). Most of the error variance is due to the temporal component, especially in the case of the chlorophyll-a index. The error variances indicate that the EPA/NES sampling strategy has provided estimates of reservoir geometric means which are typically accurate ($p < .05$) to within factors of 1.6, 2.2, and 1.7 for surface phosphorus concentration, chlorophyll-a concentration, and Secchi depth, respectively.

MONITORING IMPLICATIONS

Error analyses can be used to improve upon monitoring program designs. For example, given the objective of collecting data to be used in estimating a reservoir mean with minimum variance, the above results suggest that an increase in sampling dates would be more effective than an increase in sampling stations, because the date effect term dominates the error equation. Since the variance component estimates have been pooled, these results apply to this collection of reservoirs as a whole and not necessarily to each reservoir. The same approach could be applied using parameters estimated for each reservoir individually (n_s, n_t, N, σ_s^2, σ_t^2, σ_e^2). "Optimal" designs could be formulated based upon the error analysis framework and upon functions which relate n_s, n_t, and N to monitoring cost. Given variance components estimated from prior monitoring data, improvements in program design (changes in n_s, n_t, and N) for a given reservoir could be formulated to yield minimum error for a fixed total cost or minimum cost for a fixed total error. The approach could be expanded to include depth as a third sampling dimension. This represents a logical application for the error analysis framework in a monitoring context.

MODELLING IMPLICATIONS

In evaluating models, differences between observations and predictions can be attributed to three types of error: parameter error, data error, and model error. The first reflect uncertainty in the model coefficients, the second, errors in the predicted and/or predictor variables, and the third, influences of factors which are not considered in the model structure. Analyses of the type conducted above can be used to quantify potential data errors and separate them from the other components. This provides insights into the adequacy of a data base for use in model testing. If, for example, the data error component dominates, it would be difficult to distinguish among alternative models or to improve upon them without first improving the data base. Based upon regression analyses relating station-mean values of the index components (I_B vs. I_P, I_B vs. I_T, and I_P vs. I_T), between 48 and 55% of the error variance can be attributed to data error. The remaining error, mostly due to model inadequacy, might be reduced by modifying the index system to account for such factors as suspended sediment and nitrogen limitation. This approach will be taken in future studies of Carlson's index system and other schemes.