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Analysis of the Effect of Freshwater Inflows On Estuary Fishery Resources

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ABSTRACT

This final report details the work completed for Tasks 1 to 6 under contract with the Texas Water Development Board. The primary objective of the study is a review and extension of the work reported in Texas Department of Water Resources Report LP-106 (Lavaca-Tres Palacios Estuary: A study of the influence of freshwater inflows), including comments on the questions raised through testimony in hearing. Based on Martin (1987) and the TDWR Estuarine Mathematical Programming Model, a modified methodology was developed for determining the optimal freshwater inflows into bays and estuaries for the purpose of balancing freshwater demands with the harvest of various types of estuarine resources (e.g., finfish and shrimp). There are several new features in this methodology. (a) The stochastic element of the problem, i.e. the uncertainty associated with the regression equations for salinity and harvest, is considered by expressing constraints in a chance-constrained formulation. (b) The nonlinearly formulated mathematical optimization problem is solved using a generalized reduced gradient technique. (c) The model can be extended to multiobjective analysis to examine the trade-offs between conflicting objectives, e.g. for maximizing the fishery harvest and minimizing the freshwater inflow needs.

The methodology is applied to the Lavaca-Tres Palacios Estuary, i.e. Matagorda Bay, in Texas. The results of the numerical application indicate (as expected) that the minimum freshwater inflow requirement increases as the required reliability of chance-constraints increases, and allows a quantitative determination of this inflow given a desired level of certainty. The uncertainty in the regression equations limits the maximum achievable reliability.

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SECTION 1

INTRODUCTION

In Texas, as in many areas of the U.S., such as Florida and California, the freshwater discharge of rivers has become a limited commodity. The need for freshwater inflow to maintain the productivity of downstream estuaries must compete with the demands of upstream users, viz. municipal and industrial uses, and agriculture. It is necessary to know the freshwater inflow requirements for an estuary, for a desired level of productivity, in order to accommodate the estuary's need in water management. This has been a major concern of the Texas Water Development Board through its Bays and Estuaries Program. The desirable approach to water resources management is to optimize flow into the estuary (by minimizing the total volume of flow, or by maximizing the diversions and storage within limits of water rights and capacity, or both) while preserving an acceptable habitat in specific regions of the estuary to accommodate the requirements of key organisms.

Salinity has been long established as an index to ecological habitat in an estuary because it measures the relative proportion of fresh water to sea water. Even for those organisms which are euryhaline, i.e. whose physiology can accommodate wide excursions of salt concentration, salinity still provides a useful habitat index because of other "information" contained in the freshwater ratio, such as nutrient supply, sediment and detritus, or stenohaline components of the food web. The salinity limits for a specific organism can be based upon the statistical association between the presence of that organism in the estuary (as reflected in catch data or harvest data) and salinity, or upon the physiological dependence upon salinity as revealed in laboratory studies. A central element in this optimization problem is the mathematical relation between salinity in the estuary and flow, $S = F(Q)$. Usually the relation is based upon statistical association, i.e., a regression form established from field data.

In the estuaries of Texas, a direct measure of organism abundance is available in the data, H_k, on commercial fishery landings taken from the estuary. This "harvest" data can be employed as an index to populations of key organism k and analyzed statistically to establish its dependence on freshwater inflow, $H_k = f(Q)$. While this might appear superior to the indirect salinity-index approach, the causal connection between flow and harvest may be obscured by unmeasureable parameters such as effort, selectivity and skill, and may be corrupted by poor reporting or the difference between locality of landing (i.e., port) and locality of catch, to say nothing of other environmental variables unrelated to inflow. This regression therefore tends to be noisy and statistically uncertain. On the other hand, it is directly pertinent to the management problem, and when the data are available, should be incorporated into the optimization problem, either as an objective function or as a constraint.

There may be other requirements placed upon freshwater inflow to the estuary. Some of these may express practical limits, e.g. the freshwater inflow cannot exceed the historical range (even though the global optimum solution may lie outside the range of historical data, as in a water-starved system). Others may correspond to specific hydrological controls identified as of separate biological significance. A minimum low flow requirement would be such a constraint. Another requirement derives from the importance of marshes to the estuarine ecology for which regular inundation is considered important. The periodic inundation of deltaic marshes serves to maintain shallow protected habitats for postlarval and juvenile stages of several important estuarine species, provides a suitable fluid medium for nutritional exchange processes, and acts as a transport mechanism to move detrital materials from the deltaic marsh into the open estuary (Texas Department of Water Resources, 1980; Valiela and Teal, 1974; Valiela et al., 1975; Van Roalte et al., 1976). This would impose a large lower limit on freshwater inflow for months (or seasons) at critical life stages of key organisms.

The Texas Department of Water Resources (1980) has made particularly extensive application of this approach in establishing freshwater inflow requirements, as a part of its Bays and Estuaries Program. This work is an extensive incorporation of water requirement for estuaries within a larger

water resources management context. Martin (1987) presented the Department of Water Resources (TDWR) linear programming (LP) model for determining the monthly freshwater inflow needs for estuaries. This model was based upon relating freshwater inflows to key indicators, such as salinity and fishery harvest, through linearized regression equations embedded as constraints in the LP model. The model was used to estimate freshwater inflow needs for seven major estuaries in Texas, the Sabine-Neches, Trinity San Jacinto, Lavaca-Tres Palacios, Guadalupe, Mission-Aransas, Nueces, and Laguna Madre estuarine systems.

Application of the Martin (1987) linear programming model involved several simplifications that may constitute weaknesses or limitations, including:

(1) The nonlinear aspects of the problem were suppressed by linearization of all constraints.

(2) The full multiobjective nature of the problem, e.g., minimization of inflow and maximization of harvest, was not addressed.

(3) Regression equations with considerable statistical uncertainty were used as deterministic constraints in the linear programming model.

Some of these have incurred criticisms of the TWDB approach, which are reviewed in Section 2. In order to overcome problems (1) and (3), the investigators have developed a method for using chance-constraints in a nonlinear programming model to explicitly account for the uncertainty in the salinity regression equation. The optimization problem is reformulated as a nonlinear chance-constrained problem. The nonlinear programming code GRG2 by Lasdon and Waren (1986) is used to solve the optimization problem.

SECTION 2

CRITIQUE OF PAST TWDB WORK

2.1 INTRODUCTION

The constraints on fishery harvests and salinity in the analysis of LP-106 are derived from statistical analyses of the dependency of these parameters upon monthly inflow. It is these statistical analyses which have engendered the bulk of past criticism, particularly in the testimonies presented in association with the Lake Texana hearings of 1984 (Certificate of Adjudication No. 16-2095). The purpose of this section is to summarize past criticisms of LP-106 and to proffer comments on these, as well as an independent critique of the methodology.

The basic statistical method employed in LP-106 is multivariate linear regression. (Nonlinear relations were explored by first transforming the data with the inverse of the postulated nonlinear dependence, then subjecting the transformed data base to linear techniques.) Multivariate regression (MVR) has become widely employed in the last 20 years because of the increase of computational power by which large data bases can be manipulated and the availability of several "canned" programs for implementing the multivariate technique. The latter has been especially manifested by the appearance of textbooks whose use presumes the availability of a MVR package (e.g., Harris, 1975). The now-routine capability for automatically producing MVR's has led to a suppression of the subtlety of the procedure, a situation which has stimulated the development of a plethora of "diagnostics" whereby one can test whether the MVR represents what one presumes it is supposed to represent, e.g., Belsey et al. (1980) and Cook and Weisberg (1982).

Generally, the criticisms of the statistical methods of LP-106 fall into two broad categories: (1) whether the statistical uncertainty of the results have been properly interpreted and correctly reflected in their application,

and (2) whether a *bona fide* relation exists and has been properly "captured" by the statistical model. These are considered separately in the following sections.

2.2 UNCERTAINTY

The implementation of multivariate regression analysis is not an automatic procedure, but in fact entails a number of judgments. Some of these judgments are "hardwired" such as the prespecification of a desired significance level (versus, say, the direct calculation of a prob value), whereas some are more subtle and *ad hoc*, e.g., the decision to retain or exclude an independent variable because of a partial, perhaps linear, relation with other independent variables. One of the great weaknesses of the presentation in LP-106 (not necessarily the methodology) is the incomplete disclosure of this judgmental process. A cross-correlation array of the five inflow variables, and the step-wise results in the partial regression analyses would be very helpful in allowing an independent reviewer to determine whether he agrees with the judgments of LP-106. For example, Whiteside (1984) found it necessary to reconstruct the step-wise partial regressions, from which she criticized the retention of variables of apparent low significance. (Although she arrived at the same regression equation, e.g. Table 8-6 in LP-106, the t values calculated from the standard errors given would suggest $P \leq 5\%$ for each variate, in contrast to her comment that Q_1 and Q_2 have higher prob values, Whiteside, 1984, page 18. Without access to both sets of calculations, this discrepancy cannot be clarified.)

A related matter of judgment is the question of retention of variables that may exhibit associations among themselves. Whiteside (1984) is critical of the use of both winter inflow (Q_1) and spring inflow (Q_2) when the two exhibit a degree of collinearity, as measured (apparently) by a linear correlation coefficient of 0.645 (Whiteside, 1984, p. 9). She observes that this results in substantial alteration of the regression coefficient of Q_2 when Q_1 is included as an additional independent variable (Whiteside, 1984, pp. 17-18). While it is true that collinearity among independent variables can be a source of corruption of a multivariate analysis, it is also true that ignoring a variate with such an association with other independent variates can produce unacceptable bias in the regression. The key question is not whether the

independent variates have a degree of association, but whether there is good reason for including both variates in the analysis (and the related concern of what exactly the source of the association is), i.e., whether the variates are physically independent. Colinearity *per se* is not a sufficient diagnostic for this judgment.

A simple example may clarify this point. Suppose we want to determine crop yield as a function of sunlight and rainfall. There are good physical reasons for expecting a dependency upon each of these variates. Yet, the two would not be statistically independent either. Rather, there would be a negative correlation between sunlight and rainfall, because the occurrence of the latter is associated with cloudy conditions. The value of multivariate regression in this case is its ability to sort out separate dependencies upon each variate, so we can examine the influence of sunlight with rainfall held constant, and *vice versa*. To exclude either sunlight or rainfall as an independent variate simply on the basis of their collinearity would weaken the applicability of the regression and probably yield a biased relationship depending upon the sampling of sunny/cloudy events in the measurements.

As a contrasting example, suppose we attempt to explain crop yields by regressing on the two variates precipitation and irrigation. As in the example above, the independent variables, now precipitation and irrigation, will be negatively correlated. In this case, however, this collinearity can yield a distorted measure of the standard error of the estimate of the regression versus that attainable with either of the independent variates alone. (Suppose the bias in the data due to the other variates not considered, e.g., sunlight and fertilization, obscures the dependency upon precipitation, so that there is no apparent correlation. The SEE will be correspondingly large and the significance of the regression low. When irrigation is included, the downward excursion in precipitation is compensated by the upward excursion in irrigation, and *vice versa*, so that the SEE of the bivariate regression is much smaller.)

These two examples illustrate that the decision of inclusion or exclusion of variates should not be based simply on their manifested collinearity, but upon the physical relationships of the variates and the conceptual model underlying their relationships.

While not pertinent to LP-106 or the criticisms of Whiteside, this homely example can be pursued to display still another trap of variable selection in multivariate analysis. Suppose the first crop yield model above is expanded to include one more variate, viz. sunshine, rainfall, and maximum height of plants in a test plot. Again, we have a case of collinearity of the independent variates. In this instance the last variate exhibits basically the same dependency upon the combination of the first two, as the dependent variable, crop yield, on the first two alone. However, in this case, upon applying a stepwise partial correlation analysis, the newly added variable of maximum plant height will be found to explain most of the variance in the dependent variable of crop yield, so that the additional explained variance resulting from the inclusion of sunlight and rainfall is negligible. Would this then imply that crop yield has no dependency upon sunlight and rainfall?

In addition to significance, one must also be concerned with the degrees of freedom in the data upon which the regression is based. This is the essence of the criticism of Whiteside (1984, p. 14) that the number of data points used in the fishery harvest analyses of LP-106 are too few given the number of variates. The analysis of LP-106 utilizes 15 values of annual harvest and potentially 5 independent variates of seasonal flow (although the important regressions, such as total shellfish, end up including only 2 or 3 independent variates). Thus there are about 3 data points per variate, in contrast to the rule-of-thumb cited by Whiteside that there should be 10 or more data points per variate. Certainly, the fewer the number of data points the less confidence one has in the regression. At the same time, if there is a sound reason for including each of the independent variates, then these variates should not be excluded simply to improve the degrees of freedom. (In fact, as the homely examples above show, to do so may actually erode the value of the regression.) Again, this is a statistical judgment call, and there is no methodological error *per se* in the approach of LP-106. There is, however, inadequate attention given to the consequences of working with a small data set.

A related concern is the effect of the 1973 "outlier" (Whiteside, 1984, p. 15). Whiteside comments, "...the shrimp harvest equations shown in LP-106 are largely the product of the fact that a year of good harvest coincided with

the largest seasonal inflow of record. Without this one observation, high spring inflows and good shrimp harvest have no significant relationship." The implication is that the resulting regression is, therefore, unreliable. Technically, the 1973 data point is not an outlier but is a high-leverage point which exerts a great deal of "influence" on the regression equation. The problem is that 87% of the data are for flows less than 600 maf, so that we have a good measure of the mean harvest for this range of flow and of the scatter about this mean. The 1973 data point gives us the greatest information about the dependence of shellfish harvest on Q_2, because it represents nearly three times this rate of inflow, but because it is the only measurement we have in this range, our ability to judge its precision is poor. This does not mean that the data point should be deleted or that the resulting regression is "unreliable". It does mean that the effective degrees of freedom upon which the regression is based are considerably less than the 15 data points would suggest. The failure of LP-106 is in not disclosing the uncertainty attending this regression, or (for that matter) the uncertainty in the uncertainty.

A similar criticism can be made with respect to the salinity statistics. Further, because salinity is bounded below by a value of 0 ppt and above by an effective limit on the order of 35 ppt, the data have to be heteroscedastic. No indications of confidence bounds are given in LP-106; the report is definitely deficient in this respect. Yet the 95% confidence limits presented by Whiteside (1984, p. 23) overestimate the uncertainty by failing to account for the heteroscedasticity of the data.

Finally, in the ultimate application of the regression relations, namely as constraints on the optimization problem of minimizing the total freshwater inflow as described in Martin (1987) and in LP-106, the salinity and harvest regressions prove to be the chief constraints (as we might expect). Yet there is no quantification of the uncertainty of this regression or of the sensitivity of the optimal solution to this uncertainty, i.e. how the optimal solution would be affected by alternate regression equations which lie within the same confidence limits as those employed. As will be described below, there are substantial differences in the Alternative I, II and III results produced by fairly modest alterations in inflow. In fact, it would appear that there would be far more variability in the inflow satisfying the optimization

problem associated with variability about the regression line than there is among the results for Alternatives I, II and III. This would imply that the noise in the data prohibits a statistically reliable discrimination between the three alternatives.

2.3 APPROPRIATENESS OF REGRESSION

There are several questions attaching to the appropriateness of formulation of the regression problem. These are, however, largely matters of subjective judgment that should be addressed in LP-106 by suitable motivation for the strategy elected or by comparison with results utilizing other strategies. A key philosophical issue is whether the model formulated represents a true cause-and-effect relationship. The method of LP-106 has been criticized by several workers, the criticism ranging from Whiteside (1984, pp. 7, 9, 20-21), who asserts the absence of the cause-and-effect relation, to Ward (1984, pp. 73-79, 95-102) who simply questions its existence. A related question is whether such a cause-and-effect relationship is indeed needed for the purposes of LP-106: perhaps a well-defined association would be sufficient.

Clearly the answer to this criticism depends upon the intended use of the regressions. If the long-term purpose is to manipulate inflows so as to achieve a desired result, or to use inflows as a basic variable for future predictions of fishery harvest, then a *bona fide* causal relationship should underlie selection of variables. The plausibility of the spring freshet producing an influx of nutrients seems to be belied by the large negative dependencies found for oysters (which also were found in the analyses for other estuarine systems); could this be because larger inflows are correlated with poor boating conditions and reduced harvests? Similarly, what other variables influence harvest which are not considered in the analyses, e.g., economics, fishing effort, technology? It is not even clear that harvest is a direct measure of the abundance of the species. It is also possibly symptomatic of limited mobility.

The approach of seasonally categorizing streamflow is laudable because it is based upon a plausible conceptual model. It would appear, however, that more exploratory research needs to be invested in the precise definition of

streamflow variables. For example, with the fishery harvest relations, it may very well be that it is the magnitude of the spring freshet that is controlling, independent of whether that freshet occurs within the Q_1, Q_2 or Q_3 seasons, and by categorizing the flow into these three seasons, a more fundamental relationship may have been obscured. Similarly, the attempt to incorporate time response of salinity to freshwater inflow by regressing on two variates, one the 30-day mean preceding the date of the salinity sample and the other the streamflow N days prior to the sample, where N is the normal (i.e. longterm mean) time of travel to the salinity sampling station, requires better definition. For example, time of travel is a strong function of streamflow, in the case of Lavaca Bay ranging from less than a day to many weeks. Further, if one accepts the value of 7 days used in LP-106, then 25% of the data in the 30-day antecedent mean should have no causal connection to the measured salinity.

Many of the criticisms of the LP-106 methodology lodged above and in the above cited testimony devolve to matters of judgment and not necessarily of procedure. There are additional nonstatistical tests which can indicate the validity of the LP-106 application. Table 2.1 summarizes the LP-106 results for the three alternatives, showing the resultant annual total inflow and the corresponding predicted shellfish harvest. (All other figure and table references that follow are to LP-106.) We should expect the regressions and the optimization routines to be capable of recovering at least the means of the variables. In the case of Alternative I, the salinity constraint turns out to be practically the median historic salinity (as tabulated in Table 9-2), see Figures 9-2 and 9-3. Yet, the Alternative I results indicate that this median salinity can be achieved with only 75% of the annual mean inflow, with a fairly uniform reduction in the individual monthly flows. Further, this substantial reduction in inflow produces only slightly reduced harvests, on the order of 5% for shellfish (Table 1) and virtually no change for finfish, see Figure 9-7. While the explanation for this counterintuitive result may reside in such technical details as different periods of record, median versus mean salinities, and a small slope of the harvest regression versus Q, nonetheless for such a substantial reduction in inflow, one would expect larger responses.

Table 2.1 Summary of LP-106 Results

	Total Inflow (maf)	Shellfish Harvest (10^3 lbs)
1962-1976 Mean	2.900	3034
Alternative I	2.097	2894
Alternative II	2.808	2928
Alternative III	2.811	3701

The difference between Alternative I and Alternative II results is just as counterintuitive, the latter requiring fully one-third more flow than Alternative I to achieve a 1.2% increase in harvest. Also, the most significant change in the species distribution of this harvest is to reduce white shrimp by 16% relative to historic means, with a compensating increase in brown shrimp. Considering that brown shrimp are usually taken offshore (in contrast to whites), one could seriously question the realism of this shift, and *a fortiori* whether it is really worth the additional 0.800 maf. A comparison of Alternative III to Alternative II shows that for a (negligible) 0.3% additional increase in inflow, a whopping 26% increase in shrimp harvest results (again entailing a further decrease in whites with a very large increase in browns).

Clearly, as these comparisons show, there are some very peculiar sensitivities of both salinity and harvest to changes in inflow. These results are so counterintuitive that considerably more justification is necessary to establish their validity, and this justification may well extend beyond a more careful documentation of the statistics and a quantification of confidence bounds.

SECTION 3

ESTUARINE MATHEMATICAL PROGRAMMING MODEL

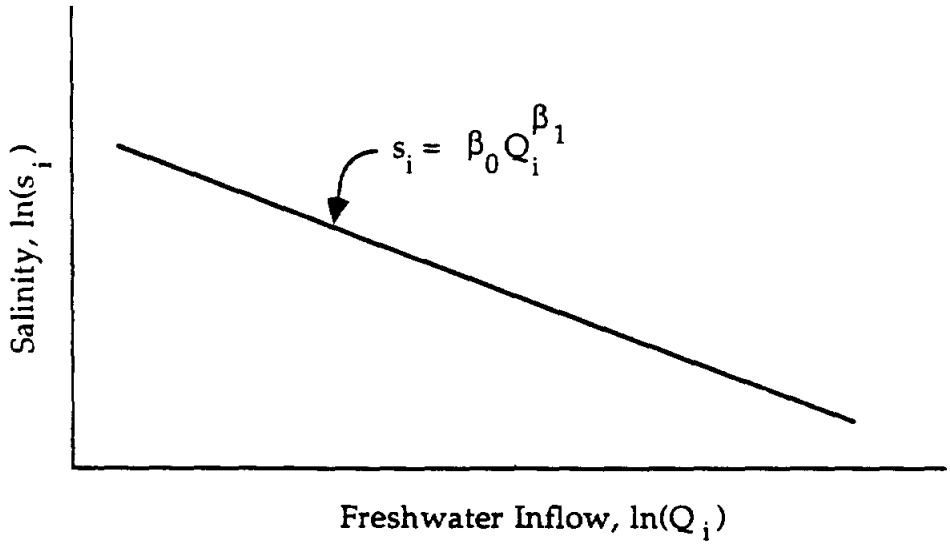
3.1 INTRODUCTION

The freshwater inflow needs for the bays and estuaries of Texas have been proposed by the Texas Water Development Board utilizing mathematical programming techniques for optimization. Specifically, annual inflow (as measured by the sum of monthly inflow values) was minimized subject to constraints on annual fisheries harvests (grouped by various species) and on the range of monthly average salinity. The methodology is described in Martin (1987) and in TDWR report LP-106 (TDWR, 1980). A key element in this optimization problem is the mathematical relation between salinity in the estuary and flow, S = F(Q).

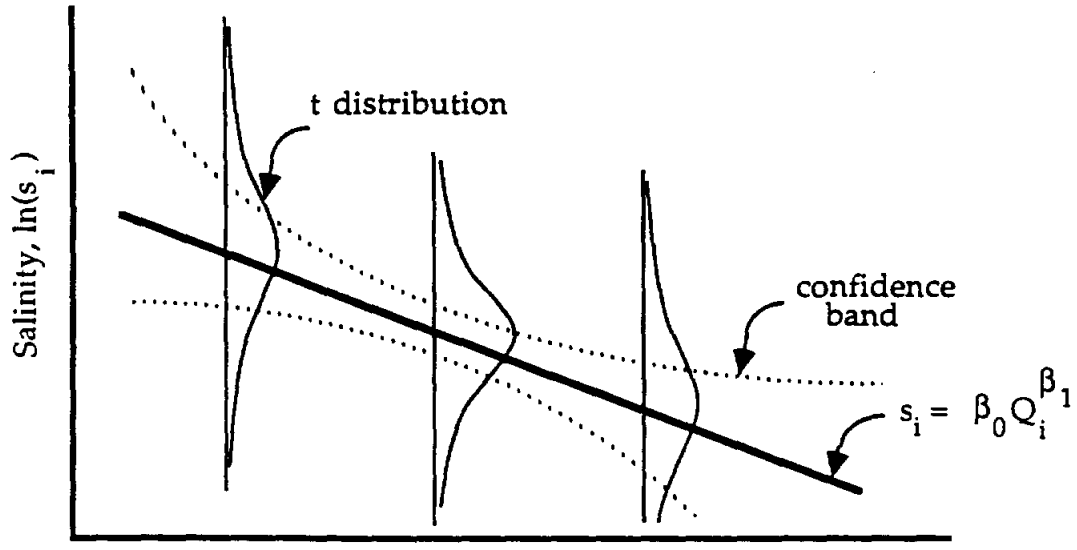
The Texas Water Development Board has made extensive application of regression analysis to establish the regression equations of freshwater inflow requirements related to salinity, and also to the harvest of various species of sea animals, as a part of its Bays and Estuaries Program. Figure 3.1 (a) shows an example of average monthly salinity-inflow relationship. The average salinity in i-th month, s_{ij}, is related to the average monthly gaged inflow from j-th river, Q_{ij}, by the equation

$$s_{ij} = \beta_0 (Q_{ij})^{\beta_1} \exp(t\, s_e)$$

where β_0 and β_1 are regression coefficients, and $\exp(t\ s_e)$ is a random component, in which t is a standard normal deviate with zero mean and unit variance, and s_e is the standard error of estimate of $\ln(s_{ij})$ on $\ln(Q_{ij})$ (TDWR, 1980). The random component is included to account for the spread of the field data points about the regression curve. In the current estuarine model (Martin, 1987; TDWR, 1980), those salinity-inflow regression relationships,



(a) Regression Equation of Average Monthly Salinity versus Average Monthly Gaged Inflow



(b) Sampling Distribution Around the Regression Curve

Figure 3.1 Regression Relationship Between Average Monthly Inflow and Average Monthly Salinity

which are subject to error, are incorporated as the deterministic constraints, and the nonlinear problem has been linearized in approximation. Such weaknesses or limitations of application of the above linear programming model are listed in Section 1.

A new methodology is developed to overcome the these weaknesses by constructing chance-constraints in a nonlinear programming model, which is proposed to explicitly account for the uncertainty in the salinity and harvest regression equations and to explore the trade-offs among the various objectives.

3.2 MODEL USING DETERMINISTIC SALINITY AND HARVEST CONSTRAINTS

The mathematical programming model can have the objective of minimizing the sum of freshwater inflows, Q_{ij}, for month i and river j,

$$\text{Min} \sum_j \sum_i Q_{ij} \qquad (1)$$

subject to the following constraints:

(1) The nonlinear relationship of estuary salinity and freshwater inflow.

$$s_{ij} = \phi_{ij}(Q_{ij}) \qquad (2)$$

(2) Upper ($\bar{s}$) and lower ($\underline{s}$) bounds on the monthly average salinity at a specified location in the estuary, for each river j.

$$\underline{s}_{ij} \leq s_{ij} \leq \bar{s}_{ij} \qquad (3)$$

(3) Lower limits on the i-th monthly inflows for the j-th river, QI_{ij}, to express seasonal biological requirements, e.g. of the estuarine marsh inundation.

$$Q_{ij} \geq QI_{ij} \qquad (4)$$

(4) The sum of monthly flows must be less than or equal to the upper limit of the total annual inflow, QT_j, from each river j.

$$\sum Q_{ij} \leq QT_j \tag{5}$$

(5) Upper and lower limits on mean monthly flows in seasons for each river j,

$$\underline{QS}_{jm} \leq QS_{jm} \leq \overline{QS}_{jm} \tag{6}$$

where $QS_{jm} \equiv \frac{1}{N_m} \sum_{i \in M_m} Q_{ij}$; M_m is the set of months in season m and N_m is the number of months in season m.

(6) The nonlinear regression relationship between the harvest of organism k and the seasonal inflow in river j.

$$H_k = \psi_k (QS_{jm}) \tag{7}$$

(7) Lower limits on annual fish harvest, $\underline{H}_k$, by species k.

$$H_k \geq \underline{H}_k \tag{8}$$

(8) Upper and lower limits on monthly inflows ($\overline{Q}_{ij}$ and $\underline{Q}_{ij}$) from each river.

$$\underline{Q}_{ij} \leq Q_{ij} \leq \overline{Q}_{ij} \tag{9}$$

3.3 ALTERNATIVE MANAGEMENT MODEL STRATEGIES

Four alternative formulations of the optimization model can be applied to achieve different management objectives, as summarized below. Other management objectives are possible, and can be similarly formulated within the general framework of (1) - (9).

Alternative I The basic formulation of the problem for estuarine management is to minimize the total annual freshwater inflow subject to salinity level control, which will accomplish the requirements of nutrient transport, habitat maintenance, and marsh inundation requirement. The corresponding mathematical model can be formulated as

$$\text{Min} \sum_i \sum_j Q_{ij} \tag{10}$$

subject to constraints (2), (3), (4) and (9).

Alternative II Maintenance of the fishery harvest. The objective is to minimize the total annual freshwater inflow while satisfying minimum seasonal flow needs to maintain the annual commercial harvest of key species at desired levels, and meeting viability limits for salinity. The constraints for Alternative II are equations (2), (3), (4), (6), (7), (8) and (9).

Alternative III Enhancement of the fishery harvest, i.e., to maximize the total annual commercial harvest of a selected organism k while meeting viability limits for salinity, satisfying minimum seasonal flow needs, and limiting an annual combined inflow no greater than its historical mean value. The objective is to

$$\text{Max } \mathbf{QS}^T \hat{\beta}_{H_K} \tag{11}$$

subject to equations (2), (3), (4), (5), (6) and (9), where $\mathbf{QS}^T$ is the transpose of vector of the seasonal freshwater inflow,$\mathbf{QS}$, and $\hat{\beta}_{H_K}$ is the vector of estimated coefficients of the harvest regression equation for species k.

Alternative IV Minimize the total annual freshwater inflow subject to the salinity restriction. This is similar to Alternative I except the minimum seasonal flow (marsh inundation) requirement, constraint (4), is removed.

3.4 CHANCE-CONSTRAINT FORMULATION

The regression equations in the optimization model for salinity and harvest are subject to uncertainty due to the variance in the basic data. This uncertainty arises because for the population of observations associated with the sampling process, there is a probability distribution of salinity and of commercial harvest for each level of freshwater inflow. Figure 3.1 (b) shows an example of this sampling distribution for the salinity-inflow regression equations. The basic application of chance-constraints in stochastic programming is to account for the uncertainty of the regression due to random variation in the regression variables by formulating the corresponding constraints into probabilistic form and then transforming them into their deterministic equivalents. (Charnes and Cooper, 1959, 1962, 1963; Charnes and Sterdy, 1966; Jagannathan, 1974; Miller and Wagner, 1965; Sengupta, 1972). In the environmental and water resources area, there are a number of papers on water quality models and reservoir design and operation models using chance constraints (Fujiwara et al., 1986; Houck, 1979; Ellis, 1987, Ellis et al., 1985, 1986; Lohani and Thanh, 1978, 1979; Burn and McBean, 1985; Loucks and Dorfman, 1975).

The concept of chance-constraints is illustrated schematically in Figure 3.2. In the problem formulation, these stochastic constraints are transformed into probabilistic statements so that each chance-constraint states the probability that the constraint will be satisfied with a specified reliability level. The salinity constraint (3) and harvest constraint (8) can be rewritten as chance-constraints

$$P_r \{\underline{s}_{ij} \leq s_{ij} \leq \bar{s}_{ij}\} \geq p_{ij} \tag{12}$$

and

$$P_r \{H_k \geq \underline{H}_k\} \geq p_k \tag{13}$$

where the salinity s_{ij} and the harvest H_k are random variables due to the uncertainty induced by regression equations (2) and (7); p_{ij} and p_k are the desired or required reliabilities.

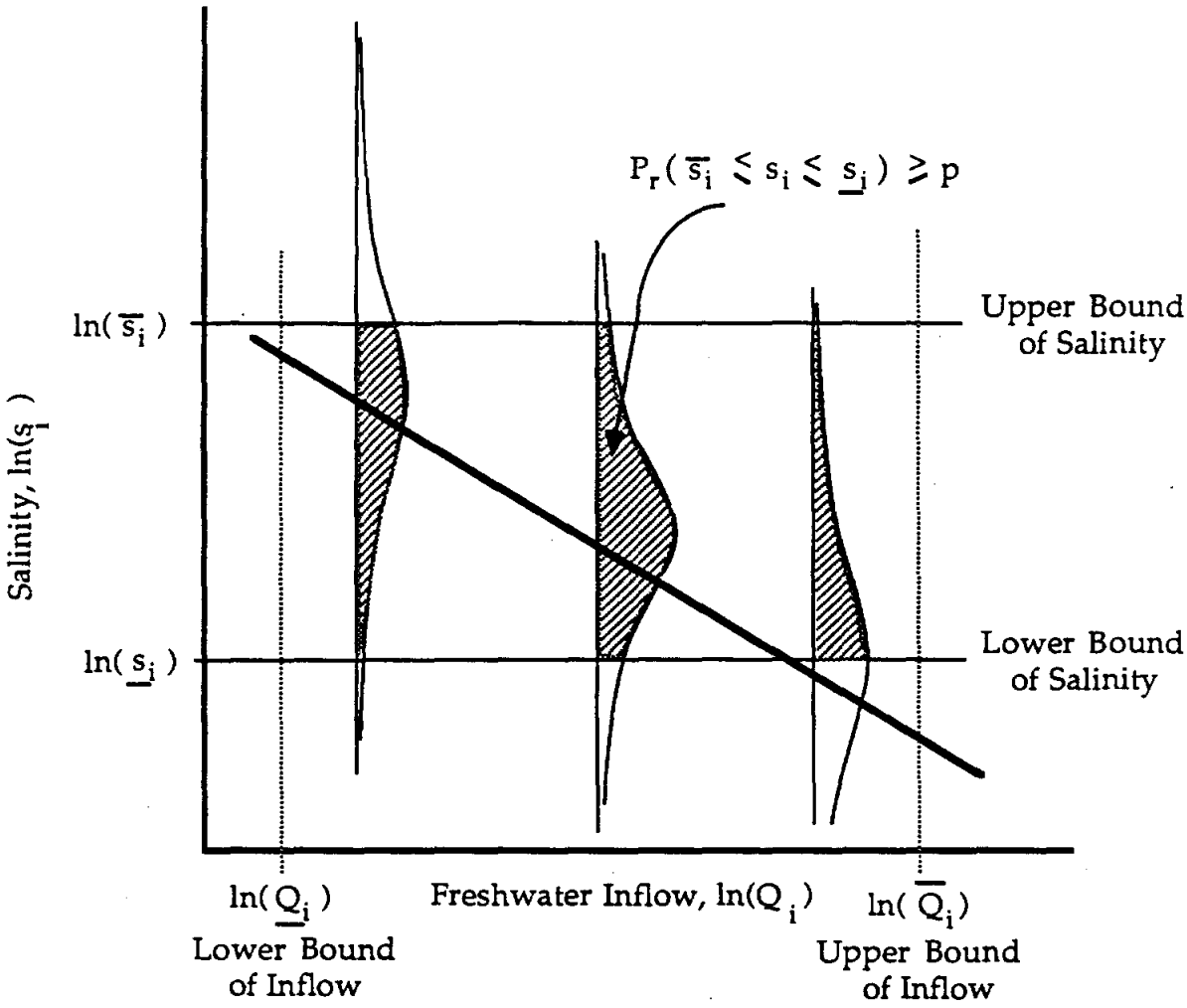


Figure 3.2 Schematic Illustrating the Concept of Salinity Chance Constraints

It is desired to transform the chance-constraints (12) and (13) to their equivalent deterministic forms in order to implement the optimization algorithm. The salinity regression expression can be written (using the regressions of the Texas Department of Water Resources, 1980)

$$\ln(s_{ij}) = \left[\ln(Q_{ij})\right]^T \cdot \beta_{s_{ij}} \tag{14}$$

The harvest regression equations are either multiple linear models or transformed linear models after logarithmic transformation of H_k and QS_{jm} depending upon the species of fish. The commercial fish harvest can be written in a linear or nonlinear form depending upon the species (again, using the regressions of the Texas Department of Water Resources, 1980)

$$H_k = (QS)_j^T \cdot \beta_{H_{kj}} \tag{15}$$

or

$$\ln(H_k) = \left[\ln(QS)_j\right]^T \cdot \beta_{H_{kj}} \tag{16}$$

The chance-constraints (12) and (13) can then be expressed respectively as

$$\Pr\left\{\ln(\underline{s}_{ij}) \le \left[\ln(Q_{ij})\right]^T \cdot \beta_{S_{ij}} \le \ln(\bar{s}_{ij})\right\} \ge p_{ij} \tag{17}$$

and

$$\Pr\left\{(QS)_j^T \cdot \beta_{H_{kj}} \ge \underline{H}_k\right\} \ge p_k \tag{18}$$

or

$$\Pr\left\{\left[\ln(QS)_j\right]^T \cdot \beta_{H_{kj}} \ge \ln(\underline{H}_k)\right\} \ge p_k \tag{19}$$

By standardizing, the salinity chance-constraint (17) can be rewritten in an implicit function form as

$$F_{t,n-v}\left[\frac{\ln(\bar{s}_{ij}) - \left[\ln(Q_{ij})\right]^T \cdot \hat{\beta}_{s_{ij}}}{A}\right]$$

$$- F_{t,n-v}\left[\frac{\ln(\underline{s}_{ij}) - \left[\ln(Q_{ij})\right]^T \cdot \hat{\beta}_{s_{ij}}}{A}\right] \geq p_{ij} \qquad (20)$$

where $A = \hat{\sigma}_{s_{ij}} \sqrt{\left[\ln(Q_{ij})\right]^T \left\{\left[\ln(QD_{ij})\right]^T \left[\ln(QD_{ij})\right]\right\}^{-1} \left[\ln(Q_{ij})\right] + 1}$

$F_{t,n-v}$ is the cumulative probability of a student t distribution for the t-th quantle and n-v degrees of freedom; n is the number of observed data and v is the number of parameters in the regression equation model; $[\ln(Q_{ij})]$ is a transposed vector with each element being the logarithm of the monthly freshwater inflow and $\ln(QD_{ij})$ is a matrix of the logarithmic transformed observed monthly freshwater inflow data used for the regression analysis; $\hat{\beta}_{sj}$ is a vector of coefficients in the salinity regression equation, and $\hat{\sigma}_{sij}$ is the estimated standard deviation associated with the salinity regression equation.

The deterministic form of equations (18) and (19) are, respectively,

$$t_{n-v,1-p_k} \cdot \hat{\sigma}_s \sqrt{(QS_j)^T \left[(QSD_j)^T \cdot (QSD_j)\right]^{-1} (QS_j) + 1}$$

$$+ (QS_j)^T \hat{\beta}_{H_{kj}} \leq \underline{H}_k \qquad (21)$$

and

$$t_{n-v,1-p_k} \cdot \hat{\sigma}_{s_{ij}} \sqrt{\left[\ln(QS_j)\right]^T \left\{\left[\ln(QSD_j)\right]^T \left[\ln(QSD_j)\right]\right\}^{-1} \left[\ln(QS_j)\right] + 1}$$

$$+ \ln(QS_j)^T \cdot \hat{\beta}_{H_{kj}} \leq \underline{H}_k \qquad (22)$$

w

here $t_{n-v,1-p_k}$ is the quantle of t - random variable with n-v degrees of freedom and the probability of 1-p_k, $\hat{\sigma}_{H_k}$ is the estimated standard error associated with the harvest regression equations, QSD_j is a matrix of the observed data of seasonal freshwater inflow used for the harvest regression equations, and $\ln(QSD_j)$ is a matrix in which each element is logarithmic transformed of the corresponding one in QSD_j.

The chance-constrained model for various alternatives is obtained by using the associated objective along with constraints (20), (21) and/or (22), replacing the respective regression relationships. Derivation of the deterministic equivalent of chance-constraints based on regression equations is shown in Appendix A.

3.5 MULTI-OBJECTIVE PROBLEM

An optimization model is called a multiobjective problem because of the existence of two or more conflicting objectives, such as minimizing the annual freshwater inflow while maximizing the annual harvest. These cannot be optimized simultaneously since, in general, the higher annual fish harvest requires a higher freshwater inflow into the estuarine environment. Furthermore, different fish species usually have different salinity preference levels, and different inflow patterns. Therefore, the optimal freshwater inflow corresponding to the optimal annual fish harvest will vary with the fish species. Different objective functions that could be considered are the following:

(1) Minimize the annual total freshwater inflow.

$$\sum_i \sum_j Q_{ij} \tag{23}$$

(2) Maximize the expected fish harvest for individual species (one objective for each species)

$$\text{Maximize} \sum_j E(H_{kj}) = \sum_j Q^T \beta_{kj} \quad \text{for species k, river j} \tag{24}$$

(3) Maximize the expected fish harvest for an individual species and minimize its estimated standard deviation

$$\text{Maximize} \sum_j Q^T \beta_{kj} - \sqrt{\text{Var}\,(Q^T \beta_{kj})} \tag{25}$$

(4) Maximize the probability that the expected annual harvest for an individual species will satisfy the harvest requirement.

$$\text{Maximize} \ \Pr\{Q^T \beta_{kj} \geq H^*_{kj}\} \tag{26}$$

where H^*_{kj} is the harvest required for species k at river j.

An example of a multiobjective formulation would be to use both objective (23) to minimize total annual freshwater inflow and objective (24) to maximize expected fish harvest for individual species.

The specific setup and coding of a multiobjective model was beyond the scope of the present study, other than to indicate how such a problem should be formulated and how it is related to the other extensions of the programming procedure, viz. chance-constraints and nonlinearity. The general approaches for solving multiobjective problems that should be considered for implementation in an estuarine management problem include:

(a) ε - Constraint Method - Select one of the objective functions to be optimized and put the rest of the objective functions into constraints.

(b) Weighting Method - Combine the objective functions into a single-objective programming format by assigning a weight for each objective.

(c) Goal programming - Minimize the sum of deviations of objectives from the goals.

(d) Utility theory - Maximize satisfaction using the individual's preference structure (utility function).

Either (c) or (d) can be used if the decision-maker wants to build his preferences into a formulation of the mathematical model.

SECTION 4

APPLICATION TO MATAGORDA BAY SYSTEM

4.1 INTRODUCTION

The nonlinear, chance-constrained models formulated in the previous section were applied to the Lavaca-Tres Palacios estuary in Texas, i.e. Matagorda Bay and its secondary (e.g. Lavaca Bay), and tertiary (e.g. Cox Bay) systems, shown in Figure 4.1. The major freshwater inflow sources are the Colorado River, which principally affects the eastern segment of Matagorda Bay, and the Lavaca River, which principally influences Lavaca Bay.

The regression equations of salinity and fishery harvest and the monthly mean salinity bounds are specified for selected locations. For the Matagorda Bay system, these two types of upper and lower limits on monthly salinity determine a salinity range as shown in Table 4.1. The first type is based on the bounds for viable metabolic and reproductive activity, and the second salinity upper bound selected is the lesser of the historical median monthly salinity level or the first type salinity upper bound, i.e. viability limits (TDWR, 1980).

Five species of fish are considered in this application, as listed in Table 4.2. The regression equations employed for salinity and fish harvest are given in Tables 4.3 and 4.4, respectively. Alternatives I, II and IV with various conditions were treated in this application, summarized in Table 4.2.

4.2 SOLUTION PROCEDURE

In general, the nonlinear chance-constrained models described above have both linear and nonlinear constraints requiring a nonlinear programming algorithm. One of the solution algorithms used in this study is a generalized reduced gradient technique, GRG2, by Lasdon and Waren (1986).

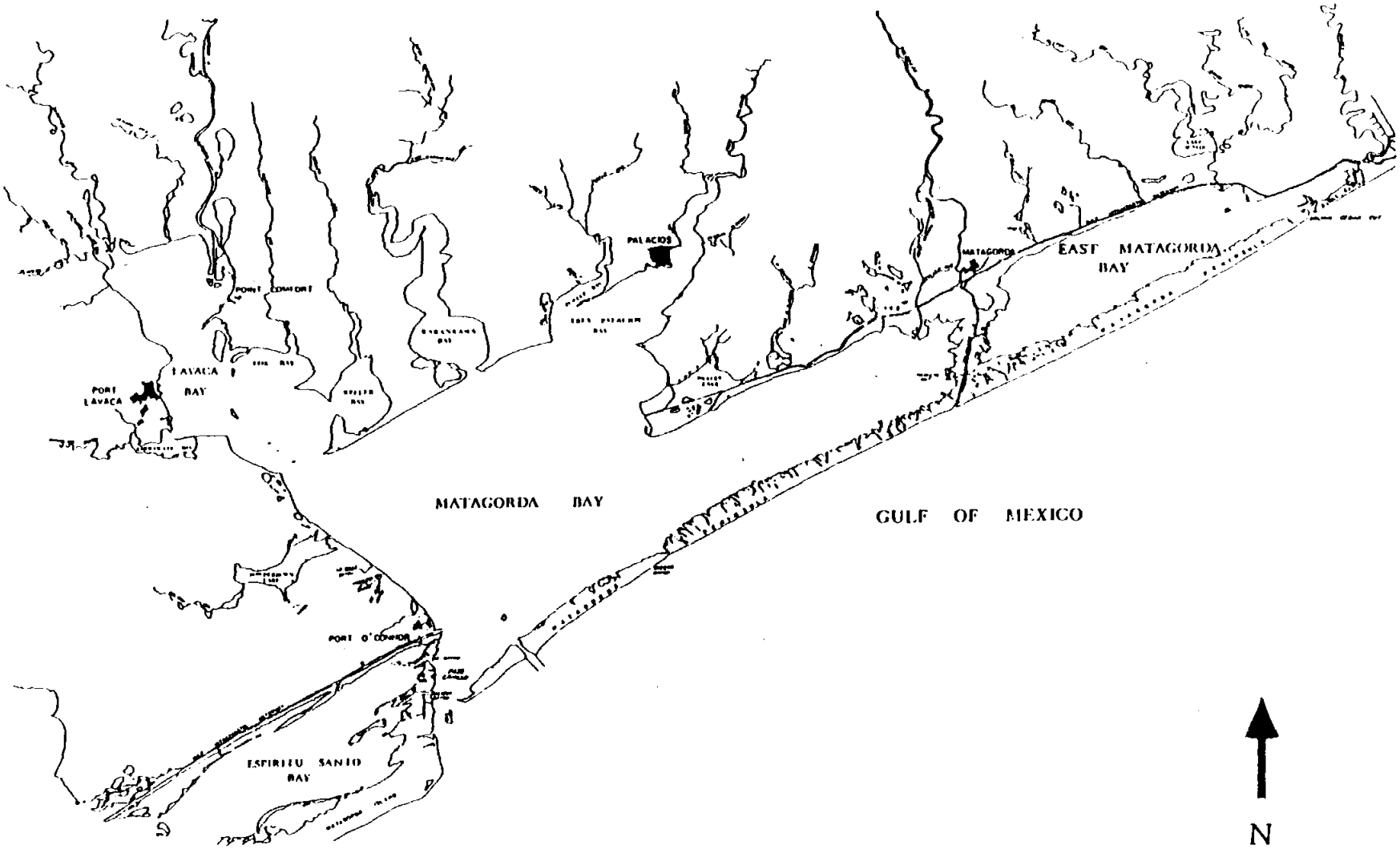


Figure 4.1 Location of Matagorda Bay System

Table 4.1 Salinity Bounds (ppt) of Upper Lavaca Bay and Eastern Arm of Matagoda Bay

Month	Lavaca Bay (Lavaca River)				Matagoda Bay (Colorado River)			
	Type 1		Type 2		Type 1		Type 2	
	Lower Bounds	Upper Bounds	Lower Bounds	Upper Bounds	Lower Bounds	Upper Bounds	Lower Bounds	Upper Bounds
January	10	20	10	13	10	30	10	19
February	10	20	10	12	10	30	10	19
March	10	20	10	12	10	25	10	19
April	5	15	5	13	5	20	5	20
May	1	15	1	10	5	20	5	19
June	1	15	1	9	5	20	5	19
July	10	20	10	11	10	25	10	21
August	10	20	10	17	10	25	10	24
September	5	15	5	13	5	20	5	20
October	5	15	5	13	5	20	5	20
November	10	20	10	13	10	30	10	19
December	10	20	10	14	10	30	10	19

Table 4.2 Summary of Various Conditions Considered in Applications of Models for Alternatives I, II, and IV

Items	Cases Considered	Description
Rivers	Lavaca River	for Lavaca Bay
	Colorado River	for Matagoda Bay
Salinity Bounds	Type 1	using viability limits
	Type 2	using historic values (Table 4.1)
Regression Equations	a	with chance-constrained
	b	without chance-constrained
Models	LP	used for comparison
	NLP	
Salinity Equations	12 Equation	one equation for each month
	1 Equation	one equation for all months
Marsh Inundation Needs	Case 1	70,000 ac-ft for each month of April and May, and 60,000 ac-ft for September
	Case 2	70,000 ac-ft for period April through June and 60,000 ac-ft for October-January
Fish Species	1	all shell fish
	2	spotted sea trout
	3	red drum
	4	all penaeid shimps
	5	blue crab

Table 4.3 Regression Relationships Between Salinity and Freshwater Inflow*
(Texas Department of Water Resources, 1980)

	Lavaca River			Colorado River		
Month	β_0	β_1	$\hat{\sigma}$	β_0	β_1	$\hat{\sigma}$
January	200.14	-0.464	0.462	84.67	-0.205	0.112
February	249.76	-0.498	0.572	87.94	-0.207	0.095
March	151.76	-0.450	0.439	98.37	-0.231	0.123
April	157.37	-0.412	0.436	132.14	-0.254	0.125
May	150.41	-0.416	0.673	129.98	-0.248	0.193
June	108.70	-0.397	0.631	98.03	-0.220	0.197
July	280.58	-0.583	0.362	214.47	-0.342	0.138
August	159.42	-0.435	0.501	397.34	-0.419	0.433
September	159.42	-0.418	0.443	122.27	-0.232	0.338
October	157.44	-0.437	0.476	77.06	-0.184	0.213
November	206.21	-0.487	0.582	89.03	-0.215	0.062
December	413.74	-0.597	0.476	111.52	-0.245	0.062

*The salinity equation has the general form of $S = \beta_0 Q^{\beta_1}$ where S is the monthly salinity in ppt, Q is the monthly freshwater inflow in cfs, β_0 and β_1 are coefficients and $\hat{\sigma}$ is the standard error.

Table 4.4 Regression Equations of Fish Harvest and Freshwater Inflow Relations
(Texas Department of Water Resources, 1980)

Index k for Fish Species	Equations	$\hat{\sigma}_k$	Inflow used in regression equations
1 : All shellfish	$H_1 = 3107.9 - 11.3QS_1 + 7.7QS_2 - 24.2QS_3$	482.8	a*
2 : Spotted seatrout	$\ln(H_2) = 6.8264 - 1.2473 \ln(QS_1) + 1.1526 \ln(QS_2) - 0.40371 \ln(QS_4)$	0.2901	b**
3 : Red drum	$\ln(H_3) = 4.3204 + 0.6937 \ln(QS_2) - 0.8718 \ln(QS_3)$	0.2900	b
4 : All penaeid shrimp	$\ln(H_4) = 1735.8 - 3.7\ QS_1 + 2.7QS_2 - 1.0QS_5$	412.0	c***
5 : Blue crab	$\ln(H_5) = 208.3 + 2.7QS_3 + 0.4QS_4 + 0.5QS_5$	259.5	c

where H_k is the commerical harvest of species k in thousands of pounds,

QS is the mean monthly freshwater inflow during the season (acre/ft):

QS_1 = January - March
QS_2 = April - June
QS_3 = July - August
QS_4 = September - October
QS_5 = November - December

and $\hat{\sigma}_k$ is the standard error.

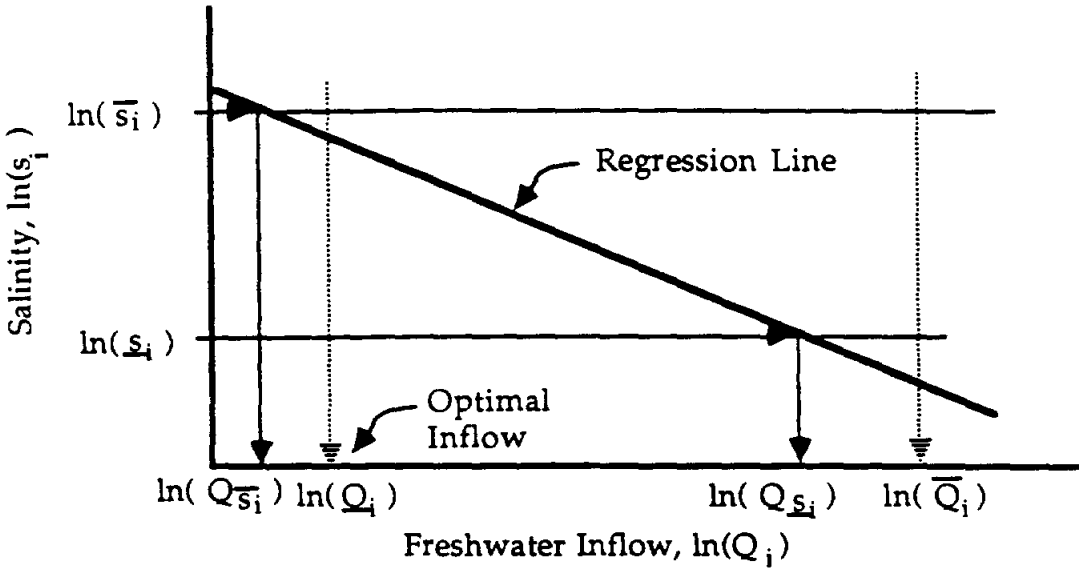
* using freshwater inflow at the Lavaca Delta
** using freshwater inflow at the Colorado Delta
*** using combined freshwater inflows from all contributing rivers and coastal drainage basins

GRG2 uses first partial derivatives of each function with respect to each variable. These are automatically computed by finite-difference approximations using either forward or central differences. The GRG2 program operates in two phases. Phase I optimization minimizes the sum of constraint violations to determine a feasible solution. Phase II optimization starts with a feasible solution, either from the Phase I or with a user-supplied, initial feasible solution. An efficient algorithm that searches for an initial solution is designed into the program to lessen the computational effort.

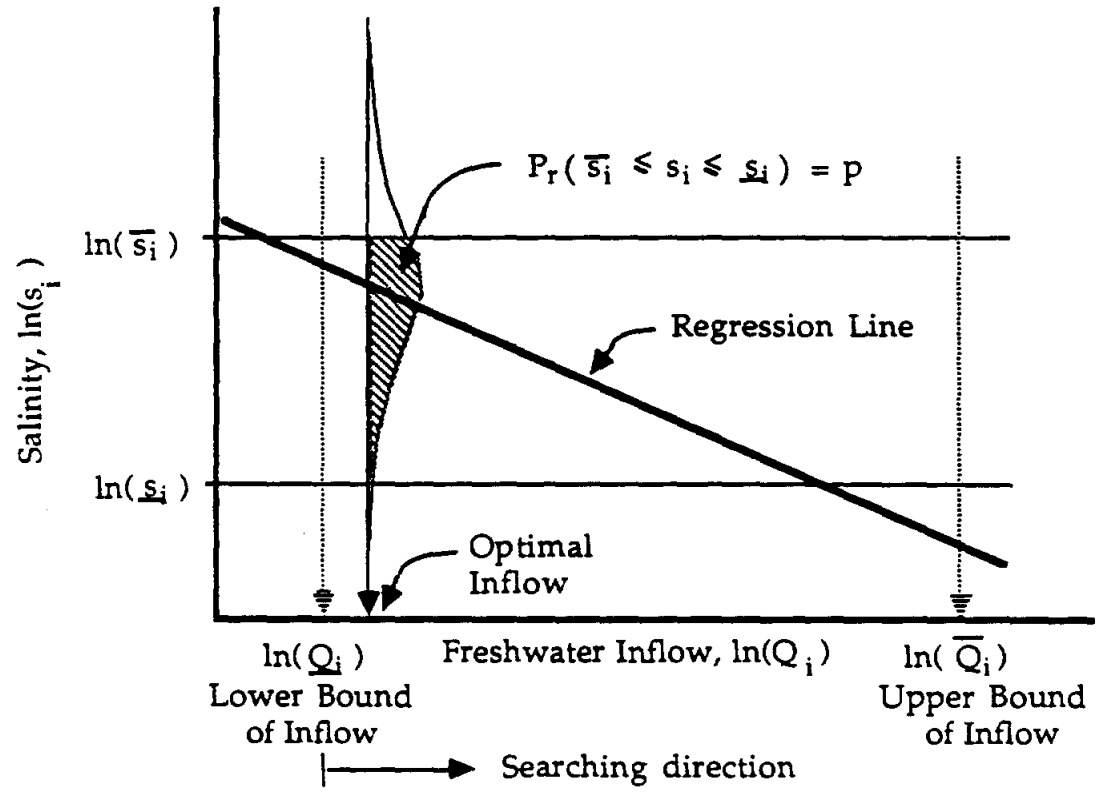
Alternative IV has a simple structure in which the average monthly salinity constraints for each river are independent of each other because each constraint has only one decision variable, the average monthly freshwater inflow. Hence, the problem can be completely decomposed into 12 x J independent subproblems, where J is the total number of rivers considered, with each having only one decision variable. The Alternative IV subproblems can then be solved directly without the GRG2 technique. Since the freshwater inflow is inversely related to the salinity and the objective is to minimize the total annual inflows, the optimal solution to the subproblem is therefore the value of inflow associated with the upper salinity bound. If the uncertainty in the regression equation is not considered, the solution to the subproblem will be obtained by simply comparing the lower bound of inflow with the inflow corresponding to the upper bound of salinity viability as shown in Figure 4.2a. The overall optimal solution is then the sum of the inflow for each subproblem.

Figure 4.2b shows the solution procedure for this subproblem for the case of using chance-constraints, in which the procedure is essentially a nonlinear one-dimensional search starting with the lower bound of inflow. The optimal solution is reached when an inflow is found for which the associated probability of salinity is equal to the desired probability.

Computer programs were written for each alternative. Program ALT14 was written for Alternatives I and IV. In ALT14 monthly inundation volume for marsh inundation requirement is used for Alternative I, therefore the problem can also be completely decomposed and solved without GRG2 techniques. Program ALT1 was written for Alternative I for the case that seasonal inundation volumes for marsh inundation requirement is used.



(a) Using Deterministic Salinity Constraint



(b) Using Salinity Chance Constraint

Figure 4.2 Schematic Sketch of Solution Procedures for Alternative IV

ALT2 was developed for Alternative II. In ALT1 and ALT2, GRG2 was used as part of the systems through the GRG2 subroutine interface, GRGSUB, in which all input and output data are communicated to and from GRG2 through the argument list of its subroutine interface. All of the programs were run on a VAX 11/780. On the average, ALT14 requires approximately 2 CPU seconds, and ALT1 and ALT2 need about 28 to 36 CPU seconds for each run.

Because the original observed inflow data records for both Lavaca river and Colorado river, on which the salinity and harvest regression equations were developed, are no longer available, reasonable monthly and seasonal historical freshwater inflows are generated using several random number generation techniques with appropriate adjustments. Figure 4.3 is a flowchart showing the major steps of the computational scheme for Alternative II.

4.3 RESULTS AND DISCUSSIONS

The results discussed in this section are part of the results of applications of the models for Alternatives I, II, and IV to the Lavaca-Tres Palacios Estuary in Texas. The objective is to search for the minimum freshwater inflow needs from the Lavaca River and the Colorado River for various conditions which are listed in Table 4.2.

In order to test the sensitivity of the model to the nonlinear algorithm, the cases were also run with the regression equations used in the deterministic way, as in LP-106. The result of the minimum Colorado inflow requirement for Alternative I obtained from the nonlinear model is plotted in Figure 4.4 to show a comparison with the result from the linear programming model developed by TDWR (Martin, 1987). It is clear that if chance constraints are not considered both nonlinear and linear programming models offer very close results.

Figures 4.5 and 4.6 are examples of optimal monthly freshwater inflow from the Colorado River and the Lavaca River for the Alternative IV problem. The desired or required reliabilities in the salinity chance-constraint, p_{ij} in equation (20), is predetermined by users, which may vary for different

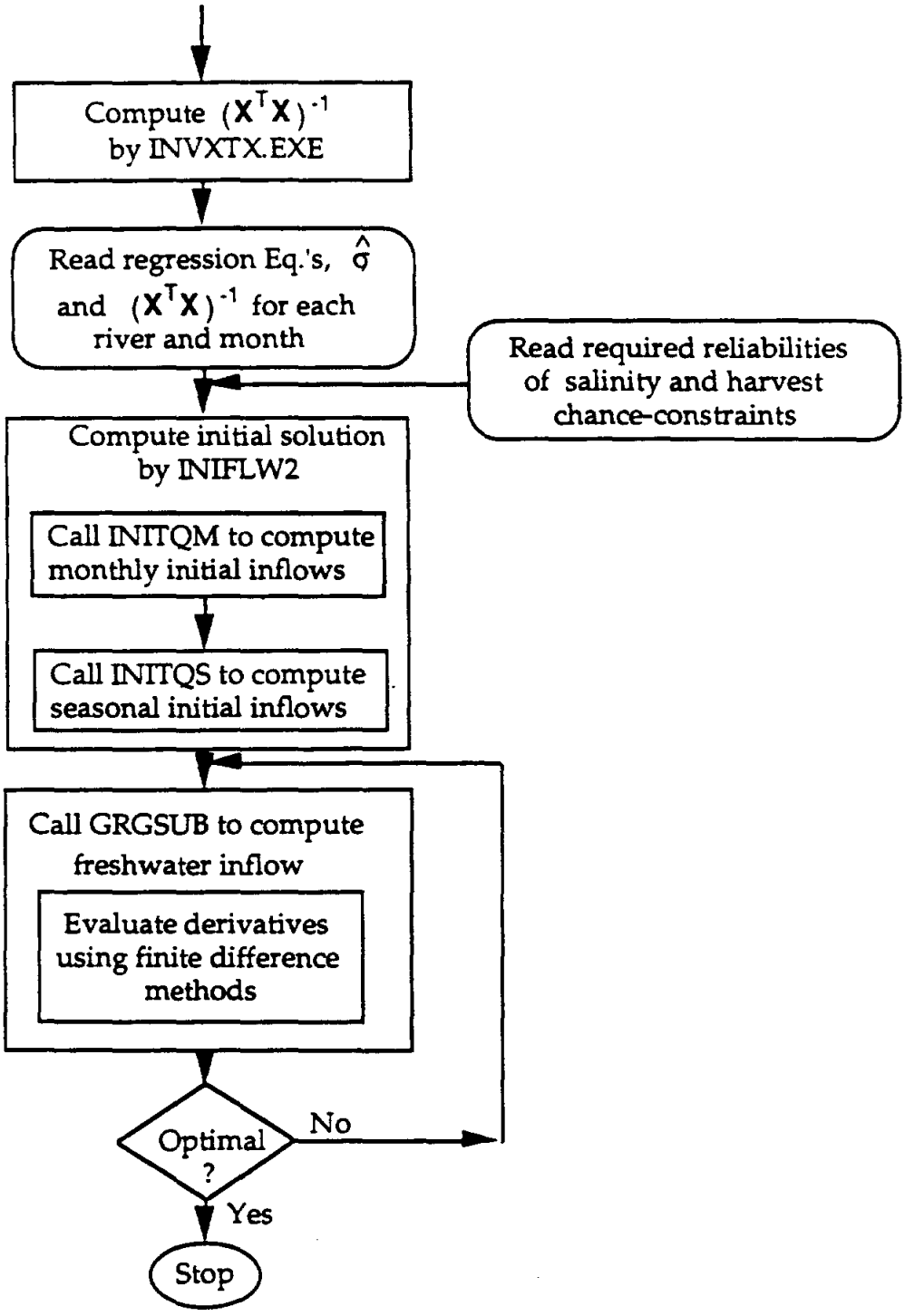


Figure 4.3 Flowchart for Computing Minimum Freshwater Inflow for Estuary for Alternatives I and/or II

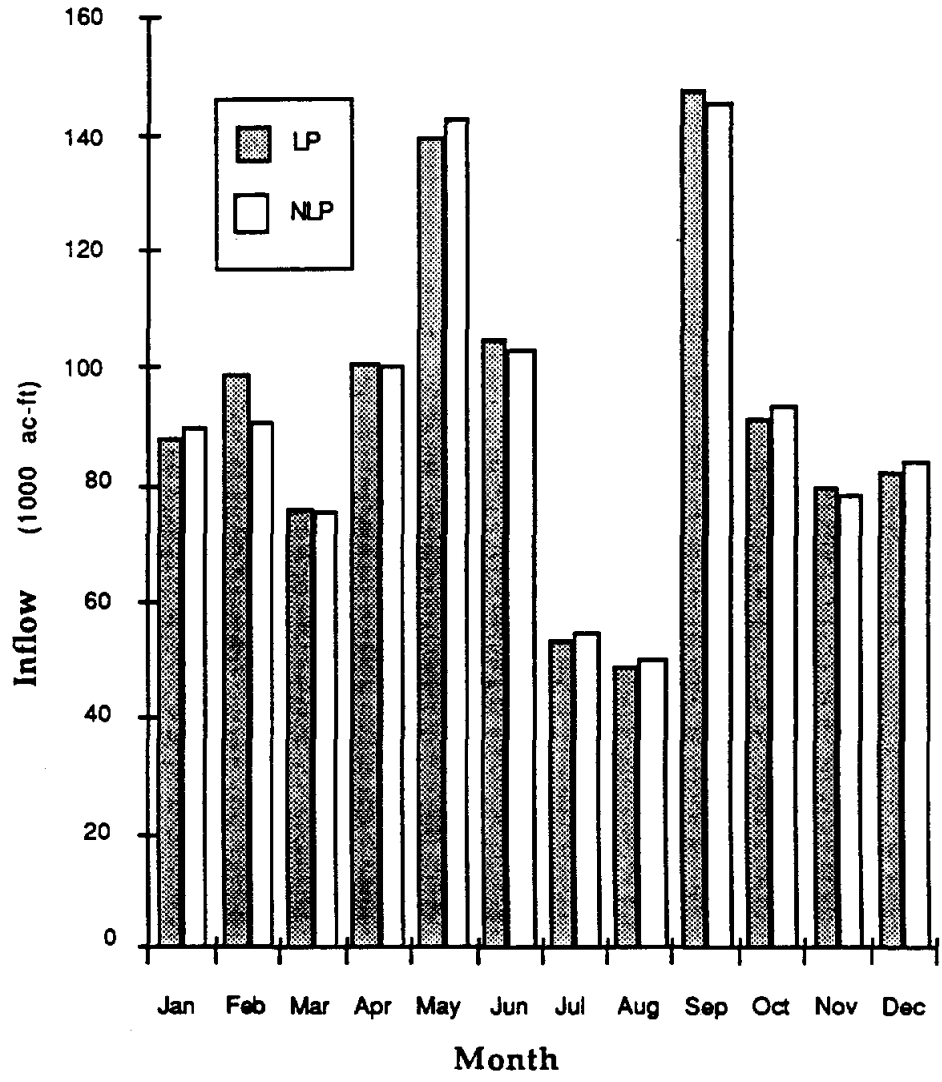


Figure 4.4 Comparsion of Colorado Gaged Inflows between LP and NLP Models under Alternative I (w/o Chance-Constraint)

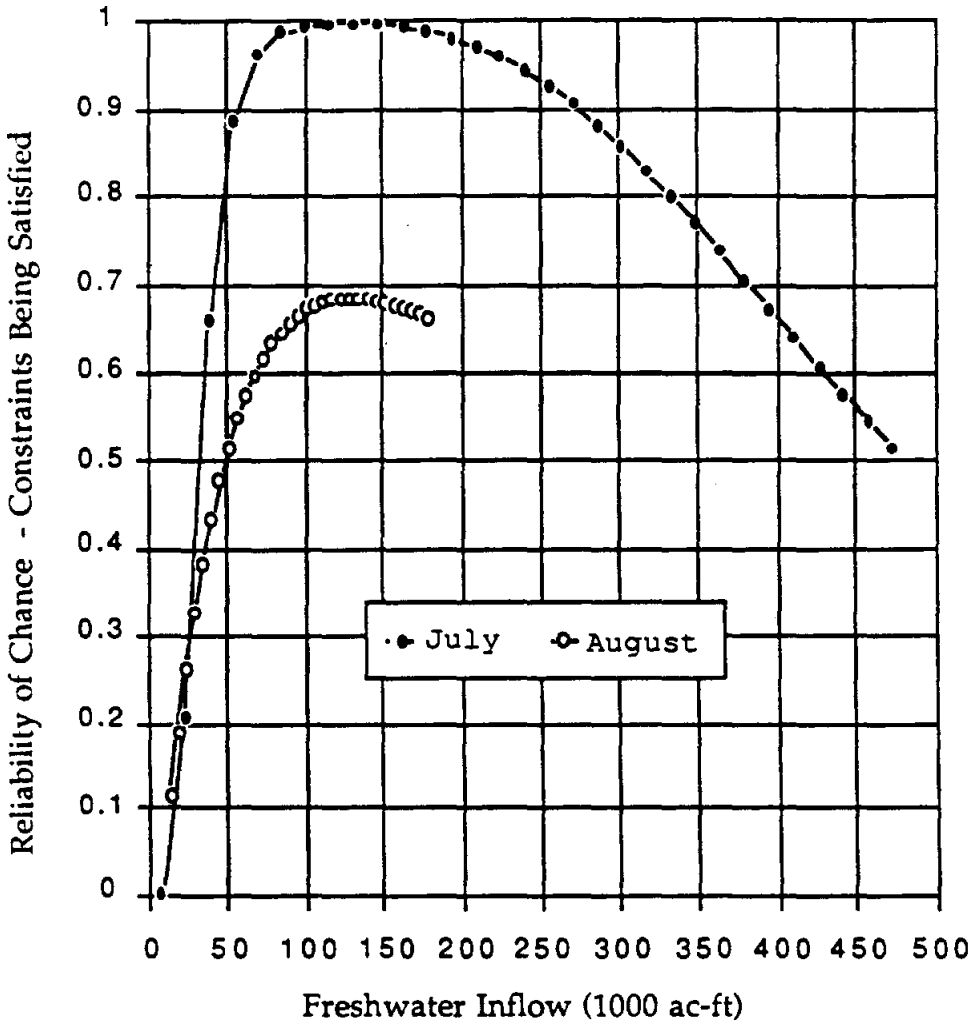


Figure 4.5 Reliability of Salinity Chance-constraint for Colorado River Monthly Inflow

(Alternatives I & IV, Using Type 1 Salinity Bounds)

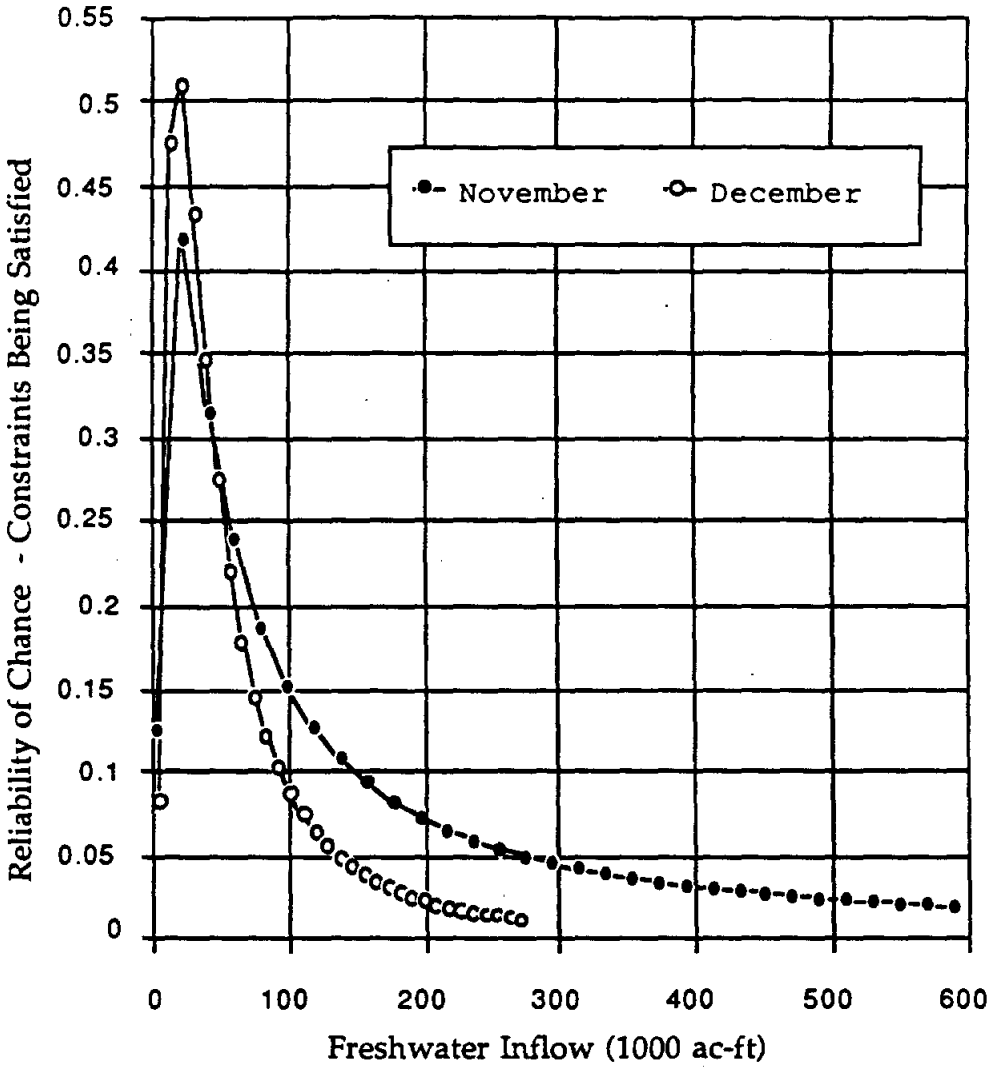


Figure 4.6 Reliability of Salinity Chance-constraint for Lavaca River Monthly Inflow

(Alternative IV, Using Type 1 Salinity Bounds)

months i and rivers j. For the purpose of simplicity, for each river, all twelve monthly salinity chance-constraints use the same desired reliability. Hence, p_{ij} is replaced by p_j. In general, the reliabilities of salinity chance-constraints increase as the inflow needs increase. As shown in the figures, there exists a maximum reachable reliability in the feasible inflow range considered. The value of the maximum achievable reliability of salinity constraints depends on the variance of the data about the regression line and the salinity limits. Once the reliability reaches its maximum achievable value, additional water releases from rivers into bays will result in a decrease in the probability of the salinity constraints being satisfied. The results of field observations and previous modeling studies suggest that the Lavaca delta marsh is most important of the peripheral marshes to the Matagorda Bay (Texas Department of Water Resources, 1980), therefore the marsh inundation requirement was imposed on Lavaca River flow in Alternative I. Since the Colorado is unaffected by this, the resulting freshwater inflow needs for the Colorado River in Alternatives I and IV are the same.

For Alternative IV, the lowest maximum achievable reliability is about 0.68 for Matagorda Bay and 0.43 for Lavaca Bay. This conclusion is true for Alternatives I, II and IV for most of the cases considered in Table 4.2. As more constraints are added into the models for other alternatives, the achievable reliability of salinity constraints for both bay regions may be significantly lower than their maximum values. This demonstrates that the information about the achievable reliabilities for the salinity constraints is so important that it should not be simply ignored. The achievable salinity reliability reflects some "confidence level" for the solution of optimal inflows. The low value of the maximum achievable reliability for Lavaca Bay is the result of the high standard error of the estimate, i.e. the low coefficient of determination (r^2), in the Lavaca salinity regression equations, in combination with the narrow salinity limits.

Figures 4.7 and 4.8 are examples of results for Alternatives I and IV for the optimal annual freshwater inflow. The maximum achievable reliability for salinity constraints for the Lavaca River is as low as 0.12 when Type-2 salinity bounds are used. The region of Type-2 salinity bounds is so narrow, for instance for the Lavaca River in July, the lower and upper bounds of

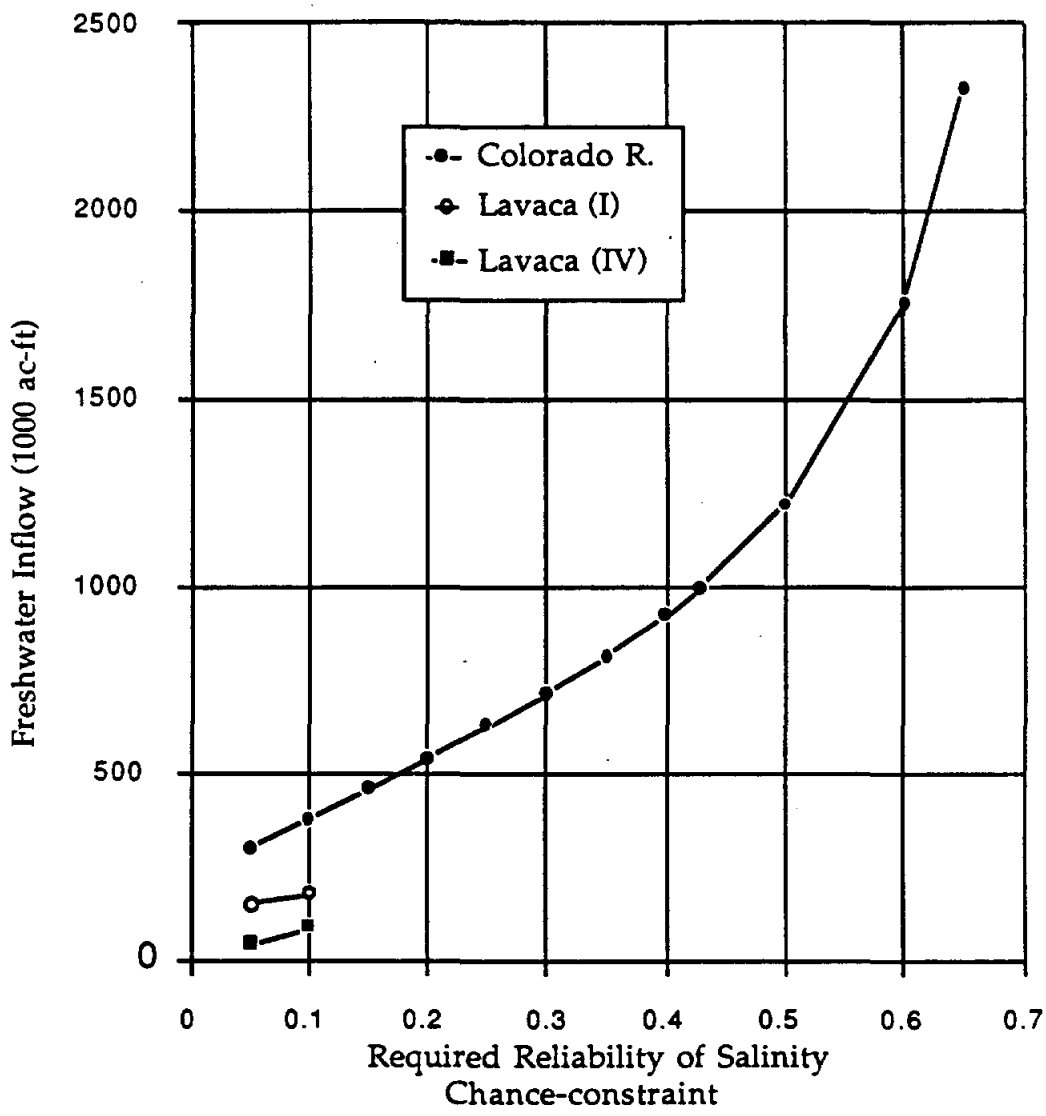


Figure 4.7 Comparison of Optimal Annual Inflows for Alternatives I & IV
(Using Type 2 Salinity Bounds)

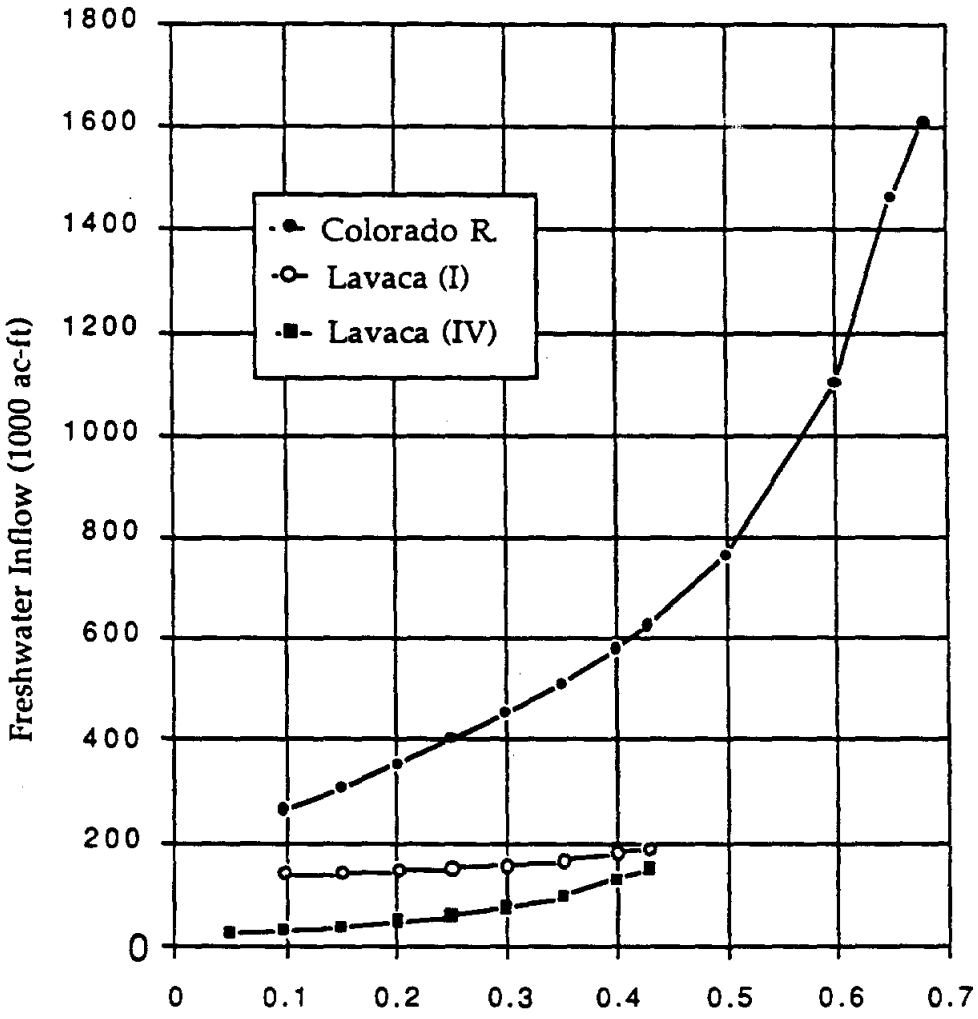


Figure 4.8 Comparison of Optimal Annual Inflows for Alternatives I & IV

(Using Type 1 Salinity Bounds)

salinity are 10 and 11 ppt, respectively, that the program will be terminated without feasible solutions when the desired reliability is greater than 0.10. Type-1 salinity bounds are wider, being based on the estimate of the limits of long-term viable species activity; however, the maximum achievable desired reliability of salinity chance-constraint is also very low about 0.43.

As expected, the optimal freshwater inflow increases as the desired reliability, p_j, increases. Although the maximum achievable reliability for salinity constraints for the Lavaca Bay is low, the achieved salinity reliability will increase from 0.10 to 0.43 for a 33% increase in freshwater inflow (46.85 thousand acre-foot). For the Colorado River, the same increase in achieved salinity reliability requires a much higher freshwater inflow.

Because the marsh inundation requirement needs more water during the time period of April through June, and October through January for the Lavaca Bay (case 2), the Alternative I yields higher inflows from the Lavaca River into Lavaca Bay, compared to Alternative IV. Such a difference in optimal freshwater inflows for Alternatives I and IV becomes smaller when the desired reliability increases. If the salinity bounds were relaxed further, when the desired probability increased to a certain value, the marsh inundation constraints would be inactive. Therefore, the optimal inflows for Alternatives I and IV would be the same.

Figure 4.9 shows an example of results from Alternative II, in which the required reliability of salinity constraints is fixed while the required harvest reliability varies for each computer run. For a given reliability of salinity constraints, the minimum annual freshwater inflow increases almost linearly with the required reliability of harvest constraint. We note that the optimal annual inflow is much higher than that of Alternative I, due to the further restriction of harvest constraints. As before, the optimal annual freshwater inflow increases as the required reliability of harvest chance-constraint increases. Because both salinity and harvest constraints are involved in Alternative II, the relationship between the freshwater inflow and the required reliability of chance-constraints is more complicated than in Alternative I.

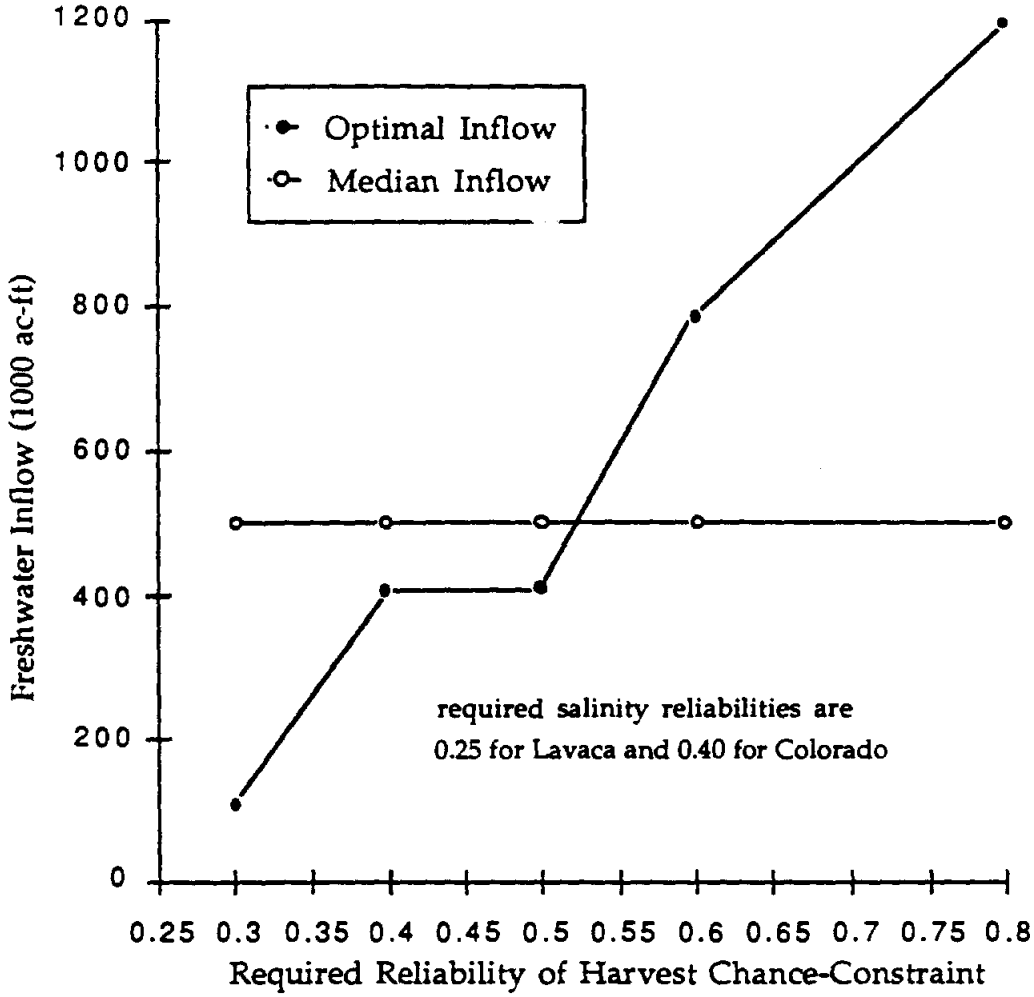


Figure 4.9 Optimal Annual Inflows of Lavaca R. using 12 Monthly Salinity Eqs. under Alternative II

(Using Type 1 Salinity Bounds)

4. 4 CONCLUSIONS

From the application of the models for Alternatives I, II, and IV to the Lavaca-Tres Palacios Estuary in Texas, the conclusions may be summarized:

(1) The developed nonlinear chance-constrained estuarine models compute not only the minimum required freshwater inflows but also the achievable reliabilities for salinity and harvest constraints. The latter plays an important role in estuarine management, since it is a synthesized term reflecting the combined effect of uncertainty in regression equations, range of salinity bounds, and possibly other types of constraints.

(2) The optimal annual freshwater inflow increases as the required reliabilities of salinity and/or harvest chance-constraints are increased. This has important implications for freshwater allocation to meet estuary needs.

(3) The regression equations of salinity can not explicitly represent the factors in the complicated hydrodynamic transport processes affecting salinity such as tides, winds and spatial variations in salinity. These processes contribute to the high variance about the regression, hence the large uncertainty in the dependence of salinity on inflow and the low achievable reliability. Some better approaches other than the use of salinity regression equations in this estuarine modeling problem are worthy of exploring.

(4) The model developed in this study can in principle be extended to consider the multiobjective nature of the problem.

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APPENDIX A

DERIVATION OF DETERMINISTIC EQUIVALENT OF CHANCE-CONSTRAINTS BASED ON REGRESSION EQUATIONS

In order to transform the chance-constraints (12) and (13) into their deterministic equivalent forms, first consider a general multiple linear regression model,

$$Y = \underline{X}^T \underline{\beta} + \varepsilon \qquad (A.1)$$

where Y is the dependent variable; $\underline{X}$ is a v x 1 column vector of independent variables, $\{1, x_1, x_2, \ldots, x_{v-1}\}^T$; $\underline{\beta}$ is a v x 1 column vector of regression parameters, $\{\beta_0, \beta_1, \beta_2, \ldots, \beta_{v-1}\}^T$; ε is the model error with $E(\varepsilon) = 0$, and $Var(\varepsilon) = \sigma^2$. Because ε is a random variable, the true value of Y and the coefficients of regression equation, $\underline{\beta}$, are never known. Replacing the Y, $\underline{\beta}$ and ε by their estimators, the regression model becomes,

$$\hat{Y} = \underline{X}^T \hat{\underline{\beta}} + \hat{\varepsilon} \qquad (A.2)$$

For a given set of independent variables, $\underline{x}_0$, the corresponding dependent variable Y_0 can be estimated as,

$$\hat{Y}_0 = \underline{x}_0^T \hat{\underline{\beta}} \qquad (A.3)$$

with the associated mean

$$E(\hat{Y}_0 | \underline{x}_0) = \underline{x}_0^T \hat{\underline{\beta}}$$

and variance

$$Var(\hat{Y}_0 | \underline{x}_0) = \sigma^2 [\underline{x}_0^T (X^T X)^{-1} \underline{x}_0 + 1]$$

where X is an n x v matrix of observed data used in developing the regression equations. Replacing the unknown population variance by its estimator, the predicted variance becomes

$$\widehat{Var}\,(\hat{Y}_0|\underline{x}_0) = \hat{\sigma}^2\,[\,\underline{x}_0^T\,(X^T X)^{-1}\underline{x}_0 + 1\,]$$

Consider a chance-constraint

$$P_r\{\underline{Y} \le Y_0\} \ge p \qquad (A.4)$$

by standardizing,

$$P_r\left\{\frac{Y_0 - \hat{E}(\hat{Y}_0|\underline{x}_0)}{\sqrt{\widehat{Var}\,(\hat{Y}_0|\underline{x}_0)}} \ge \frac{\underline{Y} - \underline{x}_0^T\hat{\beta}}{\sqrt{\hat{\sigma}^2\{\underline{x}_0^T\,(X^T X)^{-1}\,\underline{x}_0 + 1\}}}\right\} \ge p$$

which can be rearranged

$$P_r\left\{T_{n-v} \le \frac{\underline{Y} - \underline{x}_0^T\hat{\beta}}{\sqrt{\hat{\sigma}^2\{\underline{x}_0^T\,(X^T X)^{-1}\,\underline{x}_0 + 1\}}}\right\} \le 1 - p \qquad (A.5)$$

Knowing the reliability p, the standard student distribution deviate can be easily computed. Hence the deterministic equivalent of the chance constraint is

$$\frac{\underline{Y} - \underline{x}_0^T\hat{\beta}}{\sqrt{\hat{\sigma}^2\{\underline{x}_0^T\,(X^T X)^{-1}\,\underline{x}_0 + 1\}}} \le t_{n-v,\,1-p}$$

or

$$t_{n-v,\,1-p}\,\hat{\sigma}\sqrt{\{\underline{x}_0^T\,(X^T X)^{-1}\,\underline{x}_0 + 1\}} + \underline{x}_0^T\hat{\beta} \le \underline{Y} \qquad (A.6)$$

with n-v degree of freedom, and probability of 1-p.

Consider the case that the constraint is bounded on both sides:

$$P_r\{\underline{Y} \le Y_0 \le \overline{Y}\} \ge p$$

then

$$F_{T,n-v}\left[\frac{\overline{Y} - \underline{x}_0^T\hat{\underline{\beta}}}{\hat{\sigma}\sqrt{\{\underline{x}_0^T(X^TX)^{-1}\underline{x}_0+1\}}}\right] - F_{T,n-v}\left[\frac{\underline{Y} - \underline{x}_0^T\hat{\underline{\beta}}}{\hat{\sigma}\sqrt{\{\underline{x}_0^T(X^TX)^{-1}\underline{x}_0+1\}}}\right] \ge p \qquad (A.7)$$

However, the explicit expression of the deterministic equivalent of this type of chance-constraint can not be derived. The deterministic equivalents of the commercial harvest constraints can be obtained by substitution of the corresponding variables and parameters into equation (A.6). The salinity constraints can be written in the form of equation (A.7). The fact that this salinity constraint has only an implicit form must be considered when selecting programming algorithm.

Appendix B: Data Input Structure for ALT14 (Alternatives I and/or IV)

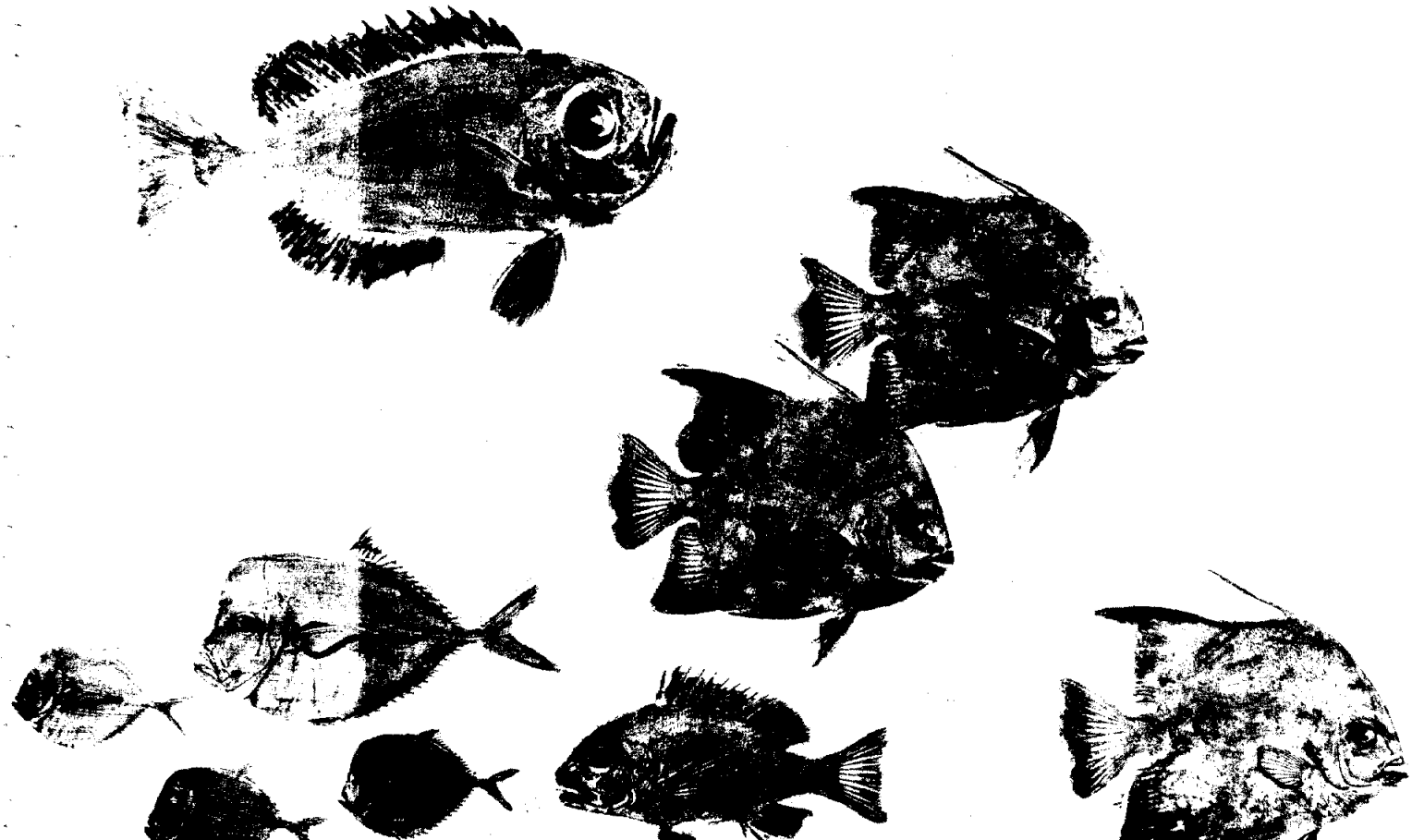
(Lavaca -Tres Palacios Estuary Management Model)

CARD	COLUMN	FORMAT	VARIABLE	VALUE	DESCRIPTION
1	1-80	5X,19A4	TTITLE		Problem specification - 1 card.
2	1-10	I10	IALT		Selection of Alternatives:
				1	for Alternative I
				4	for Alternative IV
	11-20	I10	ISOLN		The salinity constraints expressed by regression equations can be formed as chance-constraint or used in deterministic way:
				1	in chance-constraints
				2	using as deterministic constraints.
	21-30	I10	ISUB		Type of salinity constraint bounds
				1	for Type 1 salinity bounds to be used
				2	for Type 2 salinity bounds to be used.
3	1-80	F10.0	EPS		Convergence criterion of inflow in searching for the maximum reachable reliability of salinity constraints to be satisfied.
4	1-10	F10.0	RELIS		Monthly salinity reliability requirement for Lavaca river, up to 12 values on 2 cards.
5	1-10	F10.0	RELIS		Monthly salinity reliability requirement for Colorado river, up to 12 values on 2 cards.

FINAL REPORT

Data Synthesis and Analysis

Nitrogen Processes Study (NIPS)



FINAL REPORT

Data Synthesis and Analysis

Nitrogen Processes Study (NIPS)

Nutrient Distributions and Dynamics in Lavaca, San Antonio and Nueces/Corpus Christi Bays in Relation to Freshwater Inflow

Part III: Data Plots

by

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Environmental Systems Section

Texas Water Development Board

P. O. Box 13231 Capitol Station

Austin, Texas 78711-3231

December 1989

The University of Texas Marine Science Institute

Technical Report No. TR/89-007

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In response to House Bill 2 (1985) and Senate Bill 683(1987), as enacted by the Texas Legislature, the Texas Parks and Wildlife Department and the texas Water Development Board must maintain a continuous data collection and analytical study program on the effects of and needs for freshwater inflow to the State's bays and estuaries. As part of the mandated study program. This research project was funded through the Board's Water Research and Planning Fund, authorized under Texas Water Code Sections 15.402 and 16.058(e), and administered by the Department under interagency cooperative contract Nos. 9-483-705, 9-483-706, and 8-483-607.

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Property - Property Plots - San Antonio Bay
Nitrate - Salinity (November 1986 - July 1988)
Nitrate - Chlorophyll (November 1986 - July 1988)

Property - Property Plots - Nueces/Corpus Christi Bay
Nitrate - Salinity (September 1987 - August 1988)
Nitrate - Chlorophyll (September 1987 - August 1988)

INTRODUCTION

This volume contains time series data plots obtained on experimental stations during intensive process oriented samplings. Suitable shipboard space was not available during the initial phase of NIPS-I in San Antonio Bay so the temporal resolution was relatively poor. Later samplings at station locations A and C improved to hourly samples for as long as 24 hours, however sites B and D were still sampled by small boat so darkness an d inclement weather prevented some collections. Better ship availability reduced these problems during NIPS-II in Nueces/Corpus Christi Bays. Additional details of sampling and analysis methods are given in Volume 1 of this report and tabular listings are contained in Part III.

The other parts of this final report are:

Part I - Results and Discussion

Parts II - Hydrography, Nutrient and Chlorophyll data Tables

STA	DATE m	TIME local	LAT N	LON W	TEMP °C	SAL ppt	SIGMA-t density

NO3 µmole/1	NO2 µmole/1	NH4 µmole/1	PO4 µmole/1	SIO4 µmole/1	Chl a ug/l1	Phaeo ug/l	Oxygen ppm

Secchi cm	Trans percent	Depth m

Note: Salinity was measured with several often simultaneous techniques. Each type is listed separately in the data tables under the following classifications.

Sal-C This is an *in situ* measurement of conductivity from the model 4000 Hydrolab which is corrected to 25°C. The conductivity was then converted to salinity using the practical salinity scale.

Sal-CTD This is an *in situ* measurement of conductivity from the Seabird model Seacat which is a new high precision instrument (0.003 ppt). Salinity is then calculated as a function of depth (pressure) and temperature.

Sal-R This is salinity as determined by a hand refractometer.

Sal-B This is salinity as determined from bottle samples that were collected in the field and returned to the lab and analyzed for conductivity ratio by the AGE Minisal salinometer. The best accuracy is about 0.0005 ppt.

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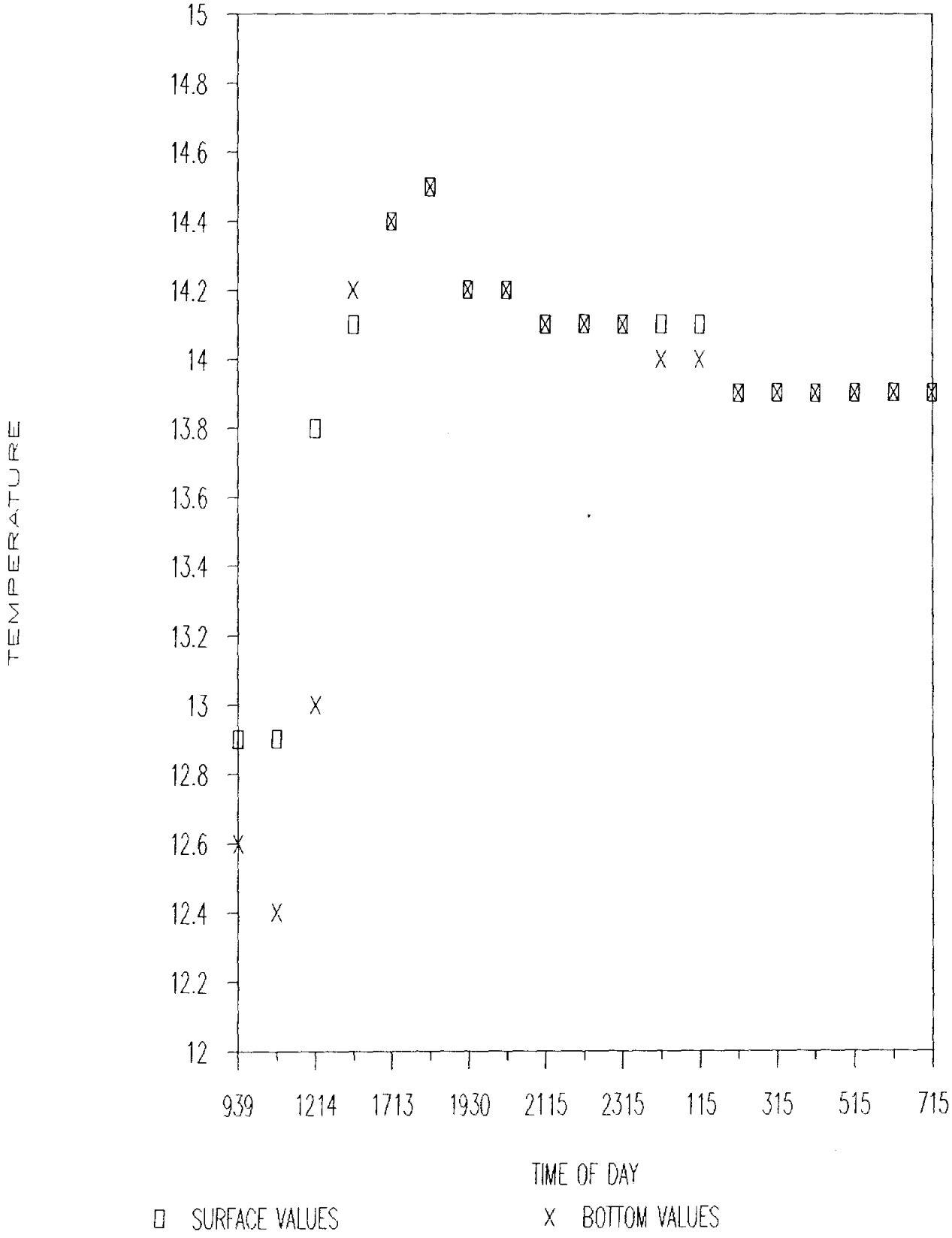

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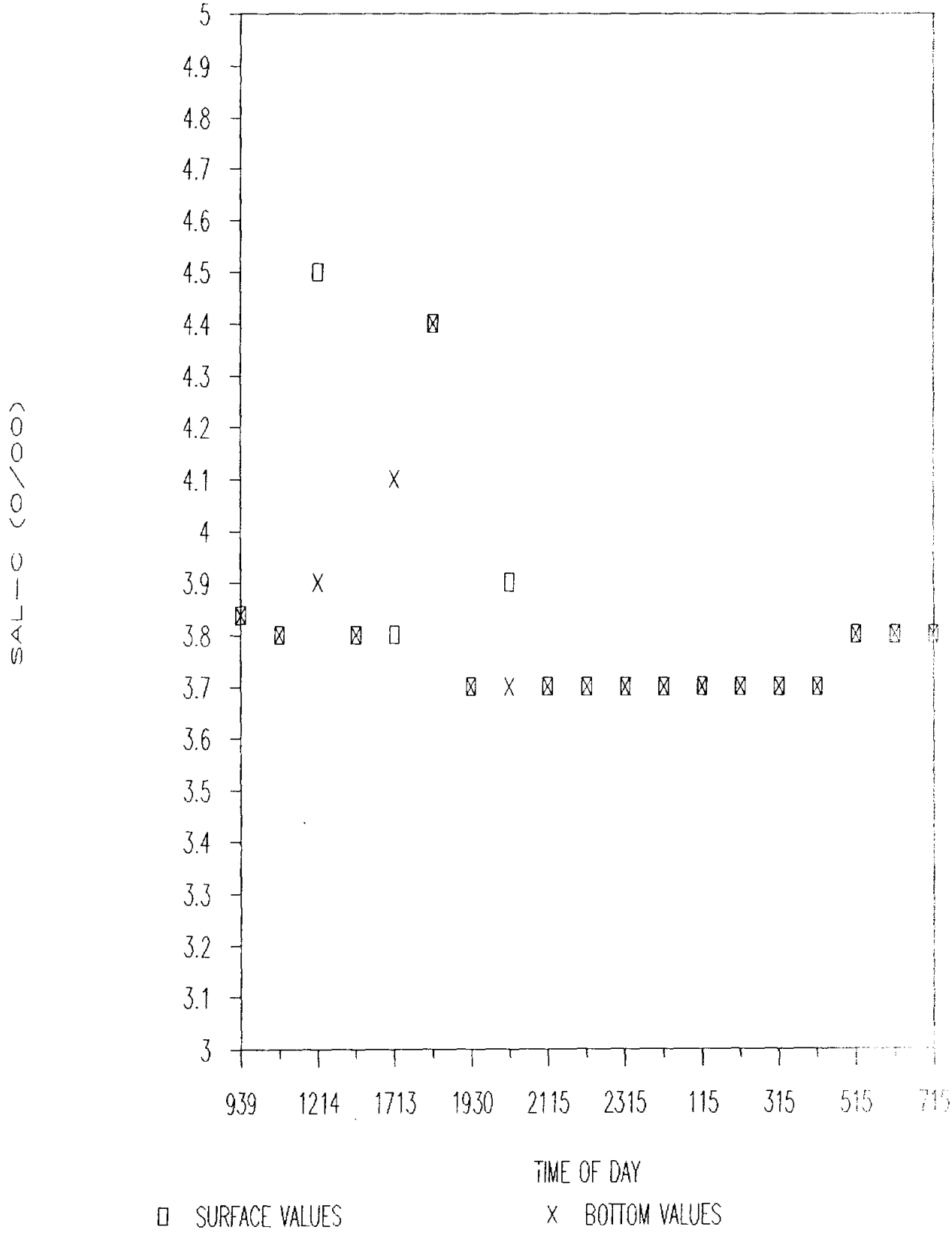

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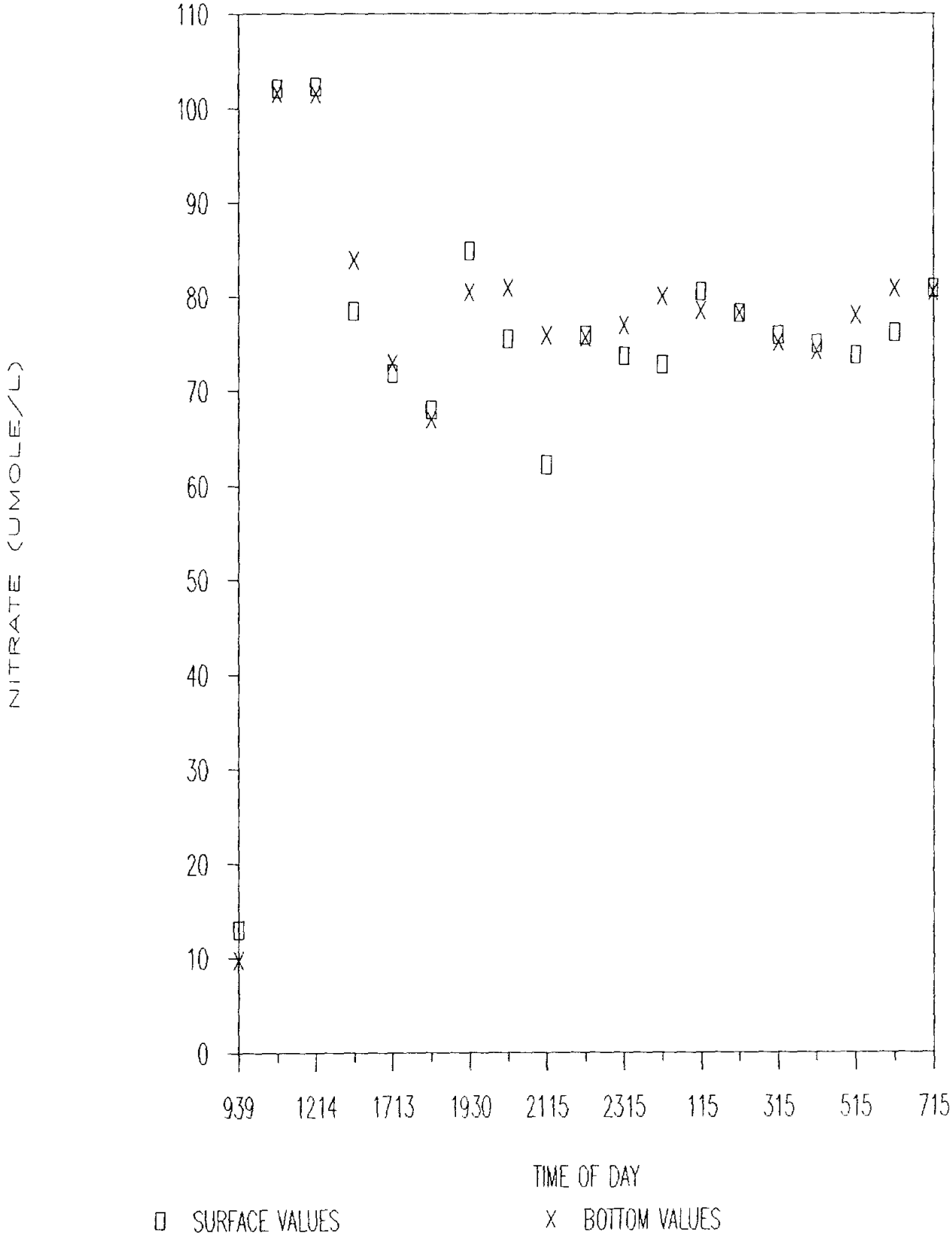

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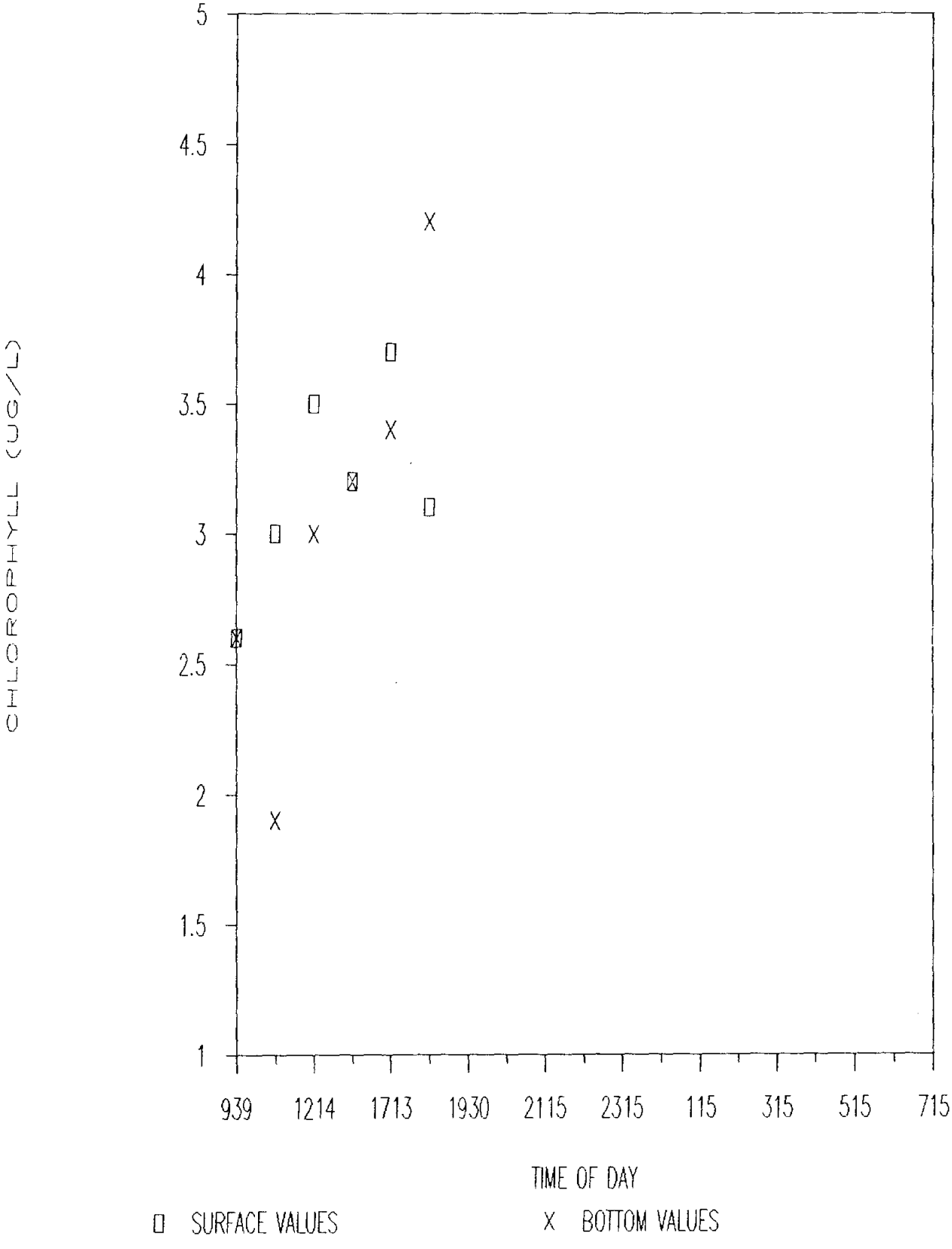

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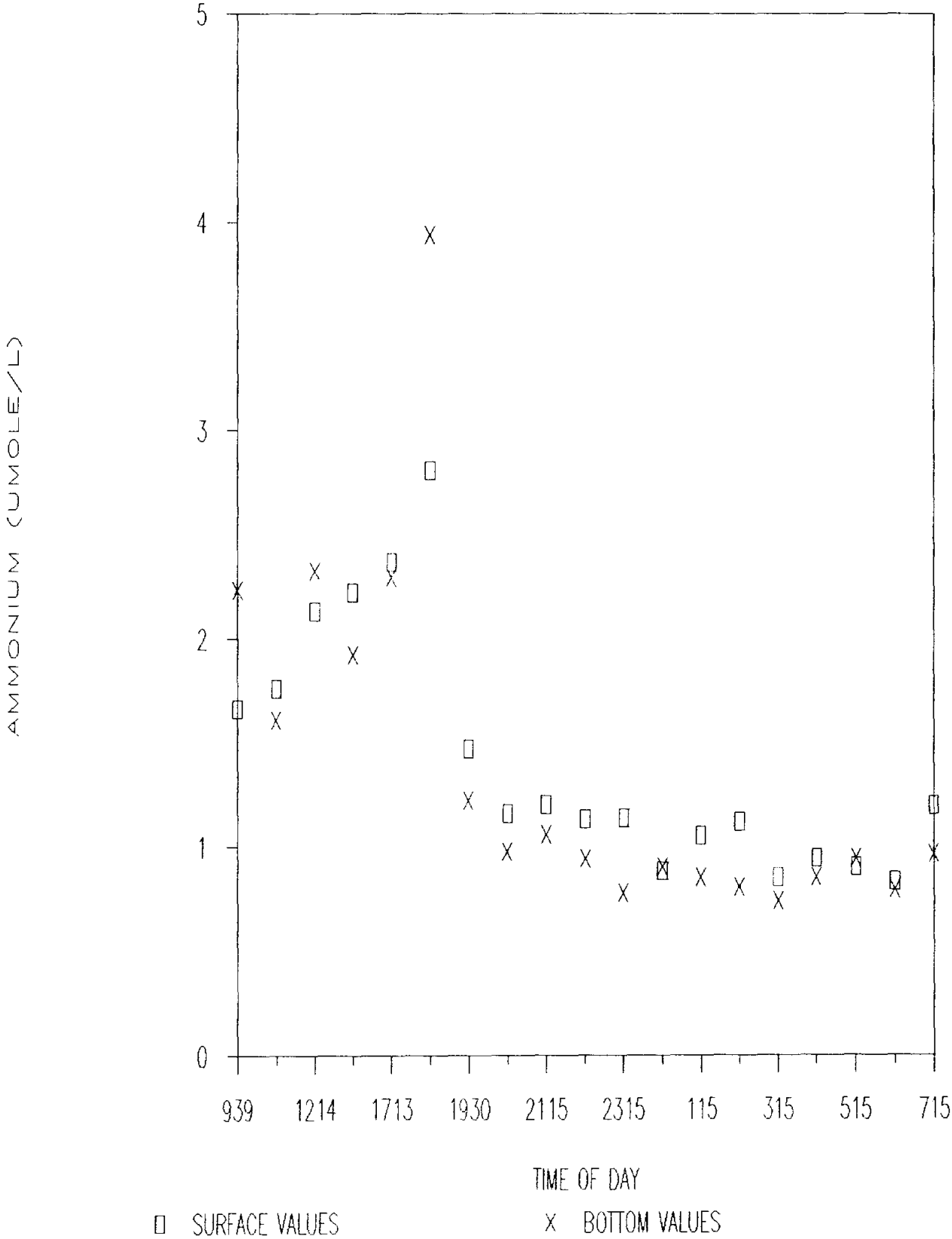

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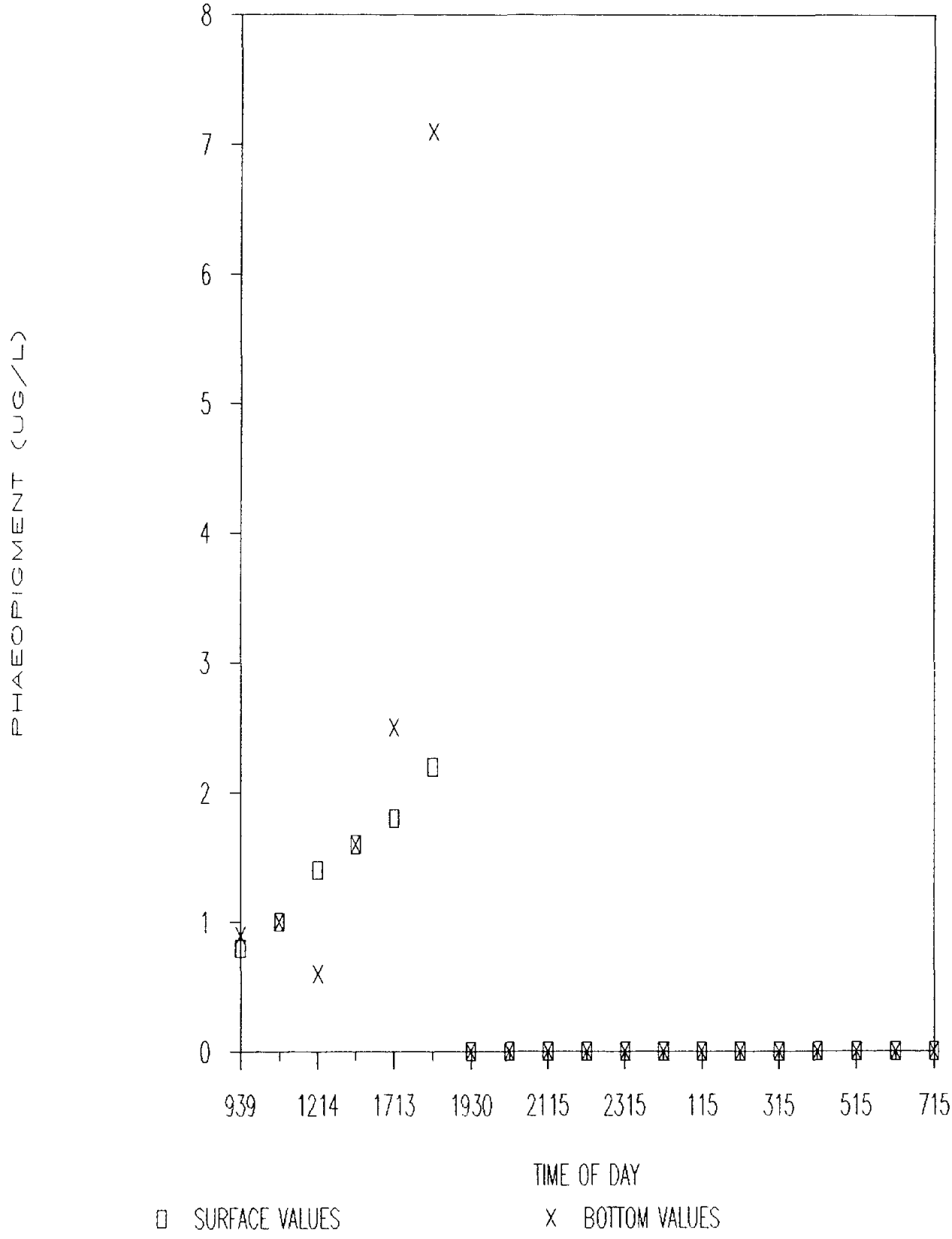

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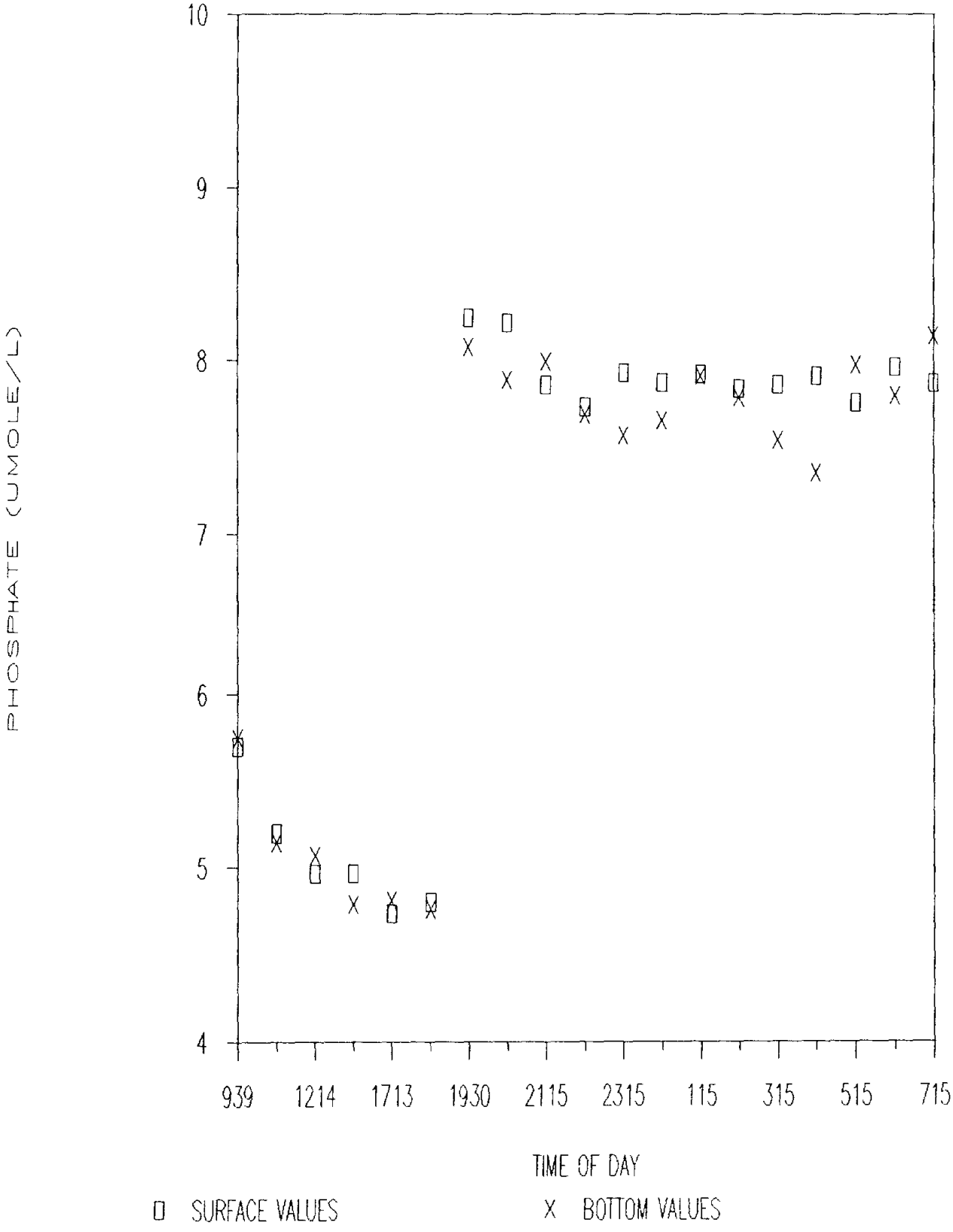

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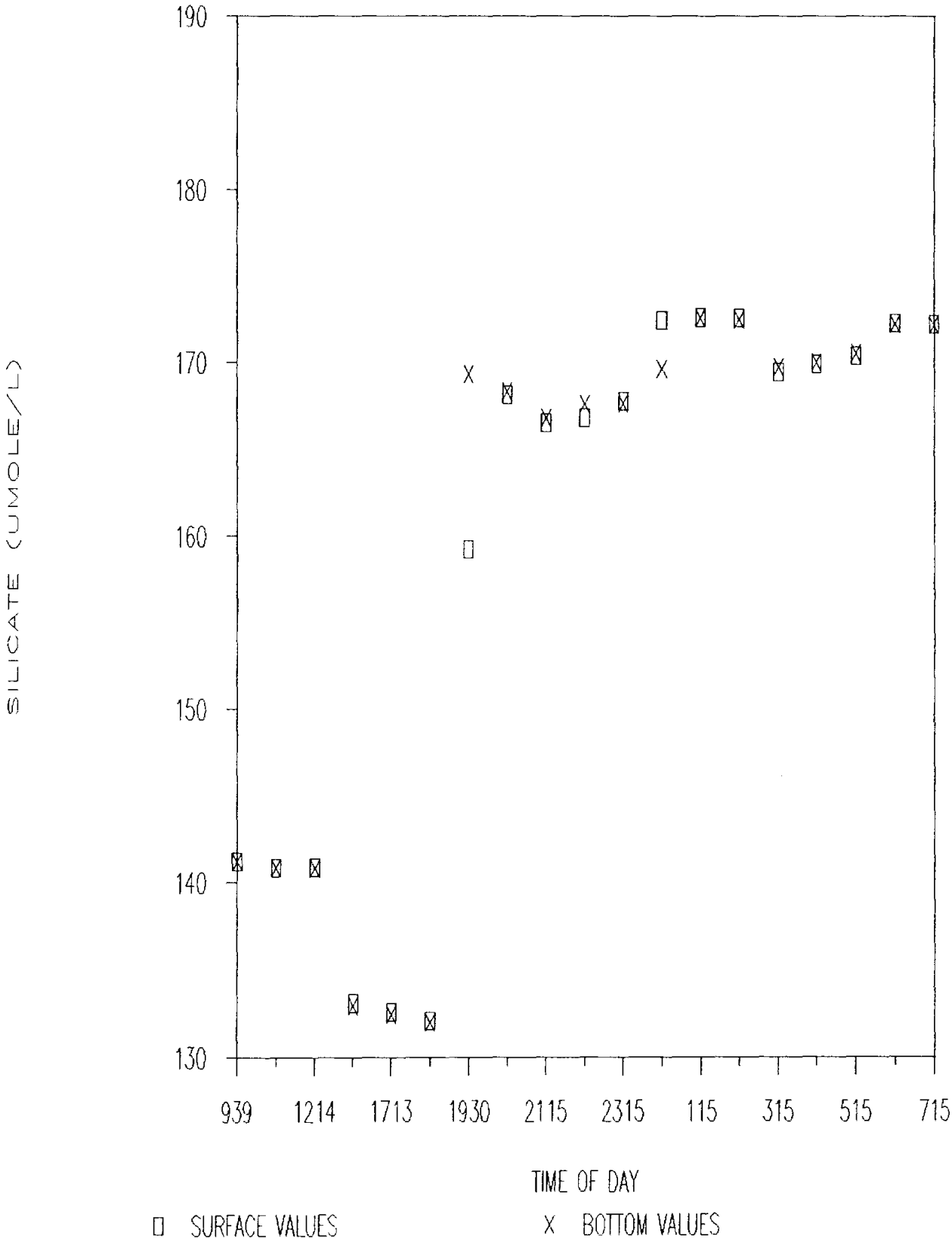

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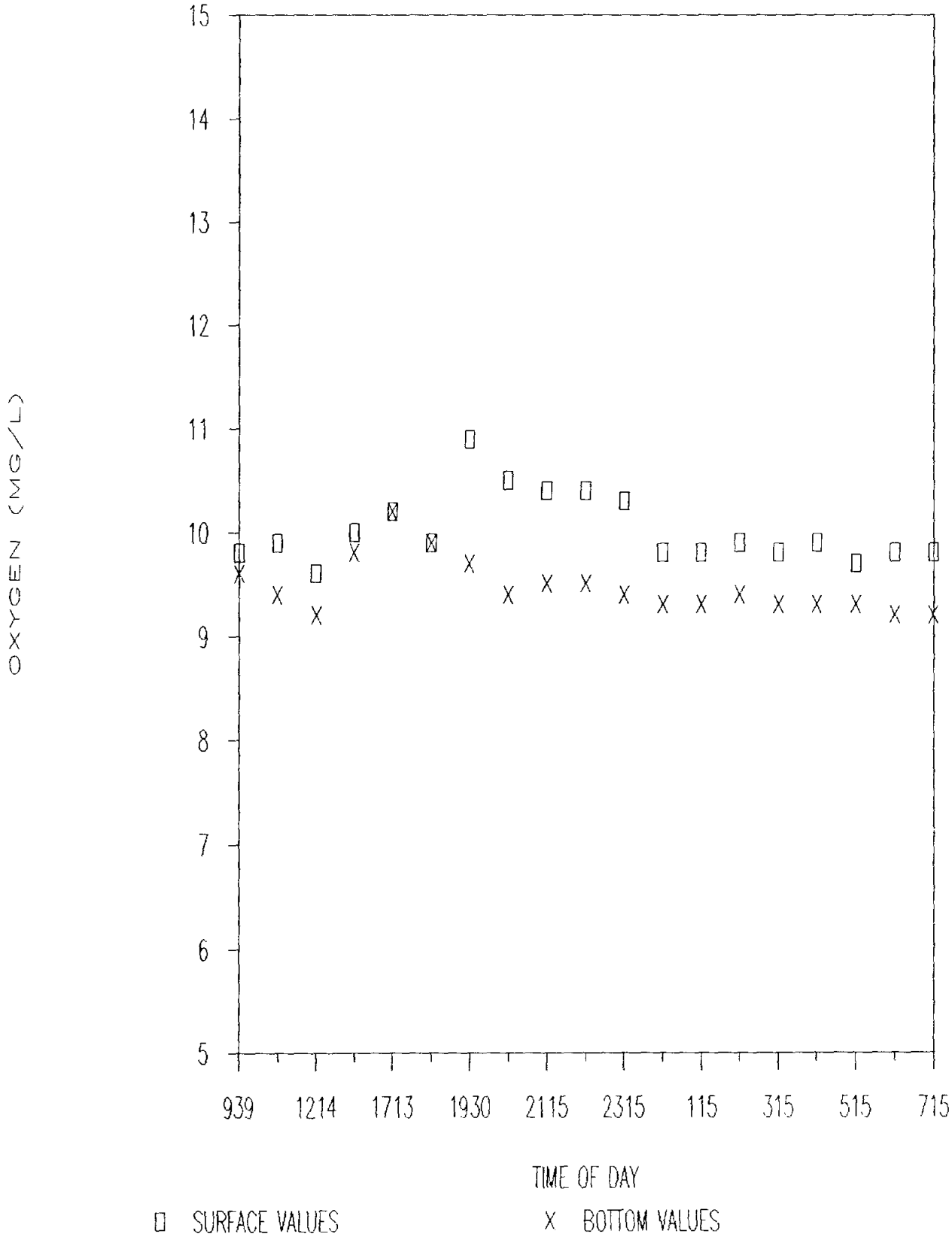

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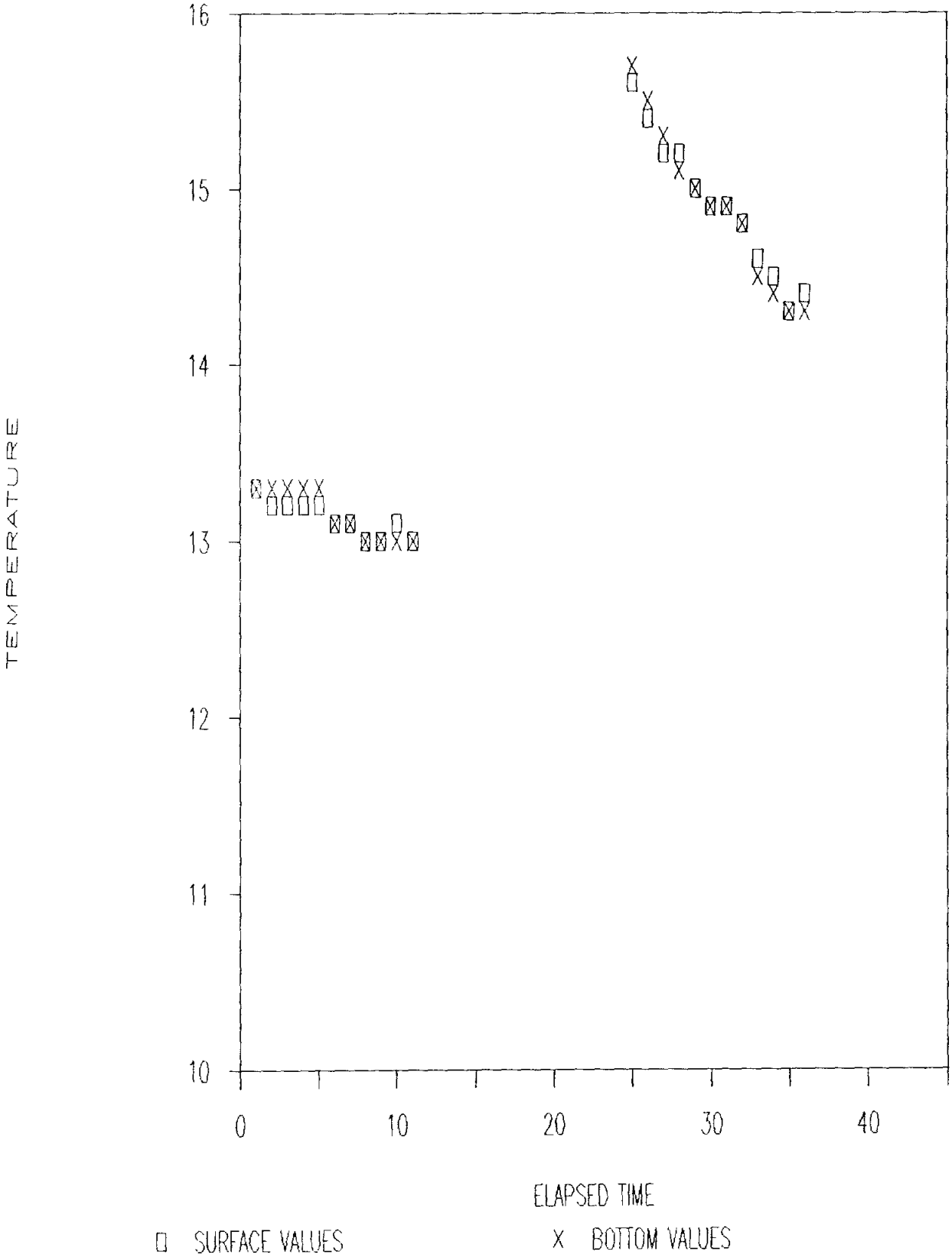

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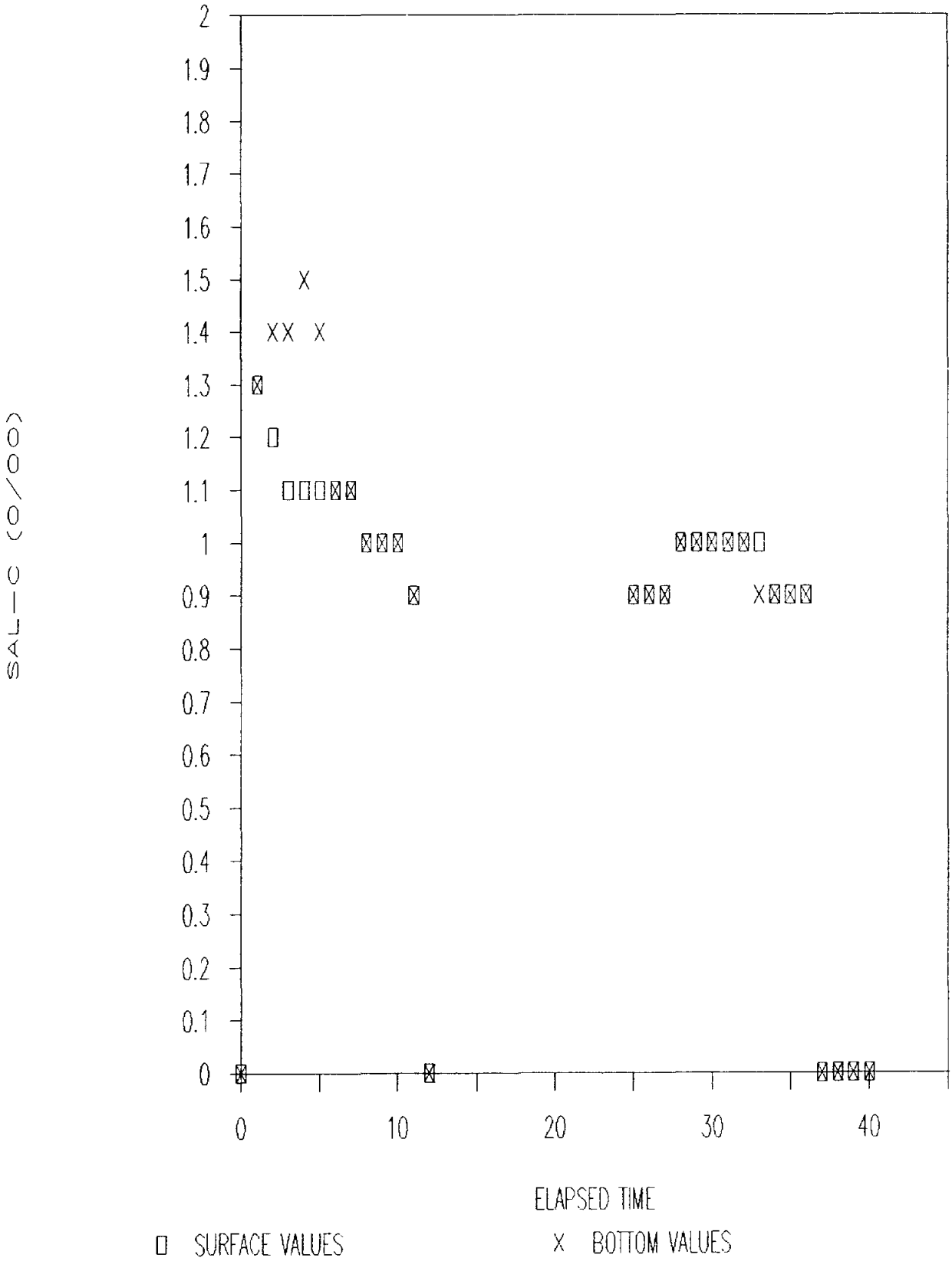

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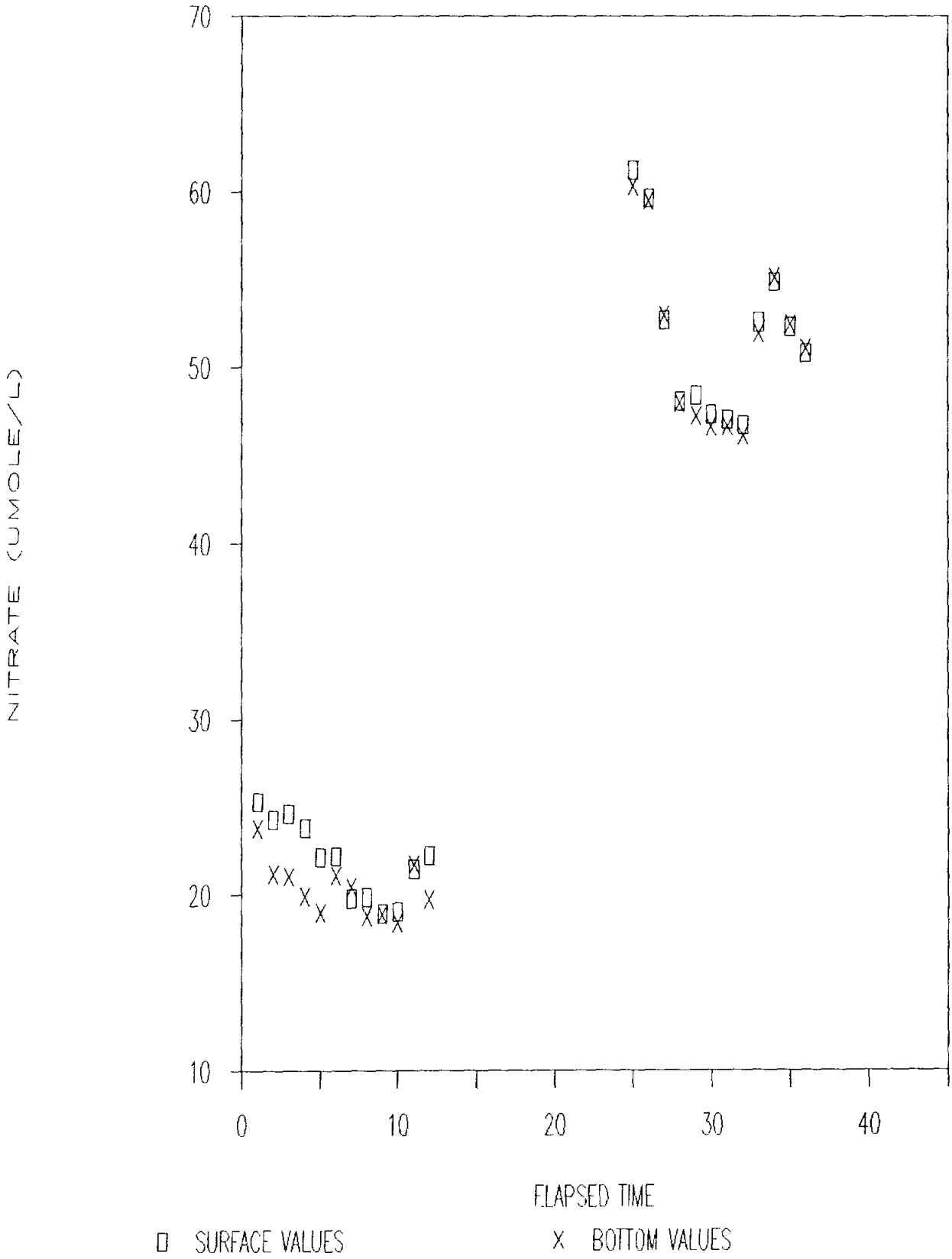

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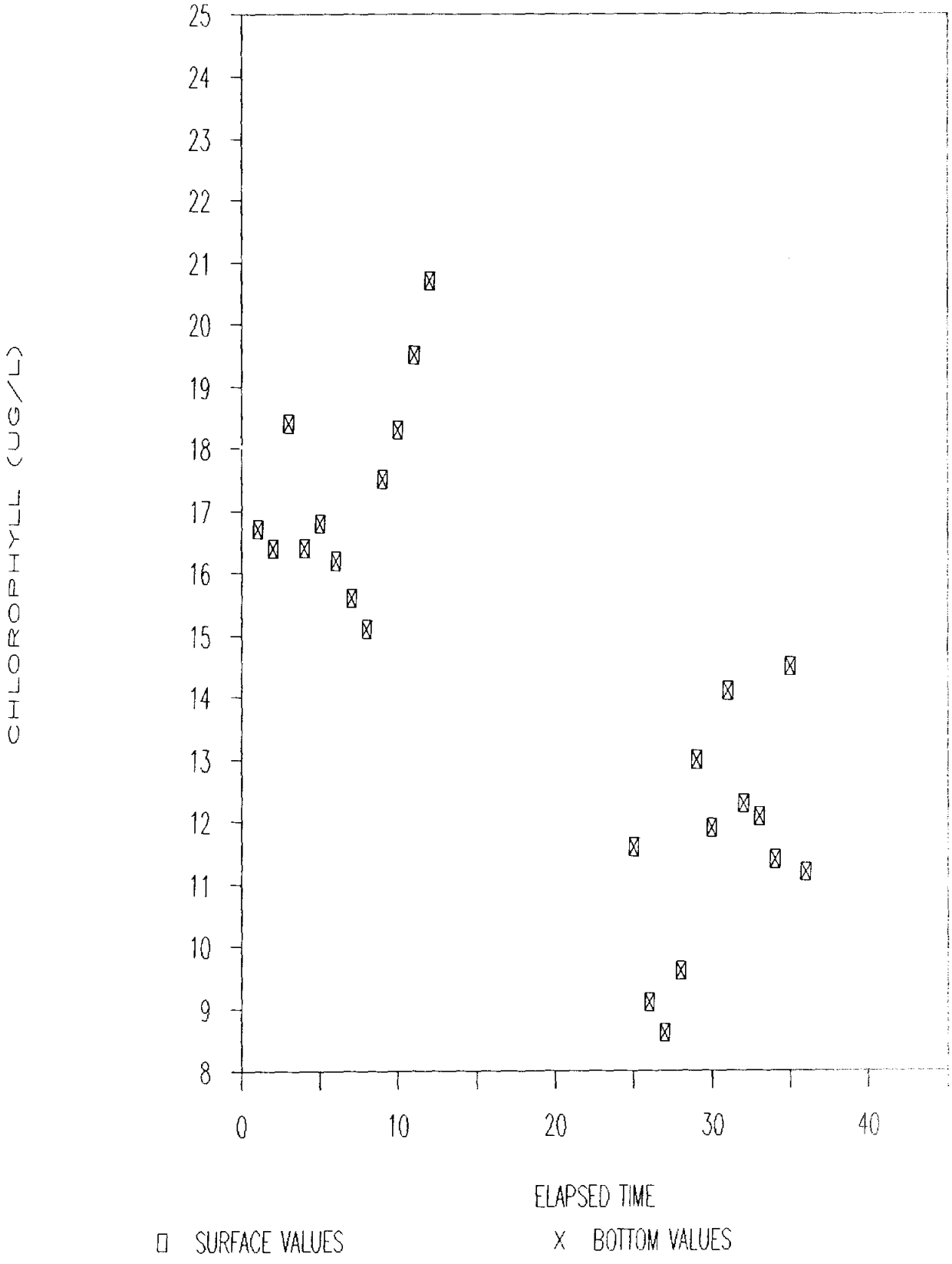

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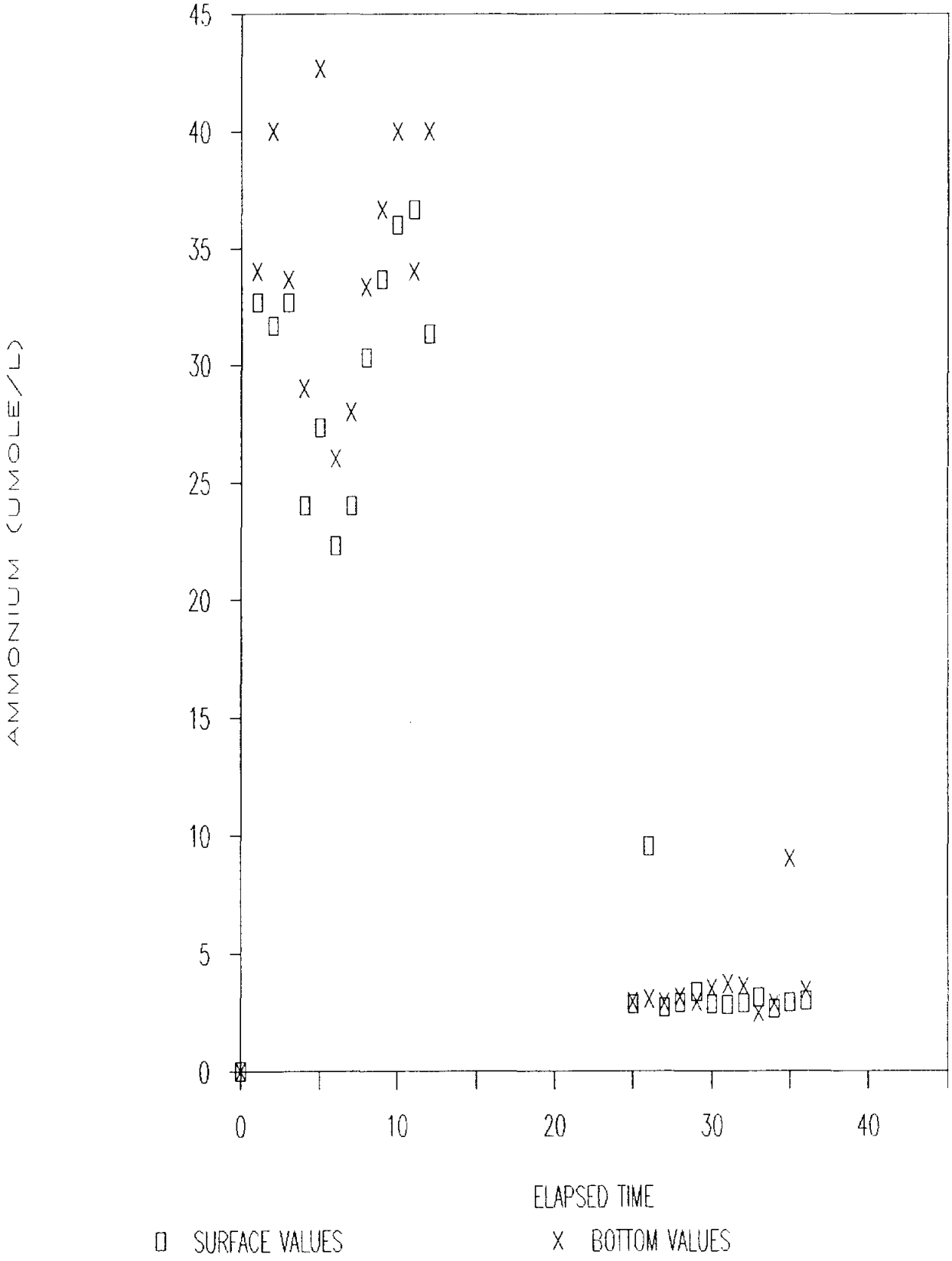

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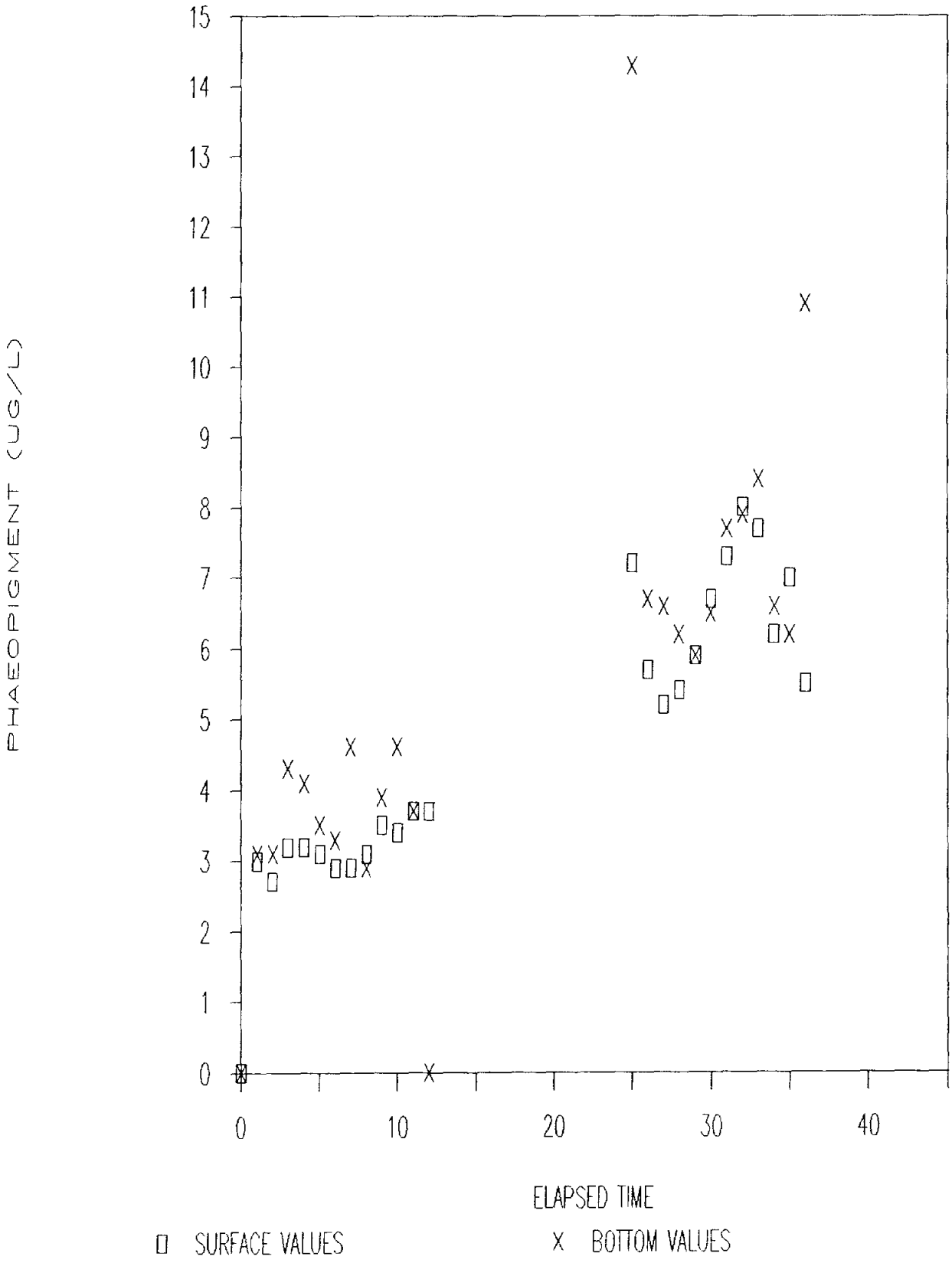

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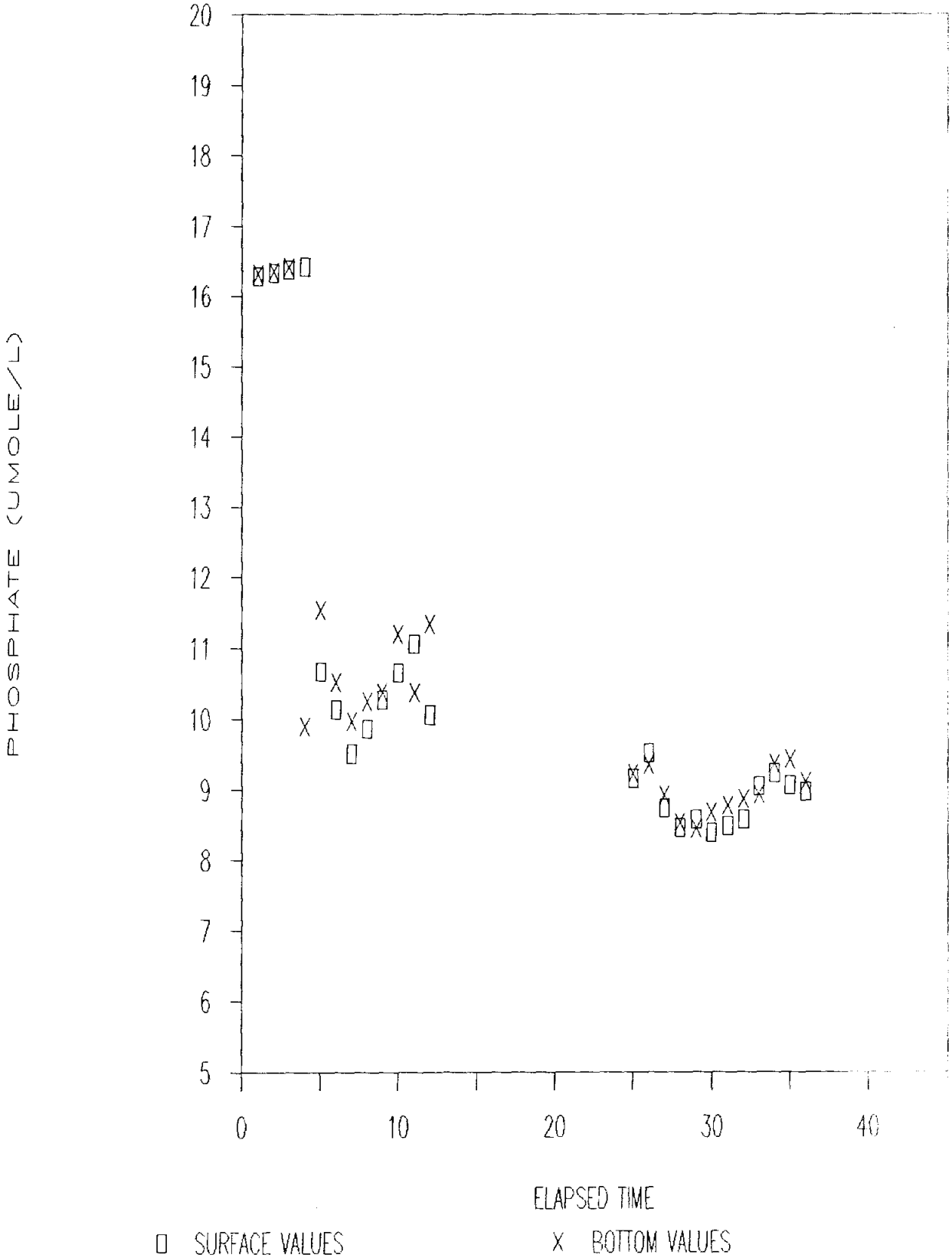

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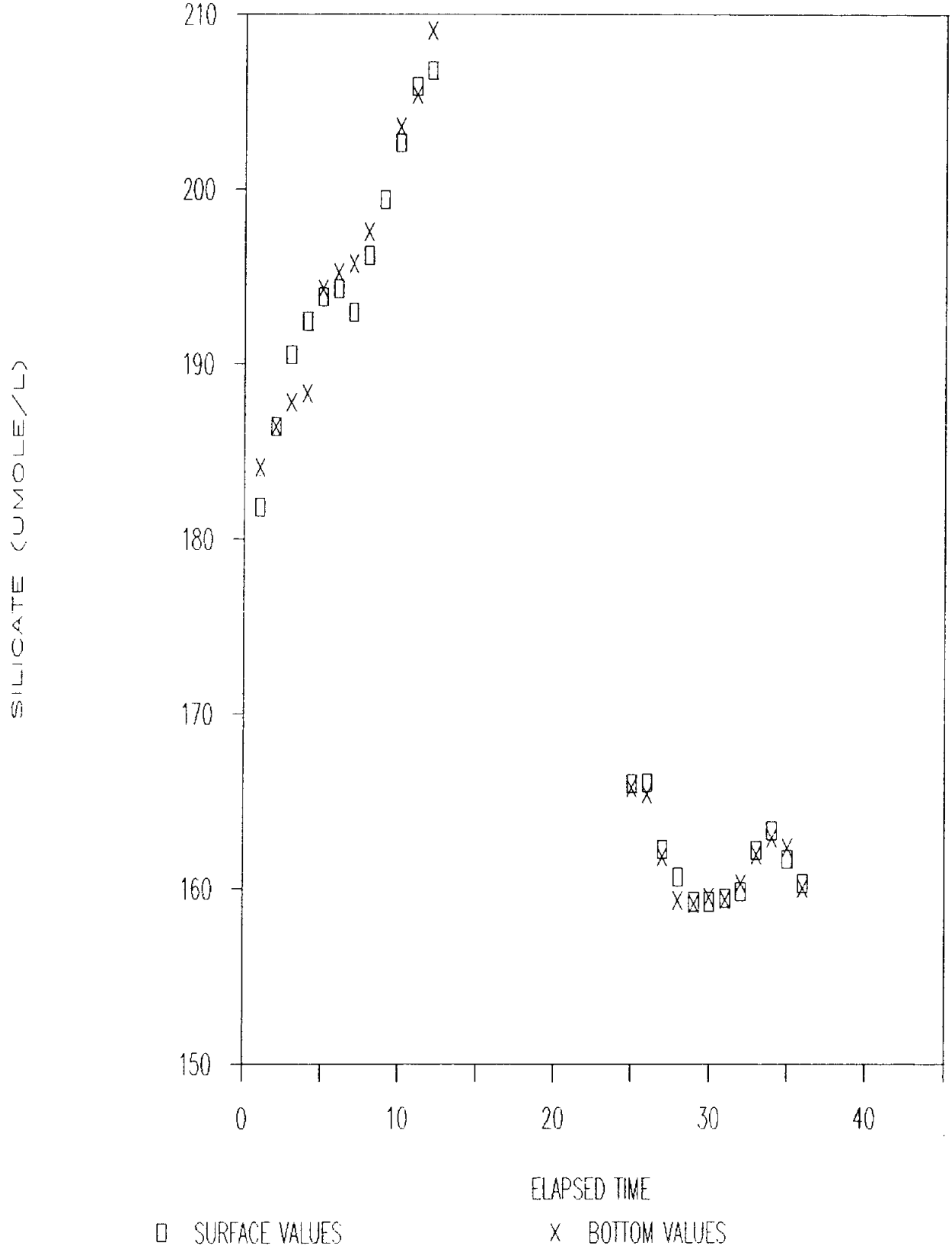

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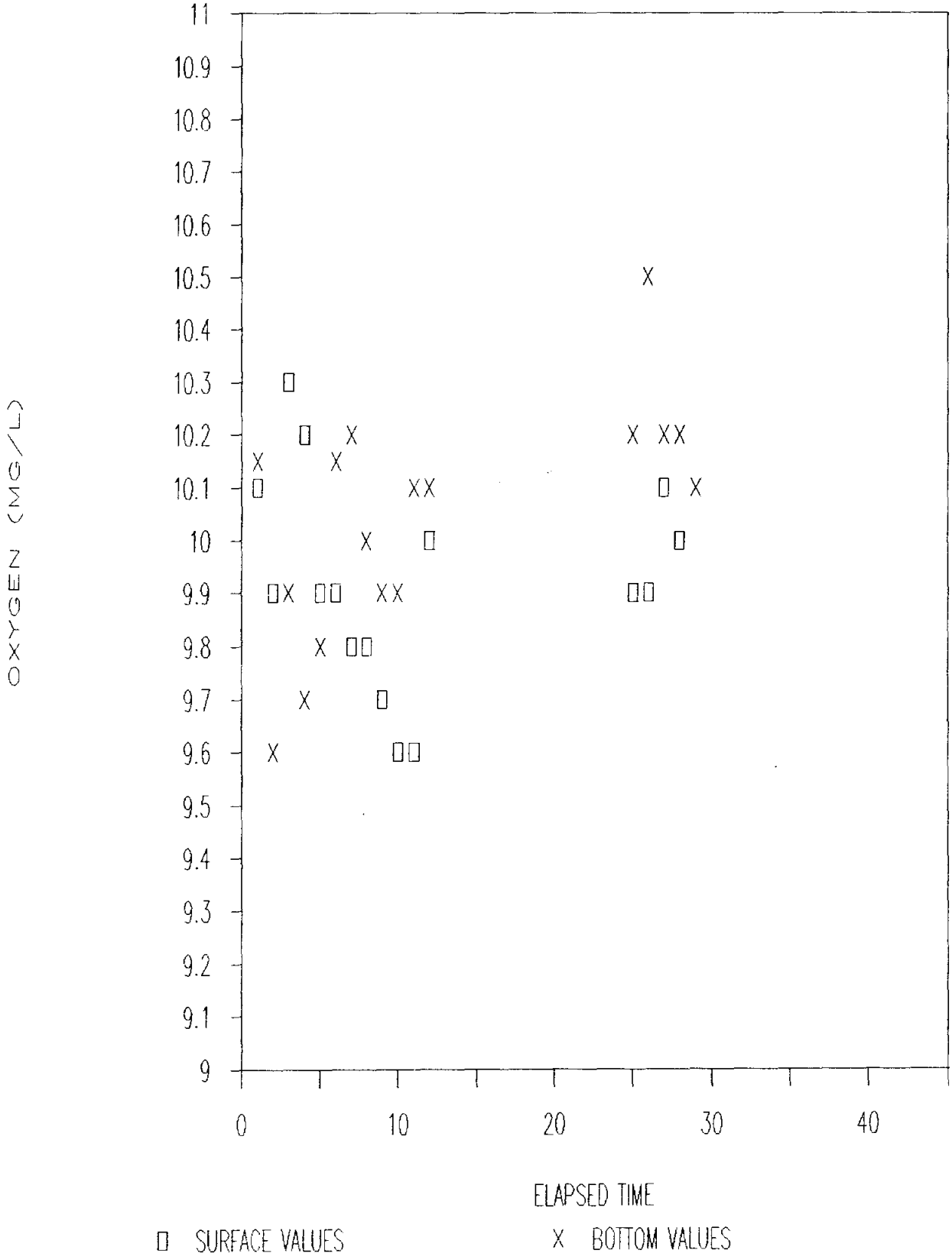

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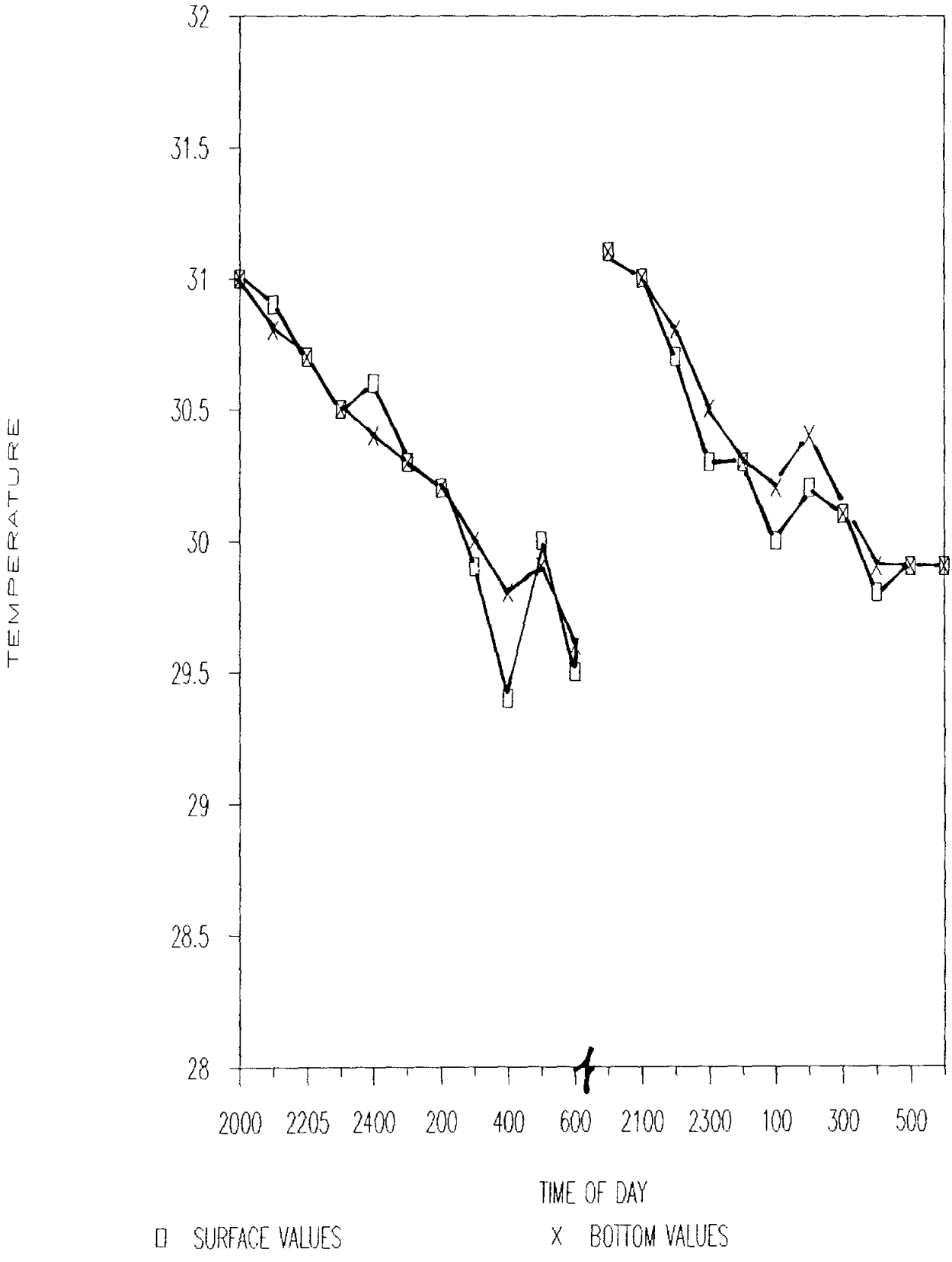

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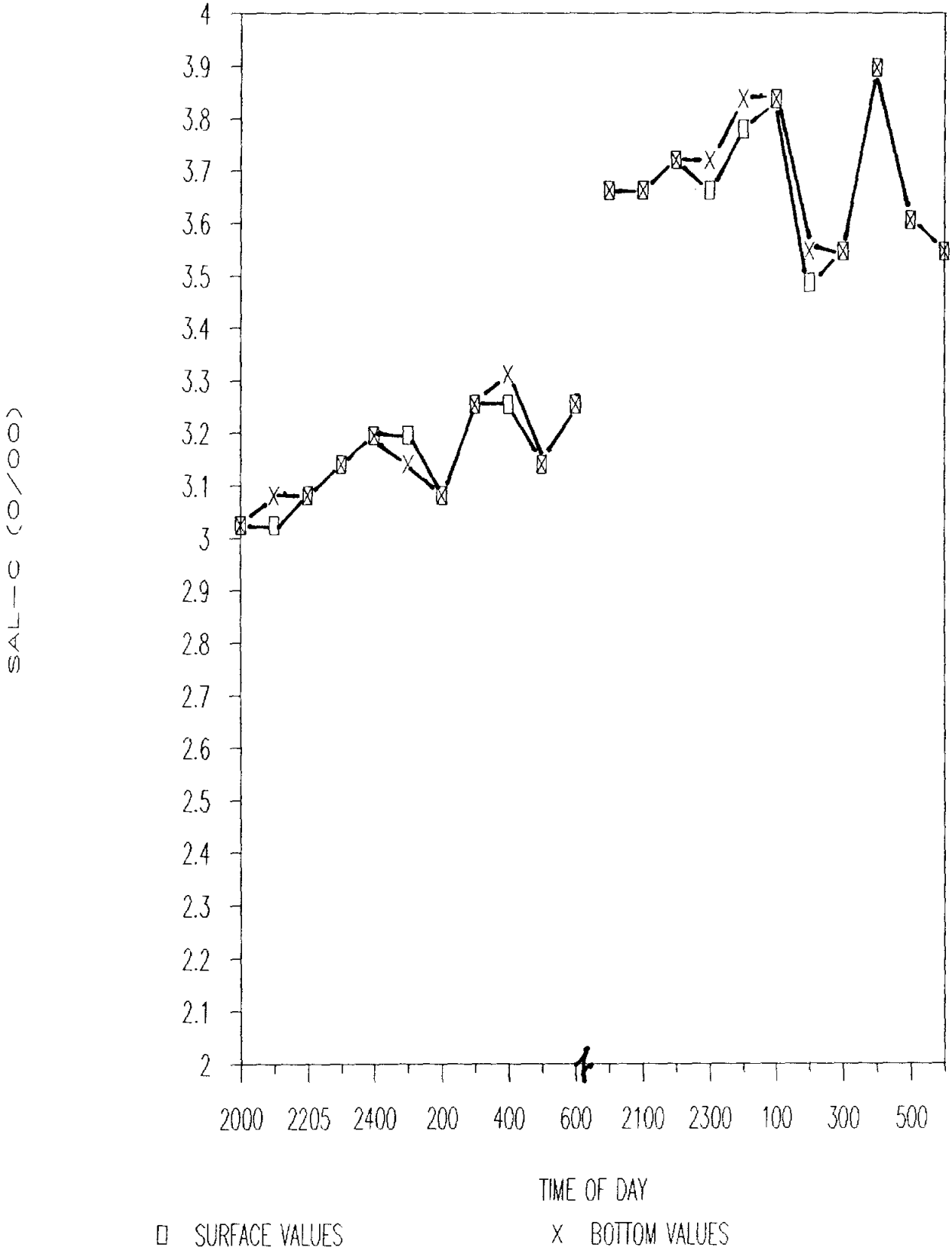
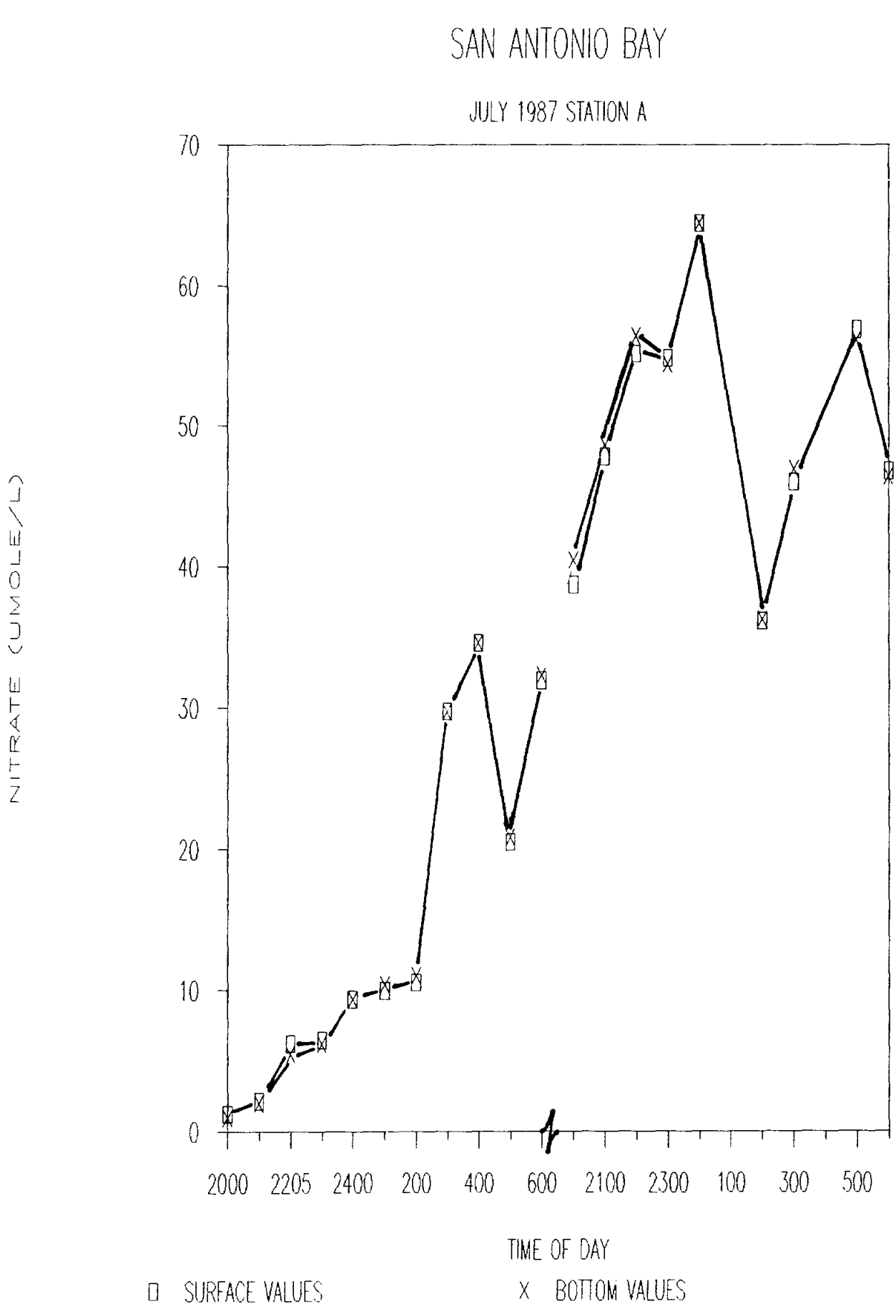
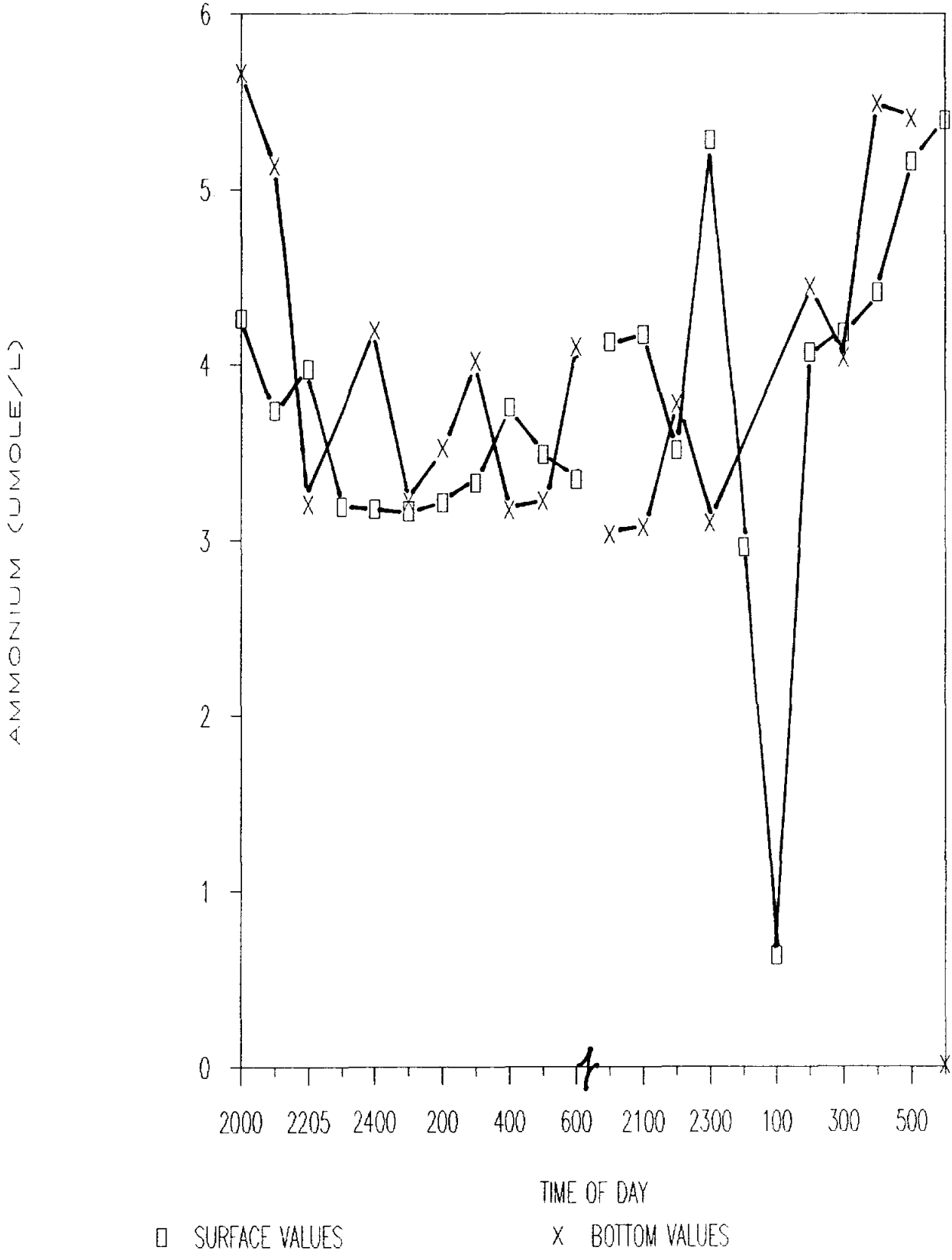



SAN ANTONIO BAY
JULY 1987 STATION A
NITRATE (UMOLE/L)
70
60
50
40
30
20
10
0
2000
2205
2400
200
400
600
2100
2300
100
300
500
TIME OF DAY
SURFACE VALUES
BOTTOM VALUES

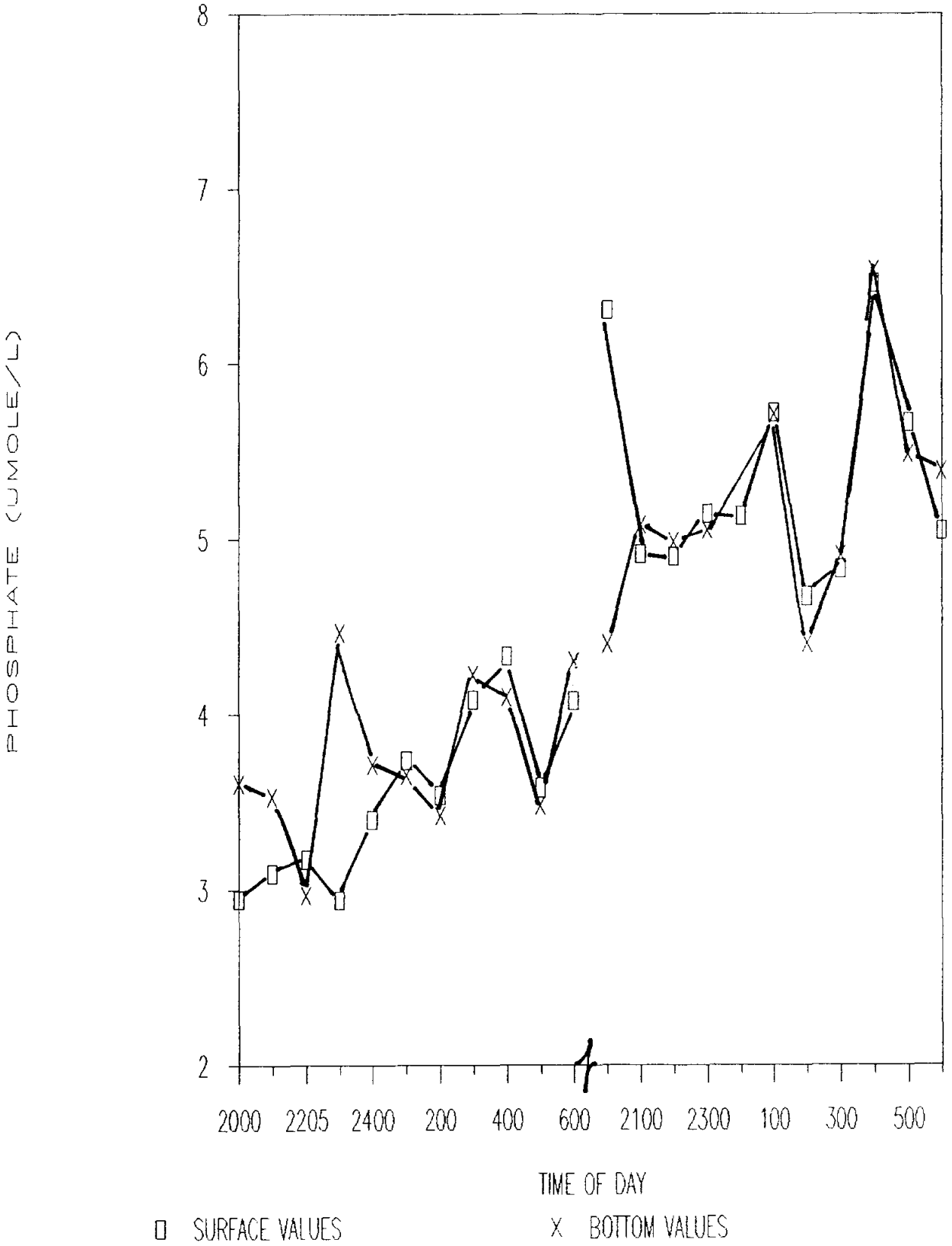
SAN ANTONIO BAY

JULY 1987 STATION A



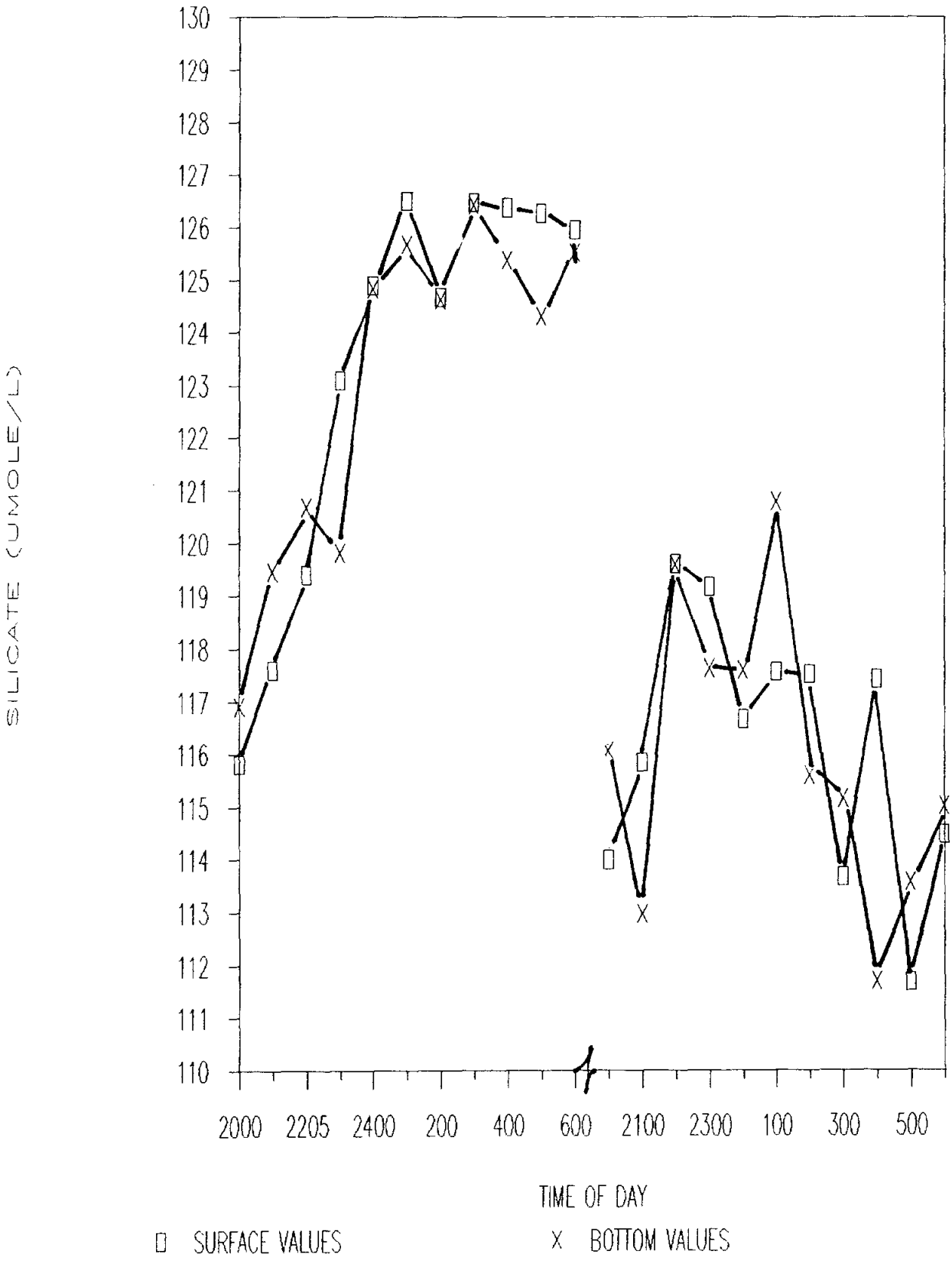
SAN ANTONIO BAY

JULY 1987 STATION A



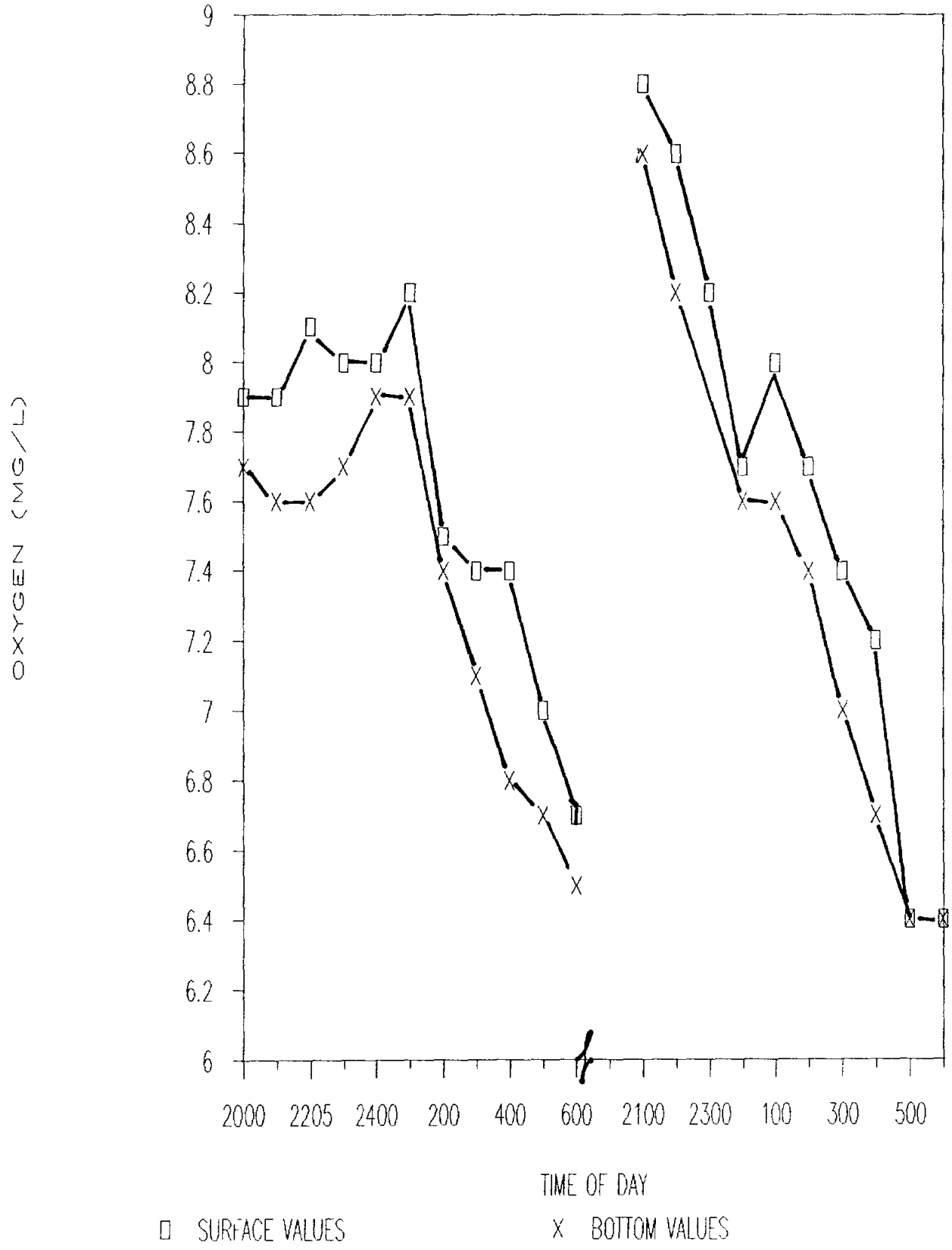
SAN ANTONIO BAY

JULY 1987 STATION A



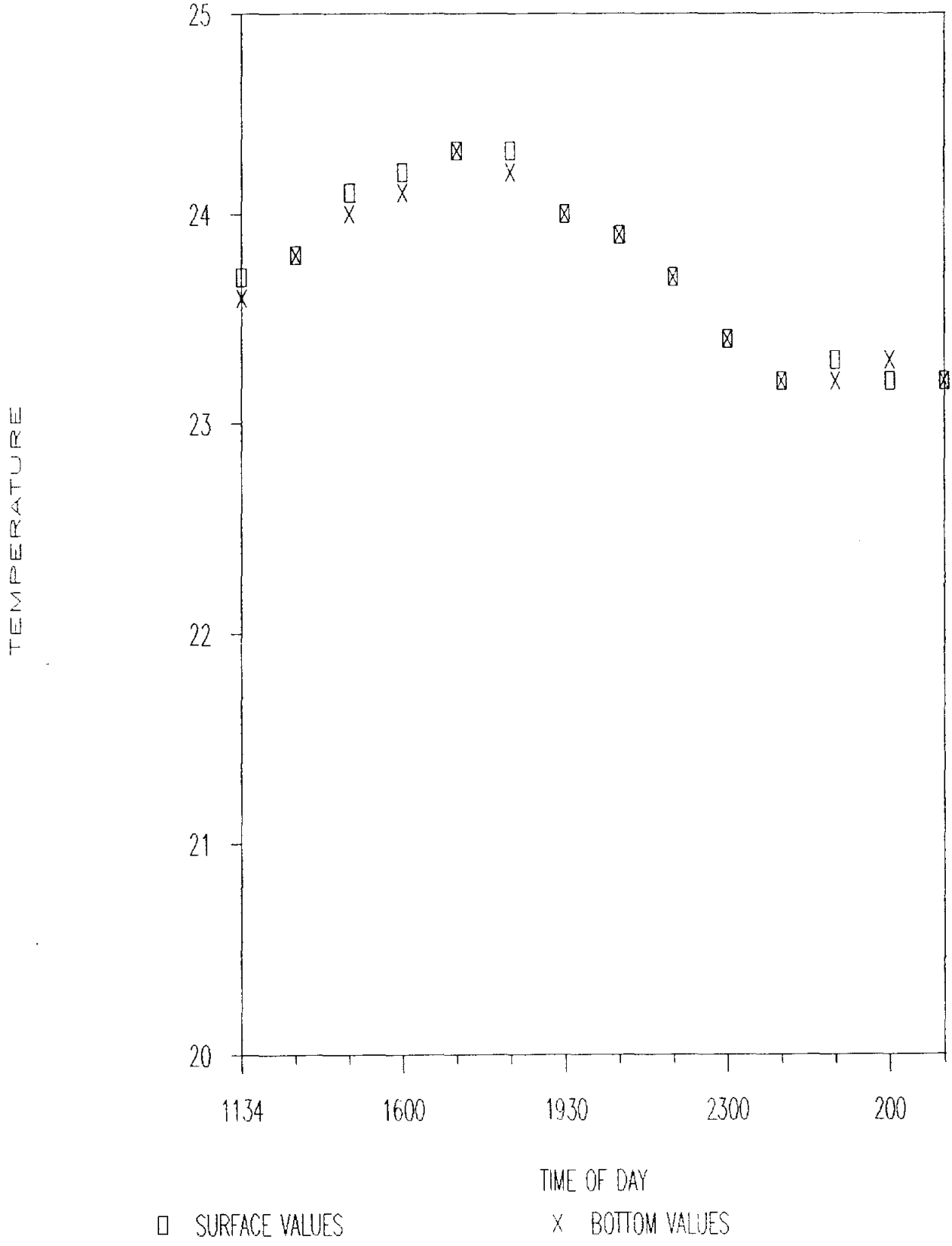
SAN ANTONIO BAY

JULY 1987 STATION A



CORPUS CHRISTI/NUECES BAYS

OCT 1987 STATION A



CORPUS CHRISTI/NUECES BAYS

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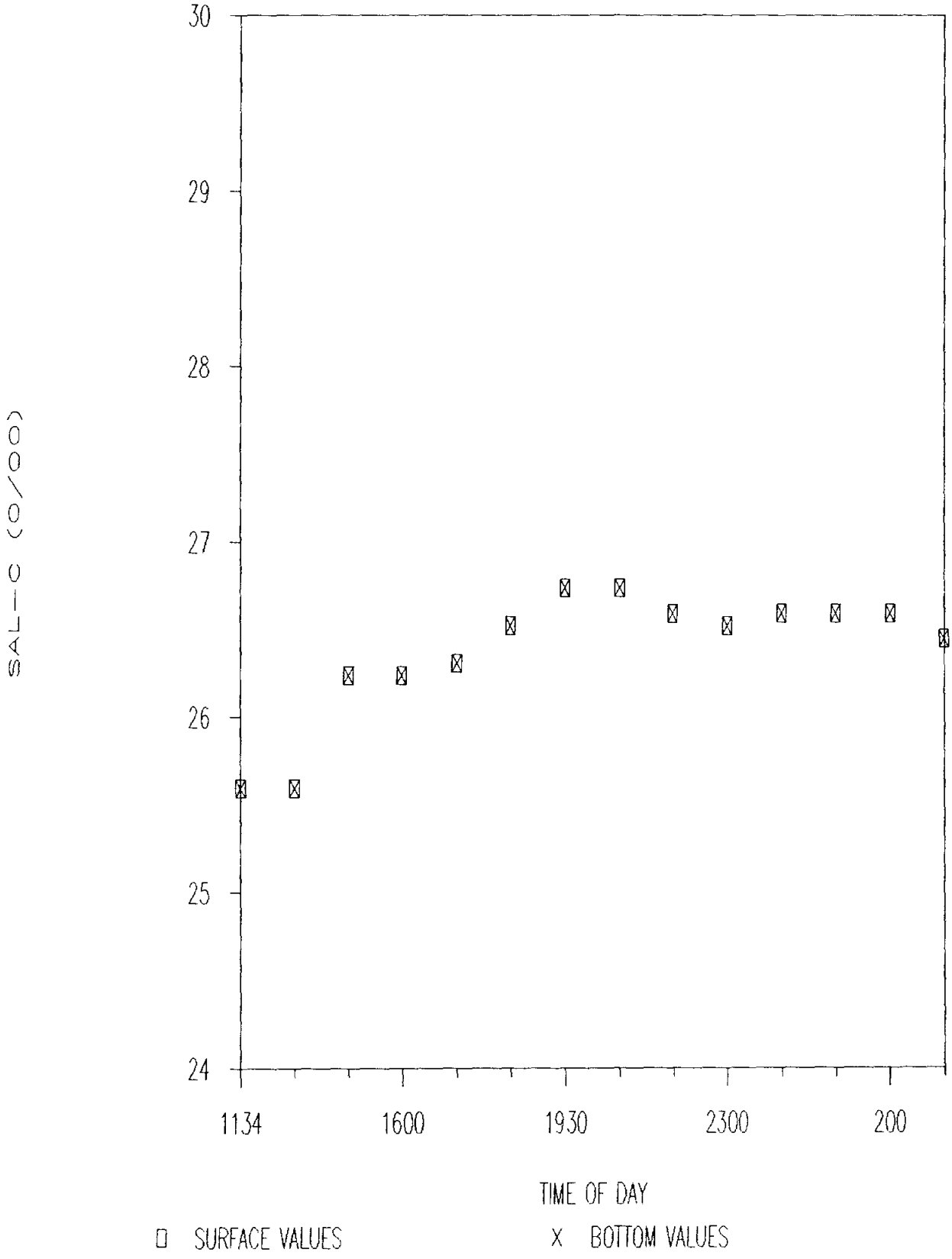

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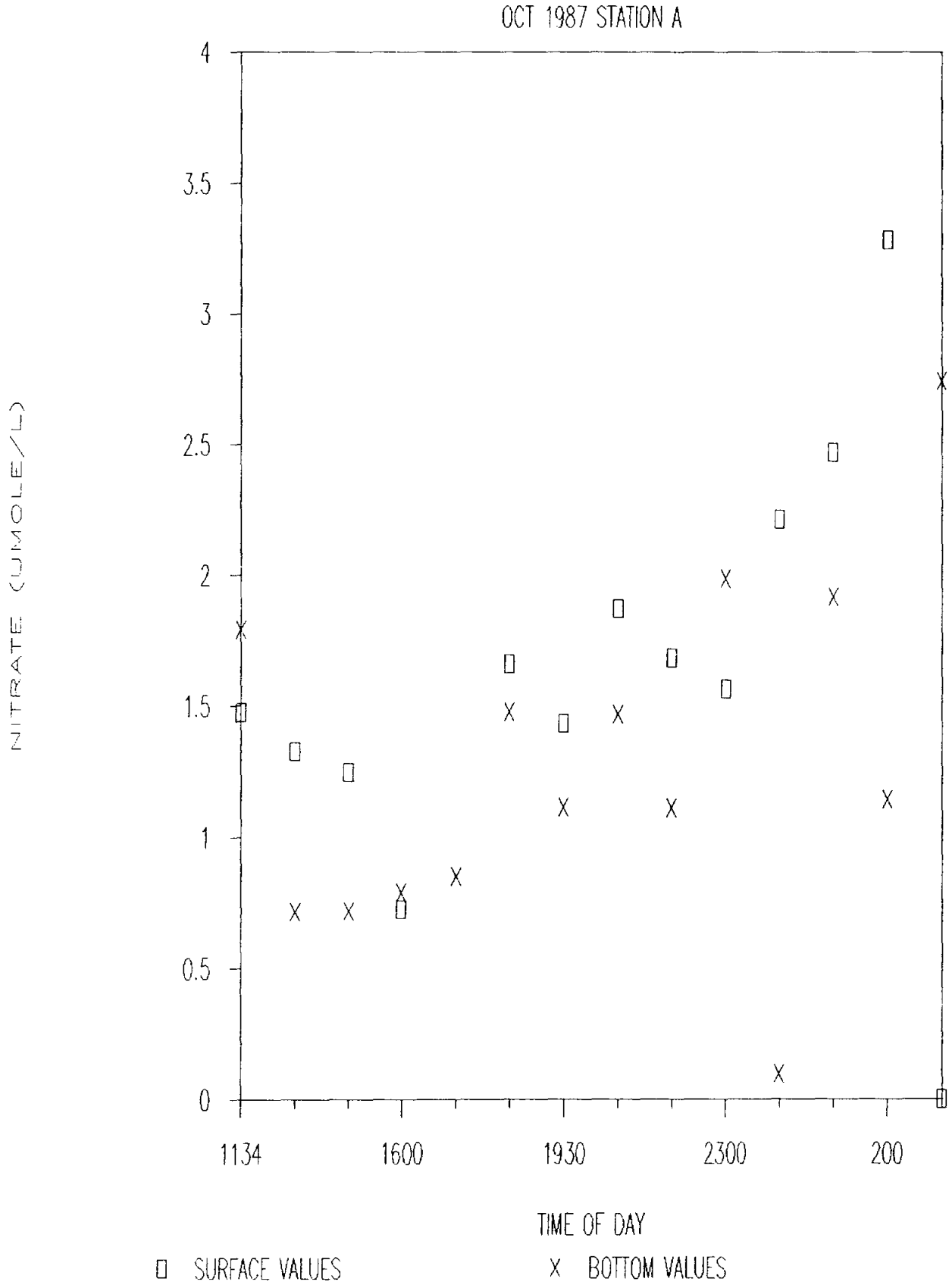

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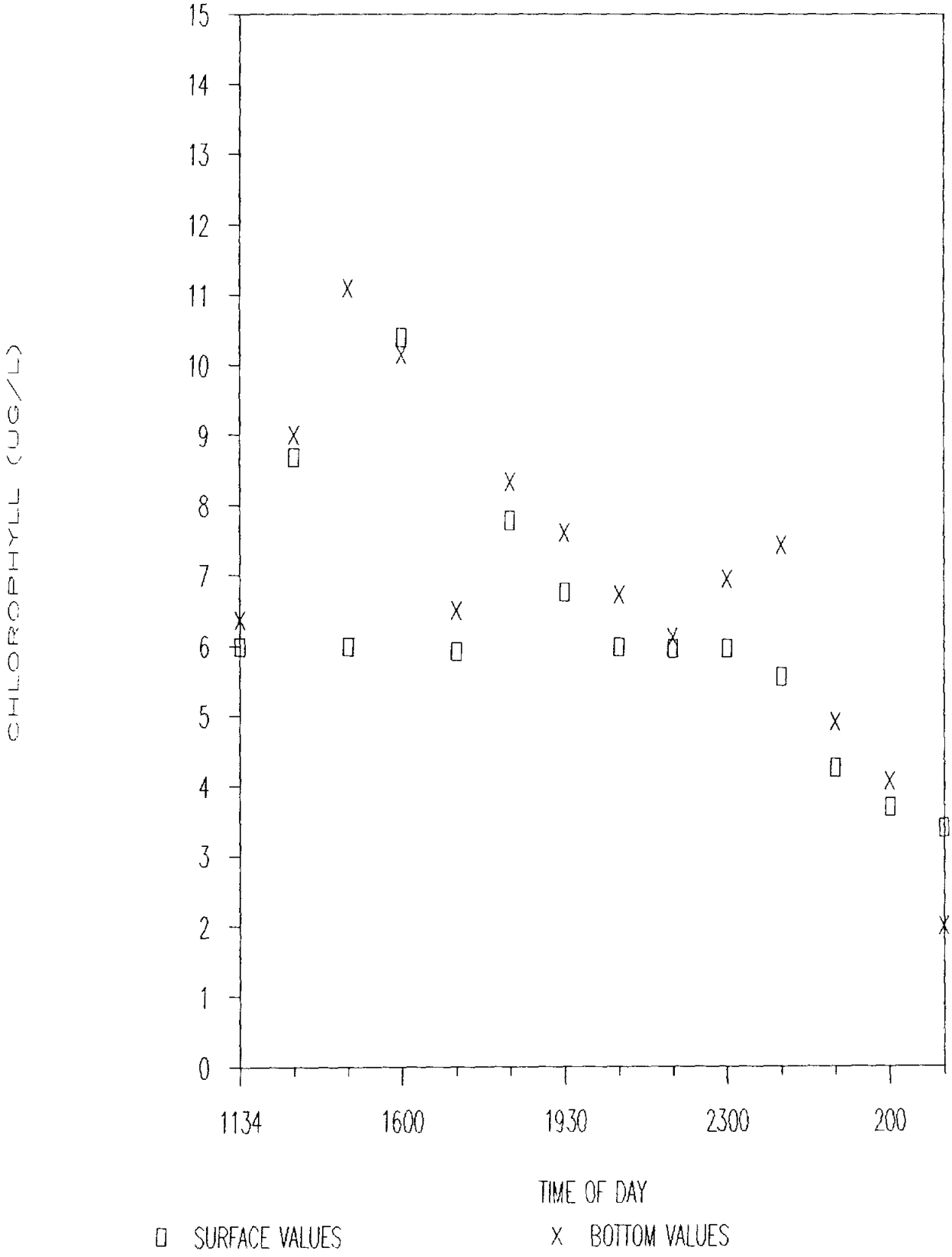

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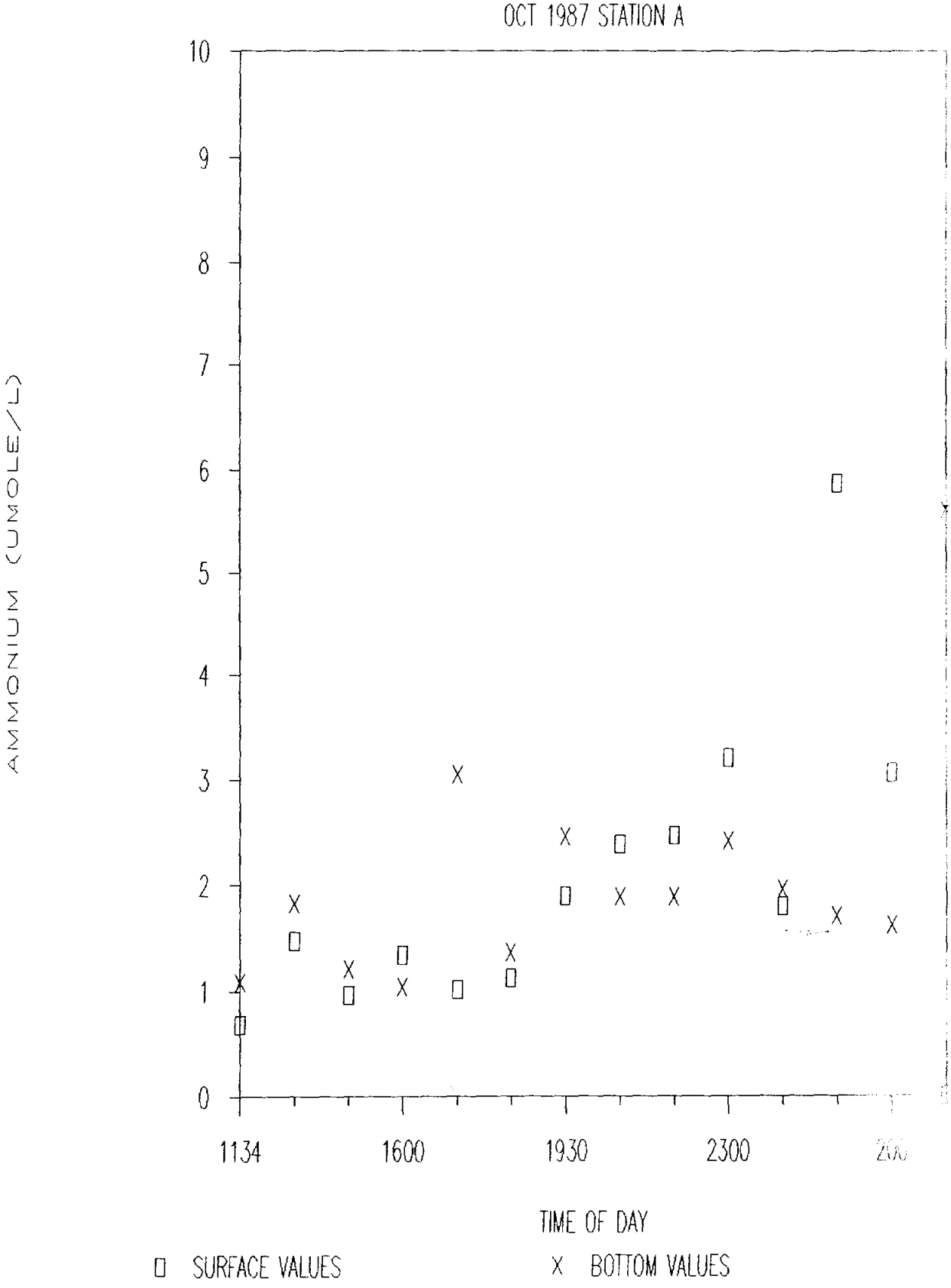

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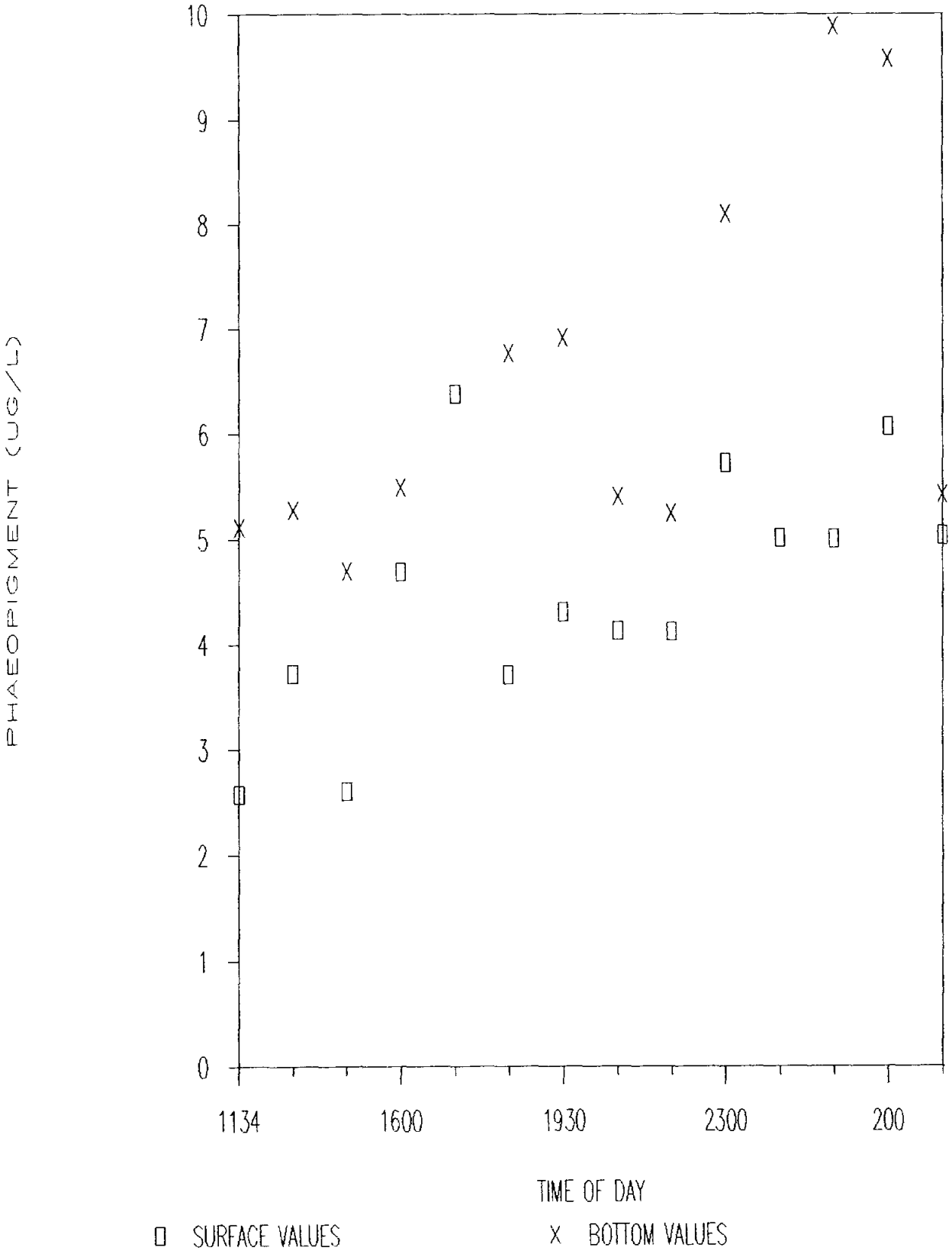

CORPUS CHRISTI/NUECES BAYS

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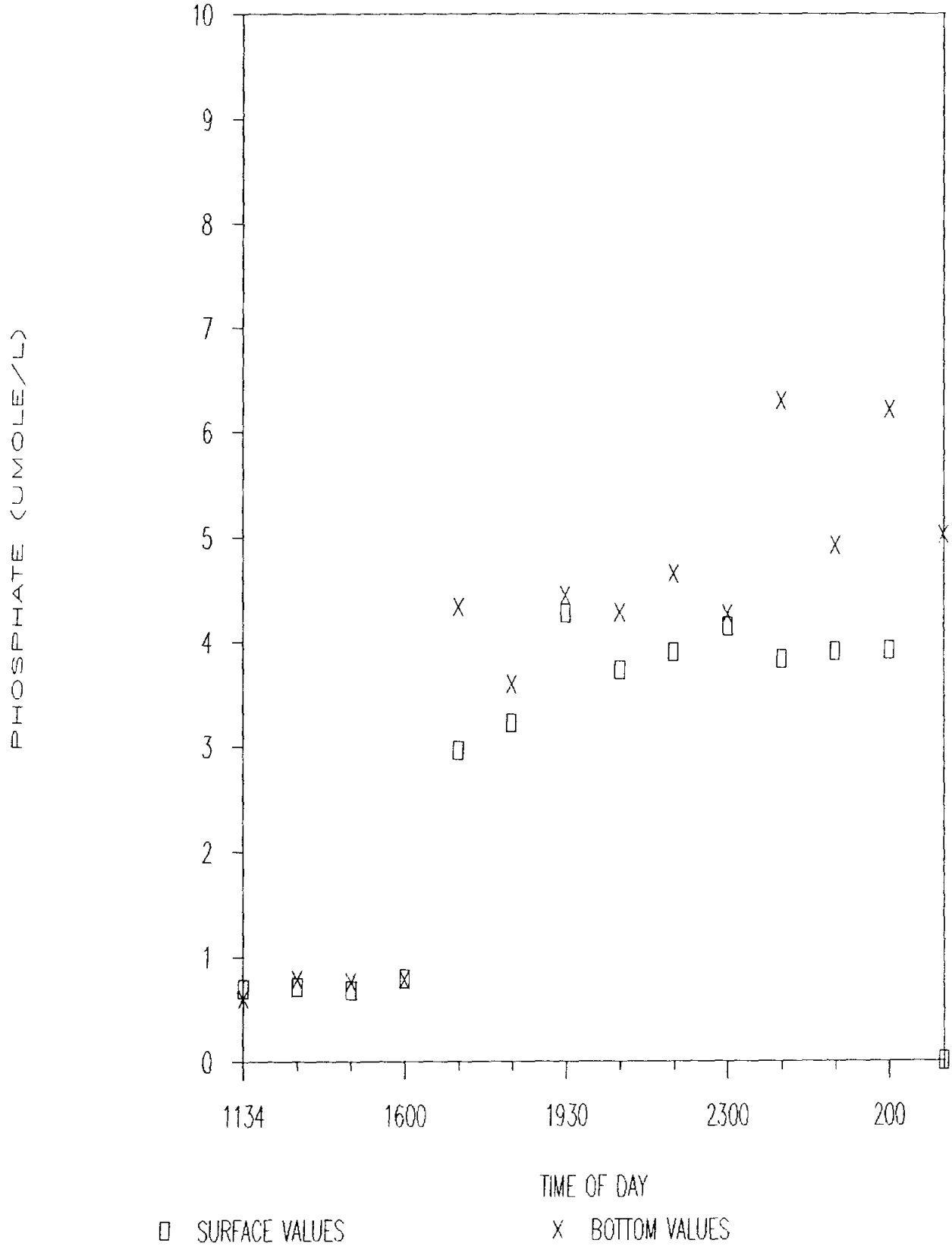

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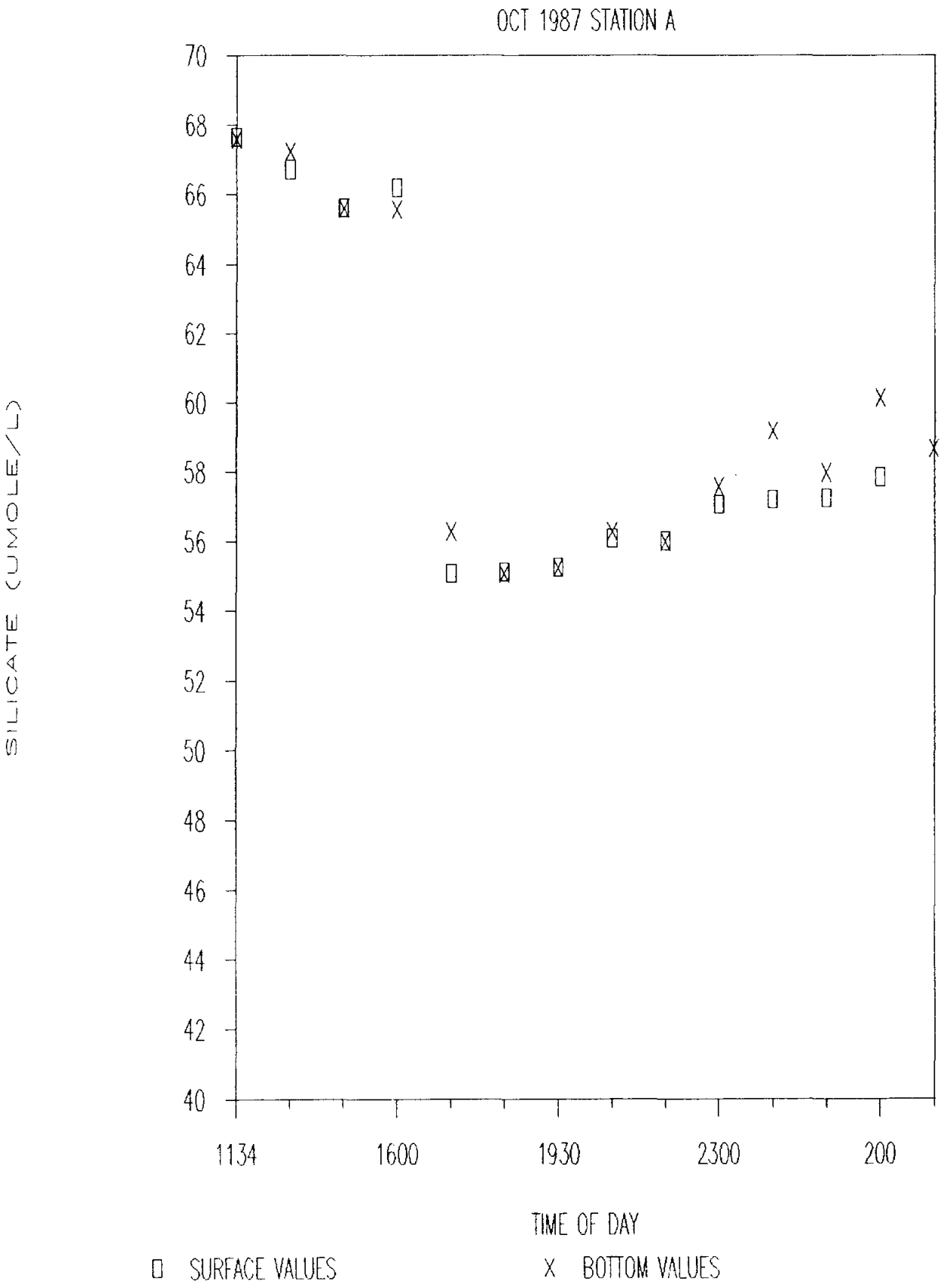

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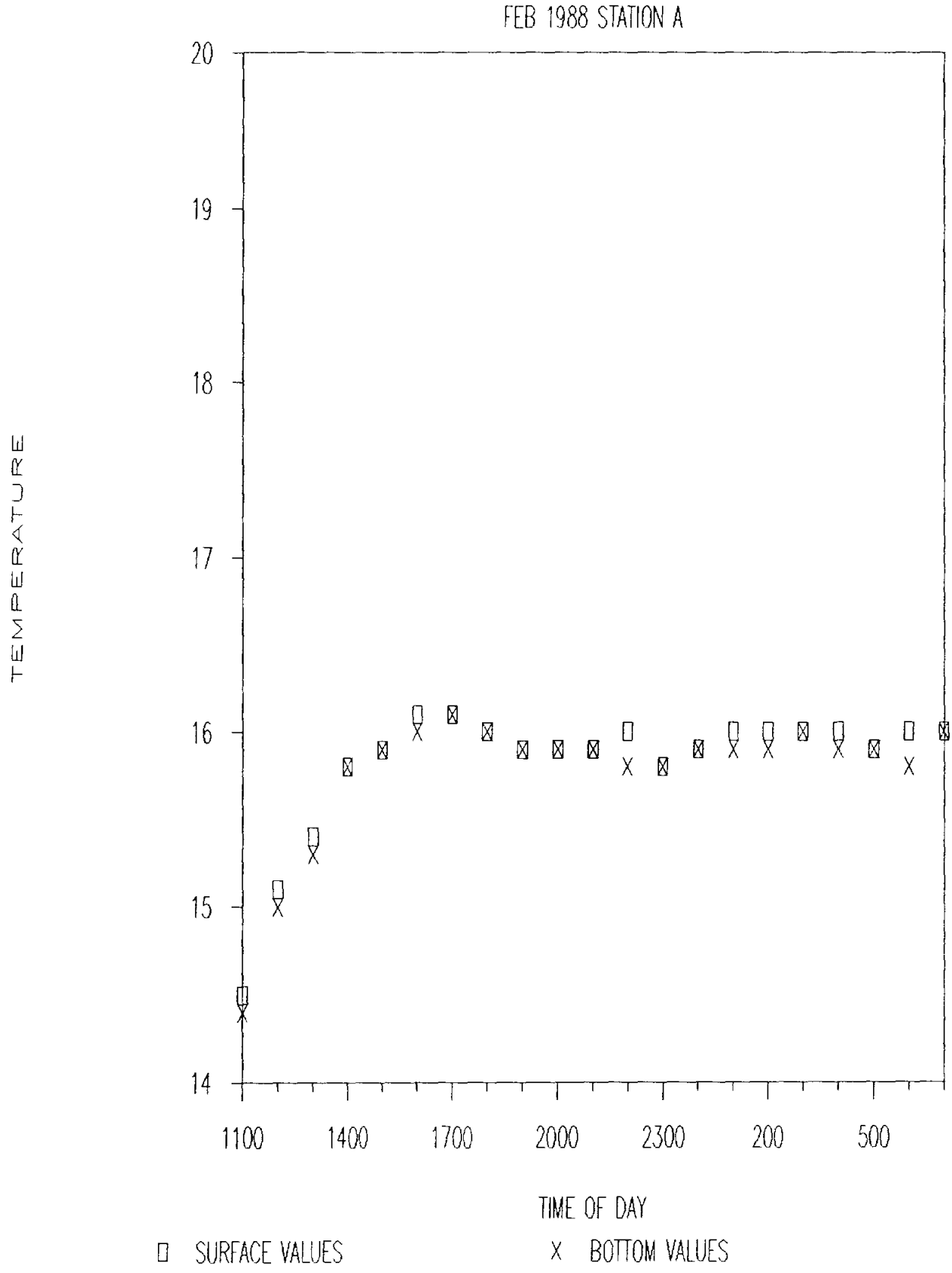

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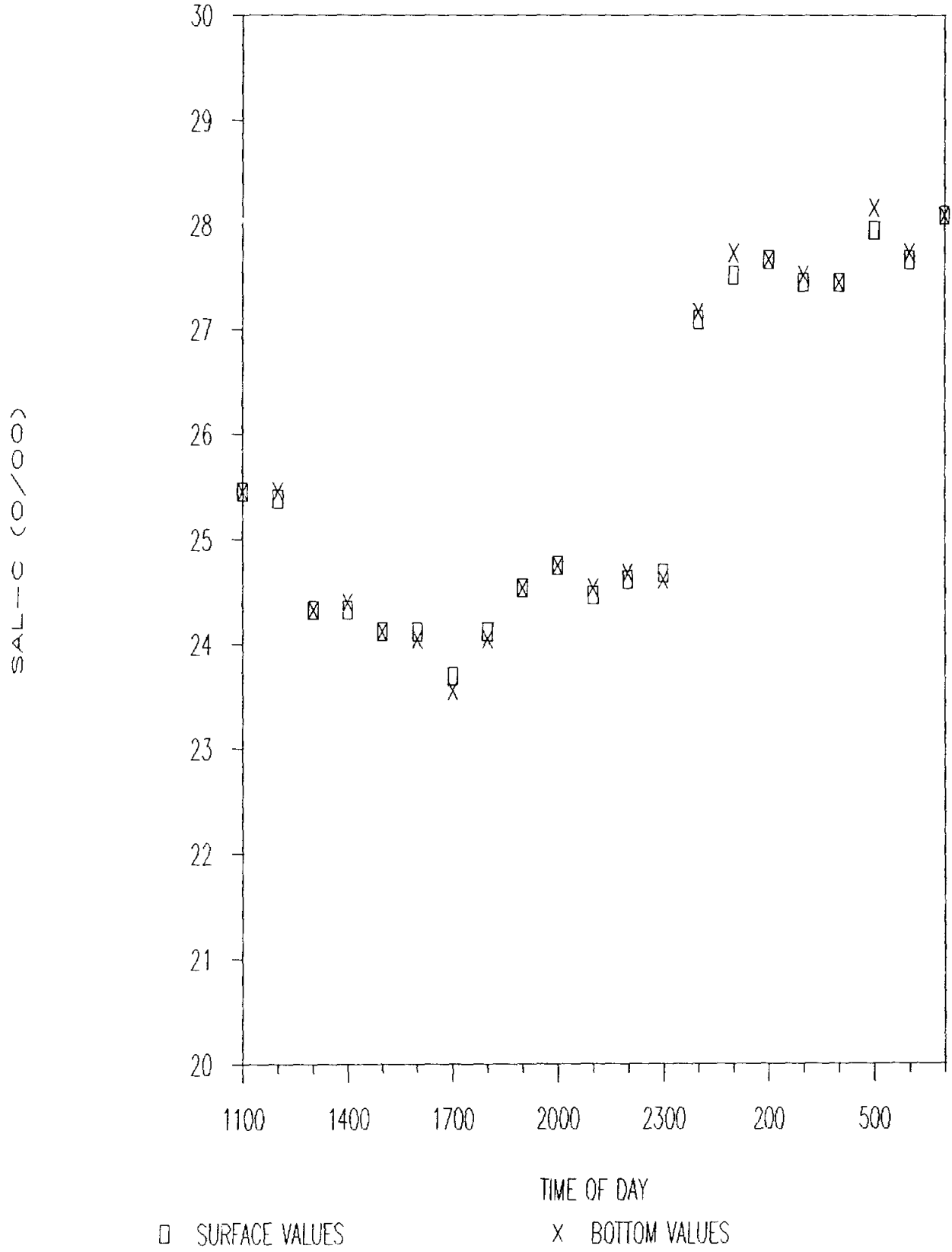

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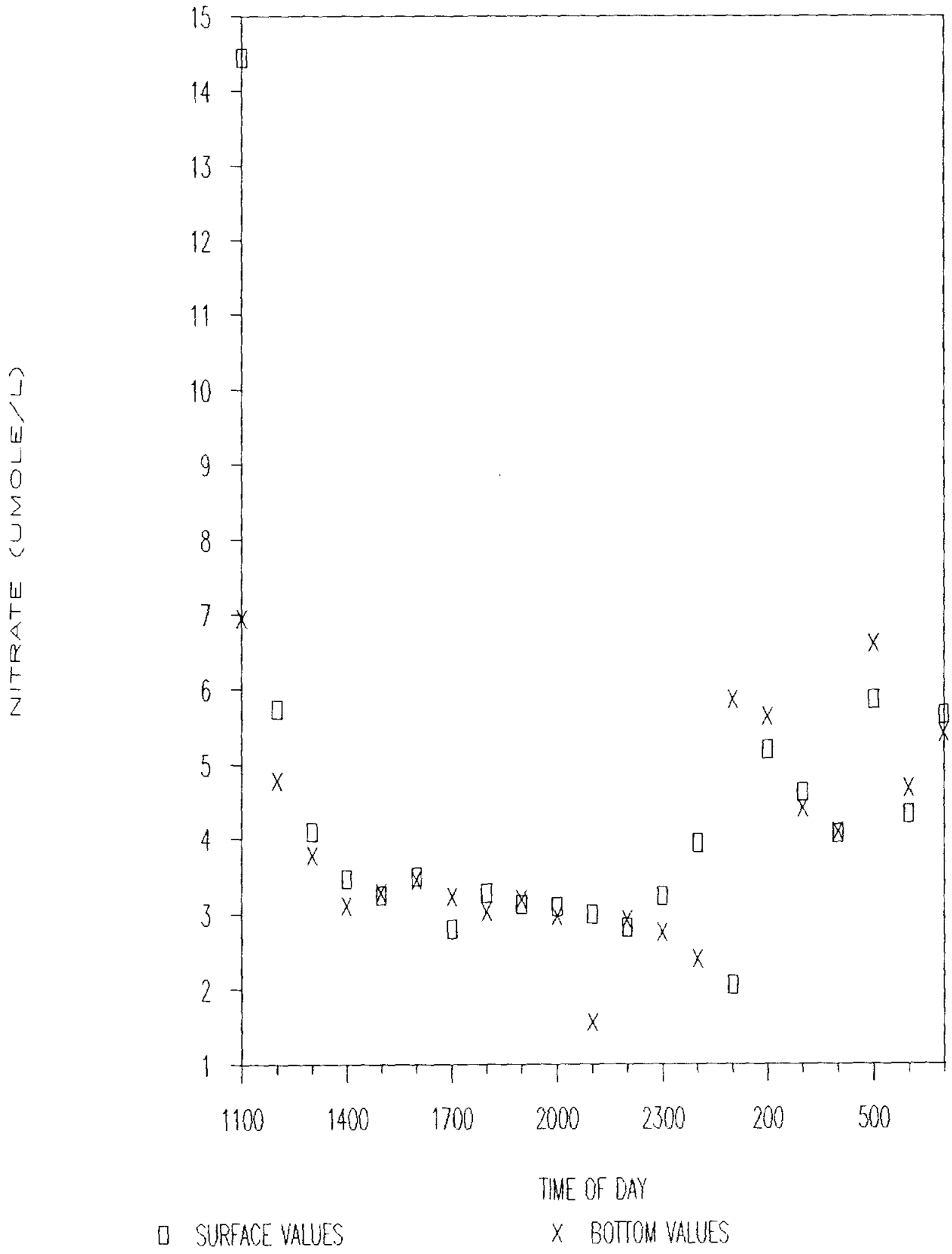

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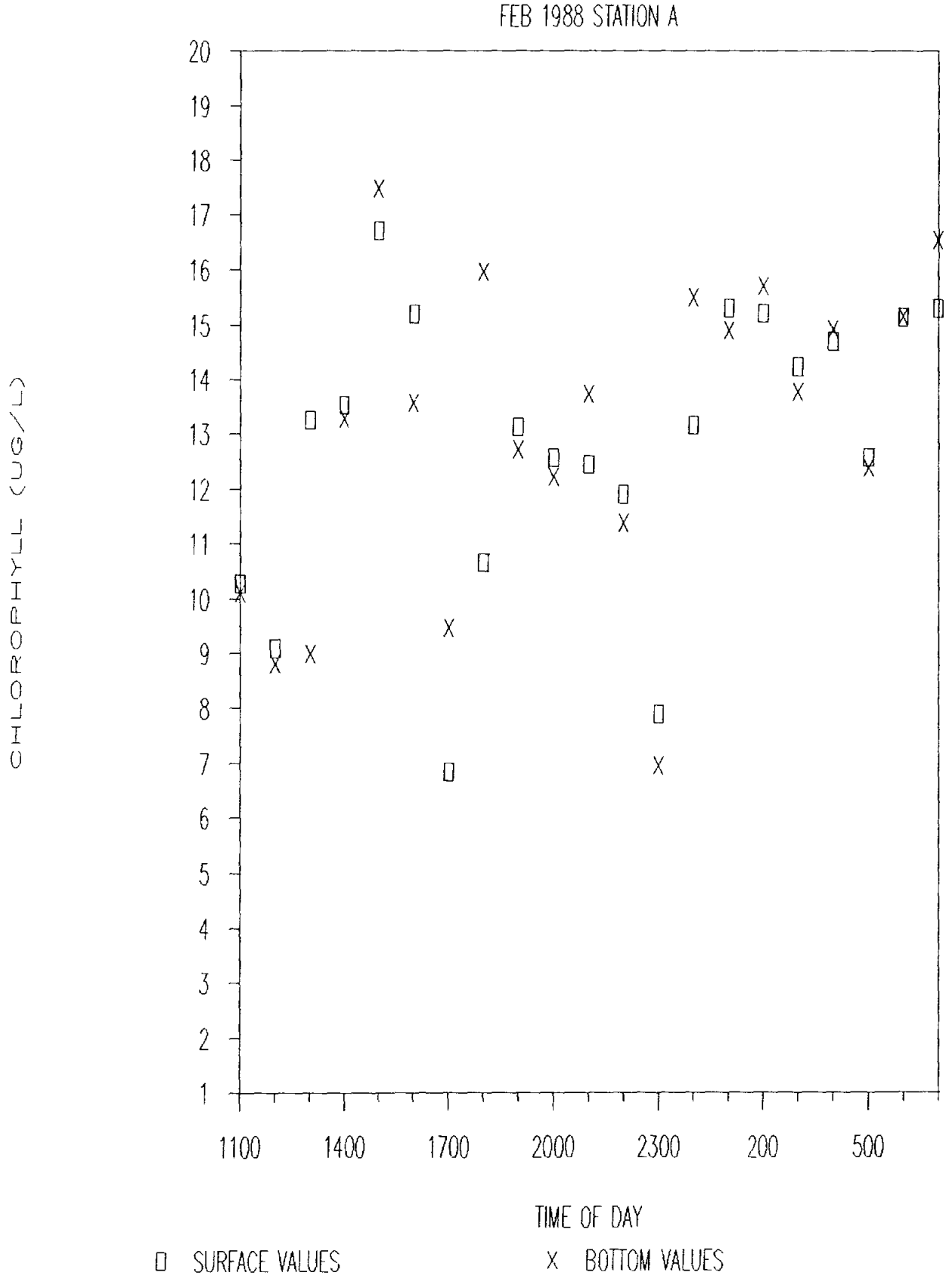

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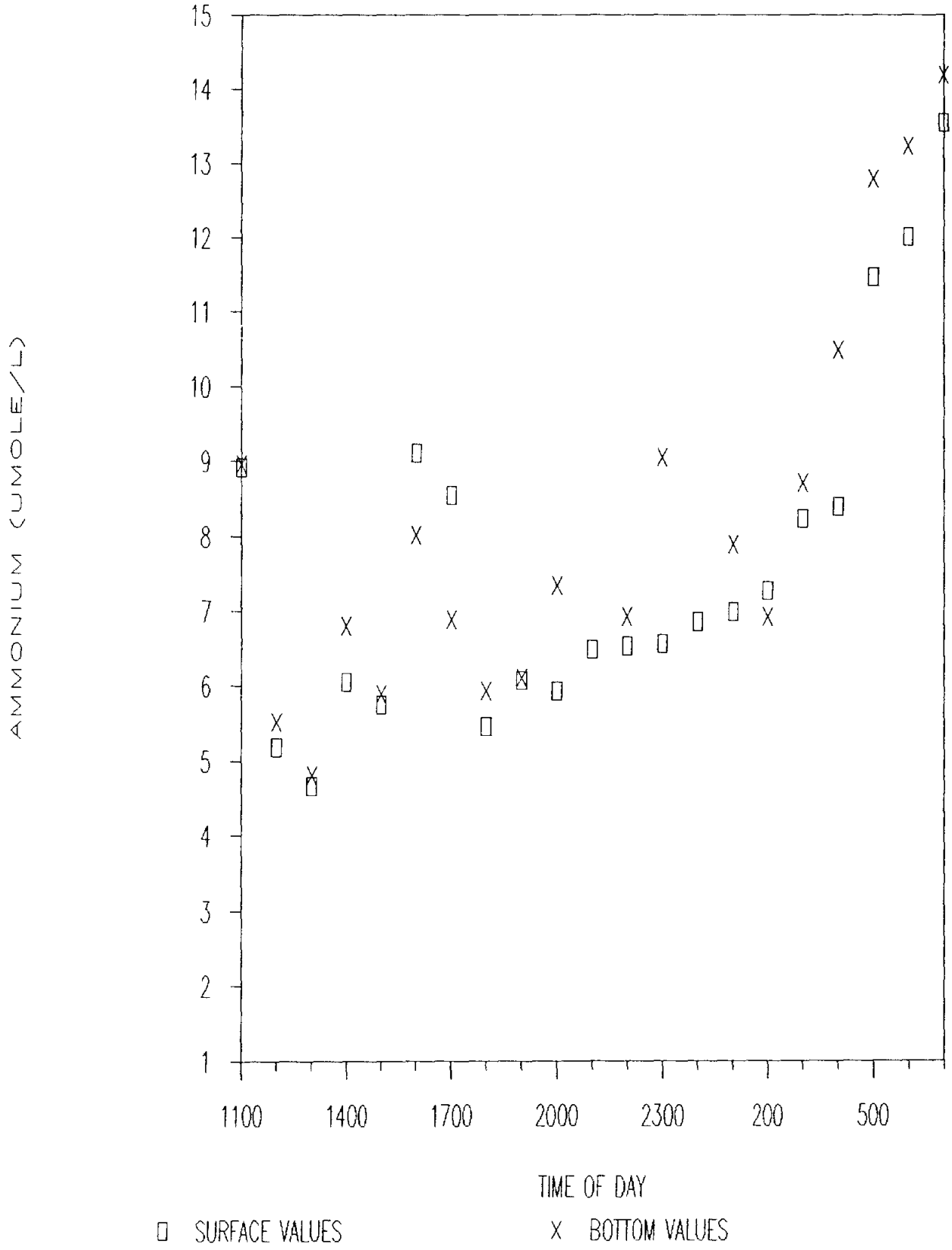

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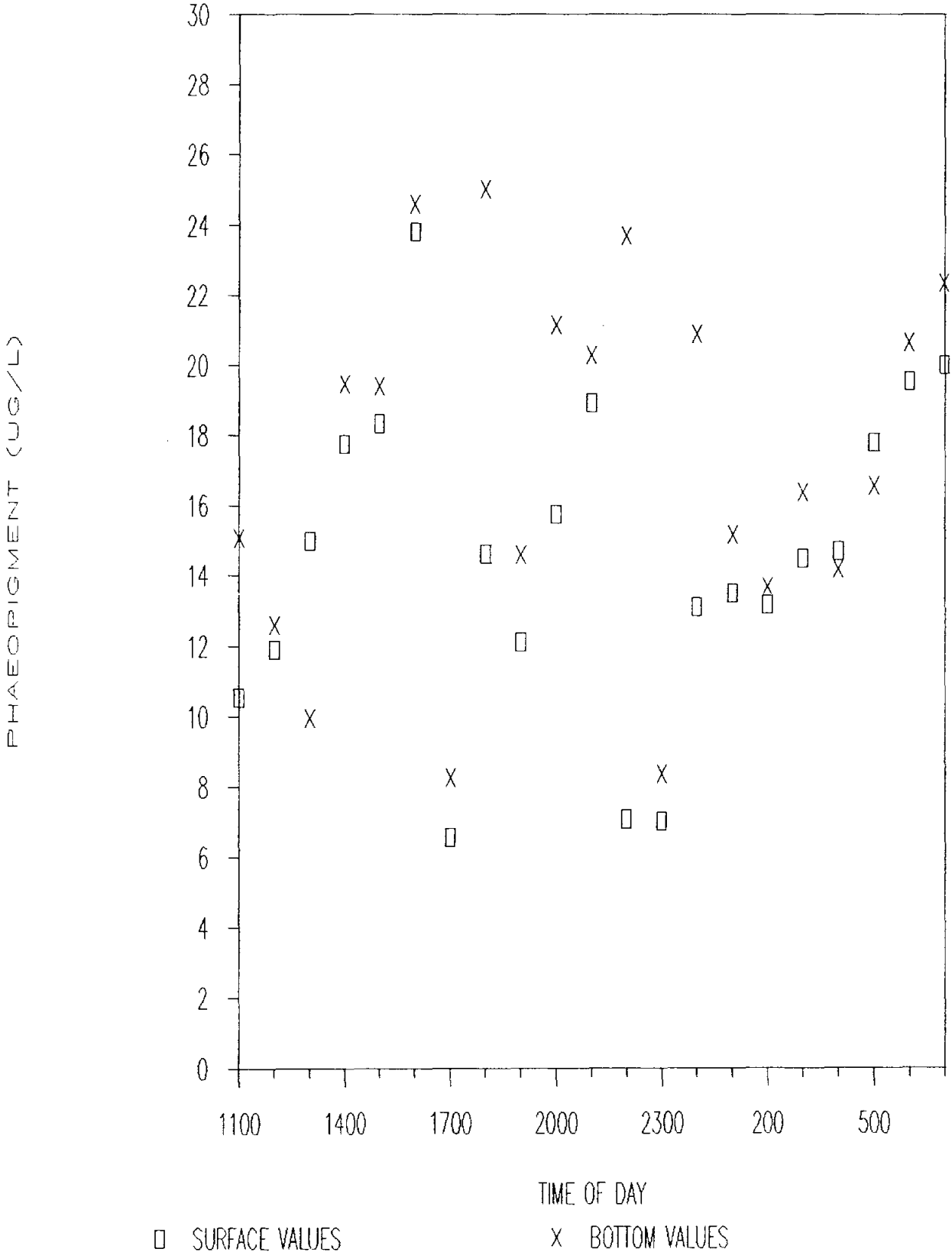

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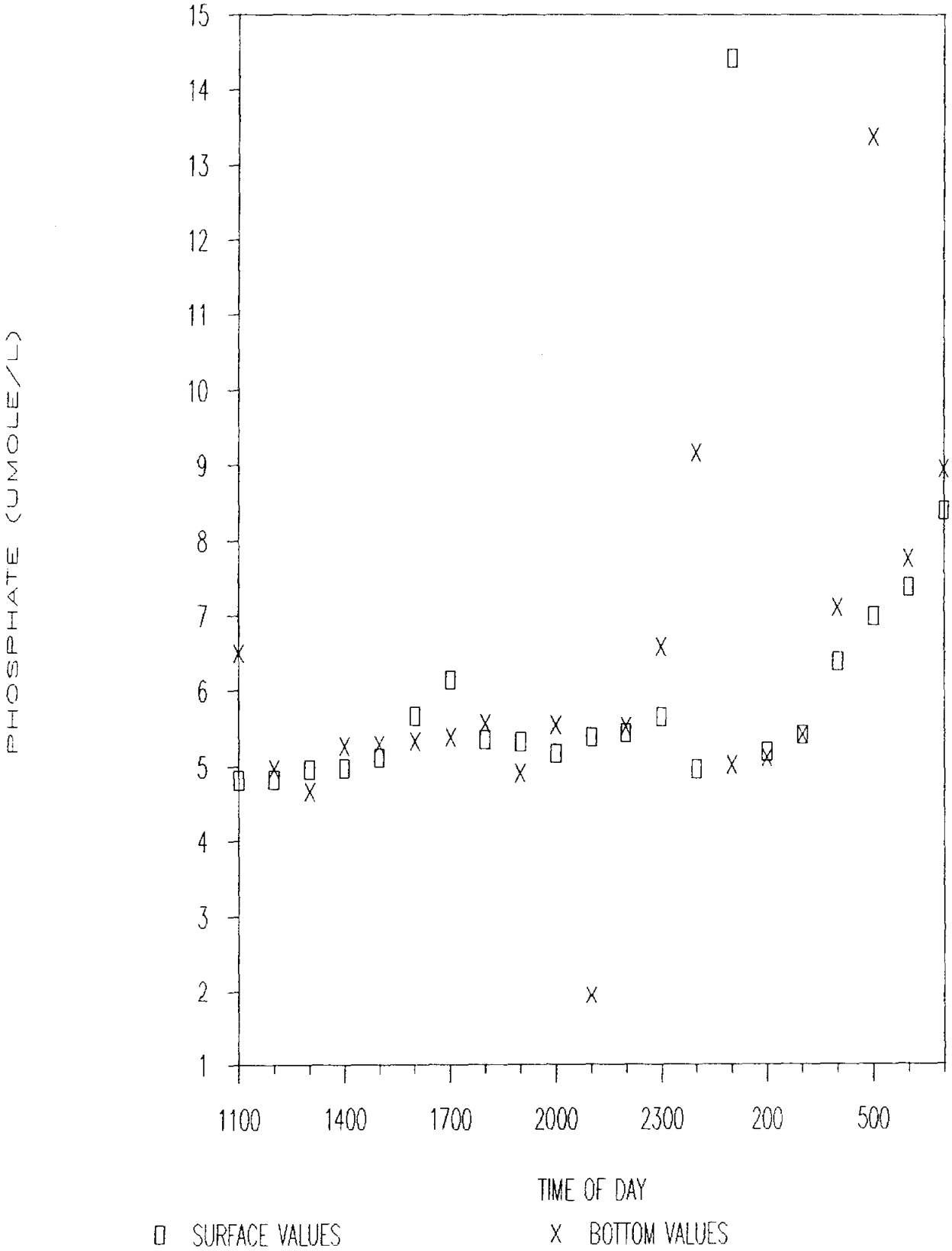

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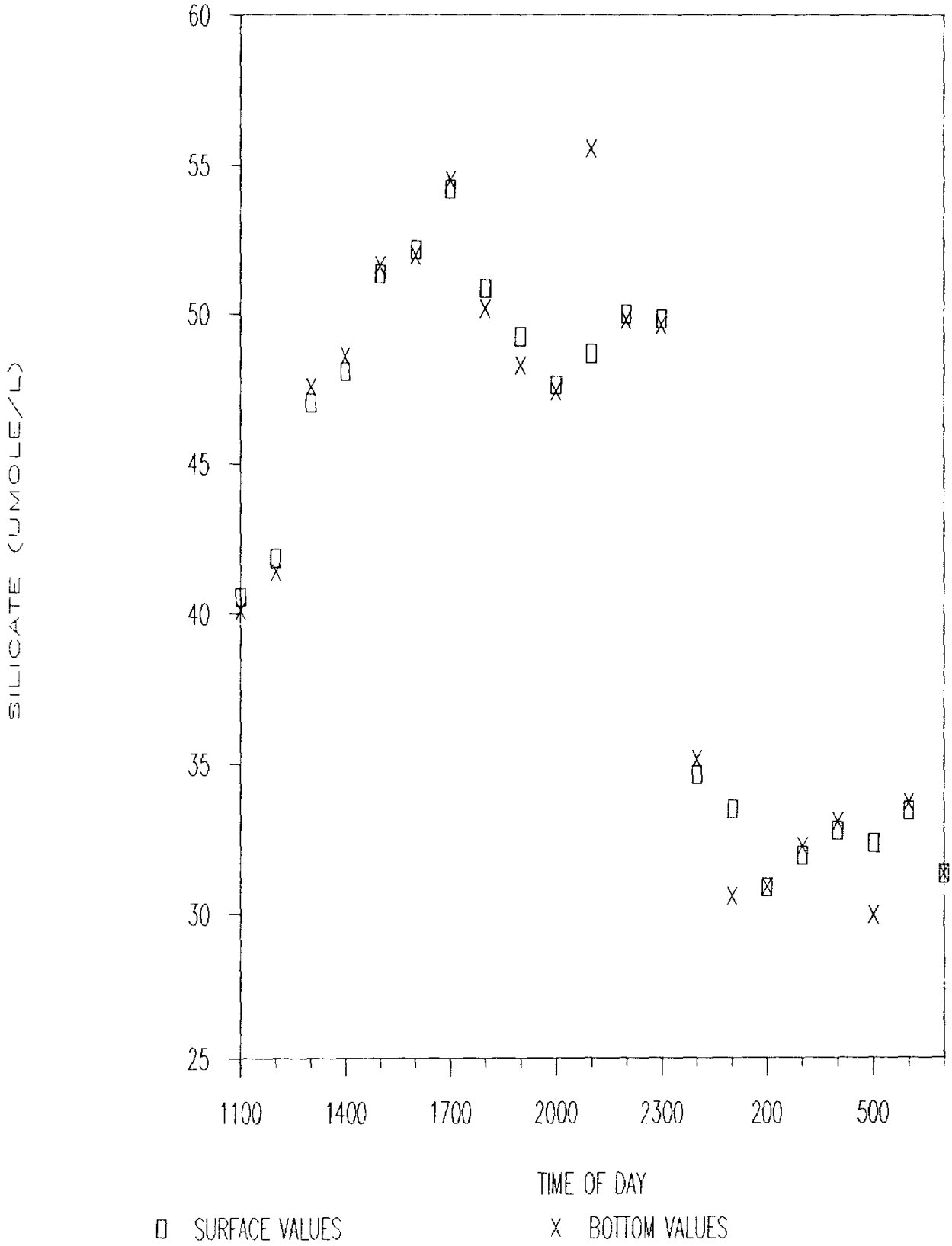

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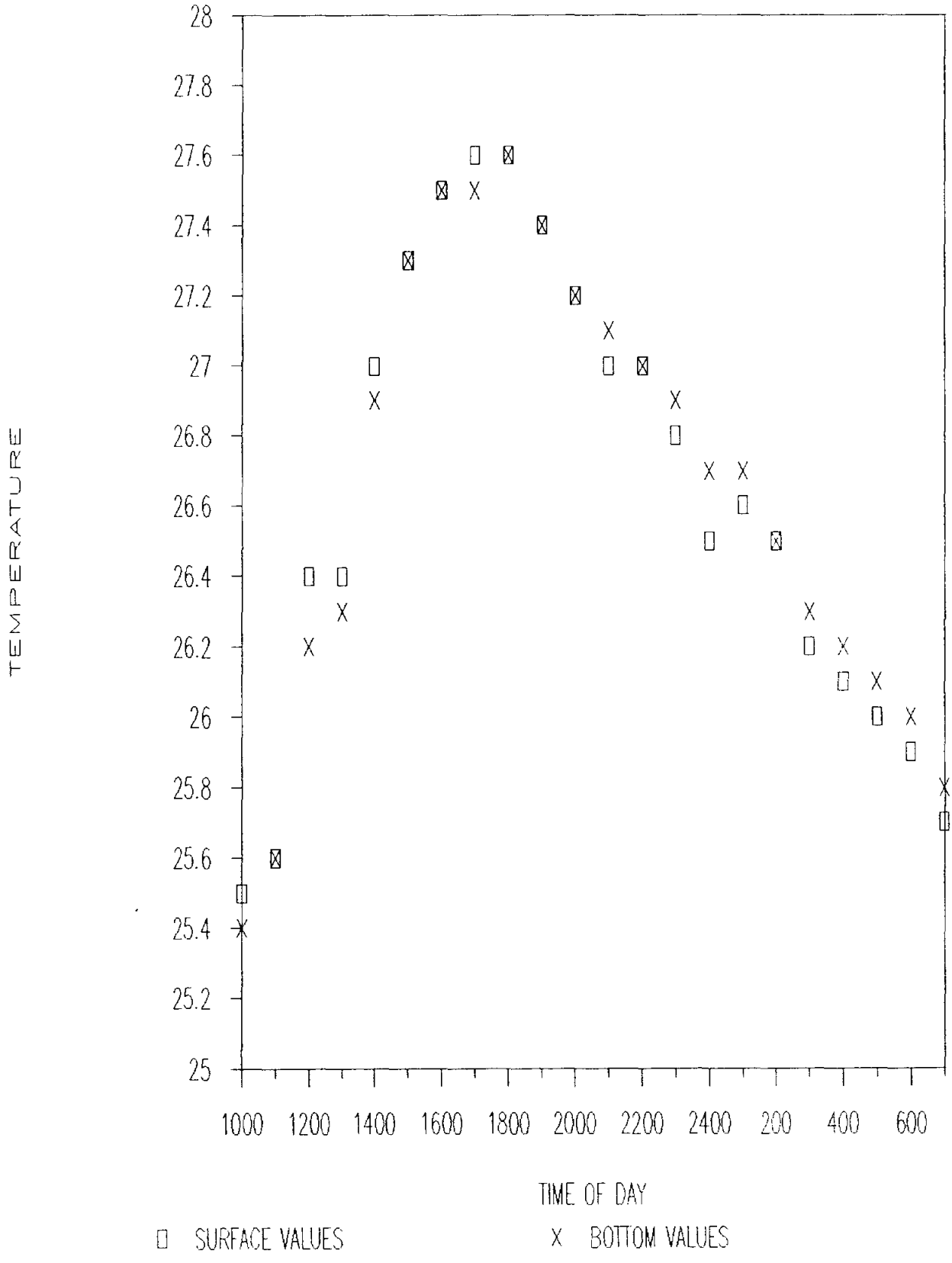

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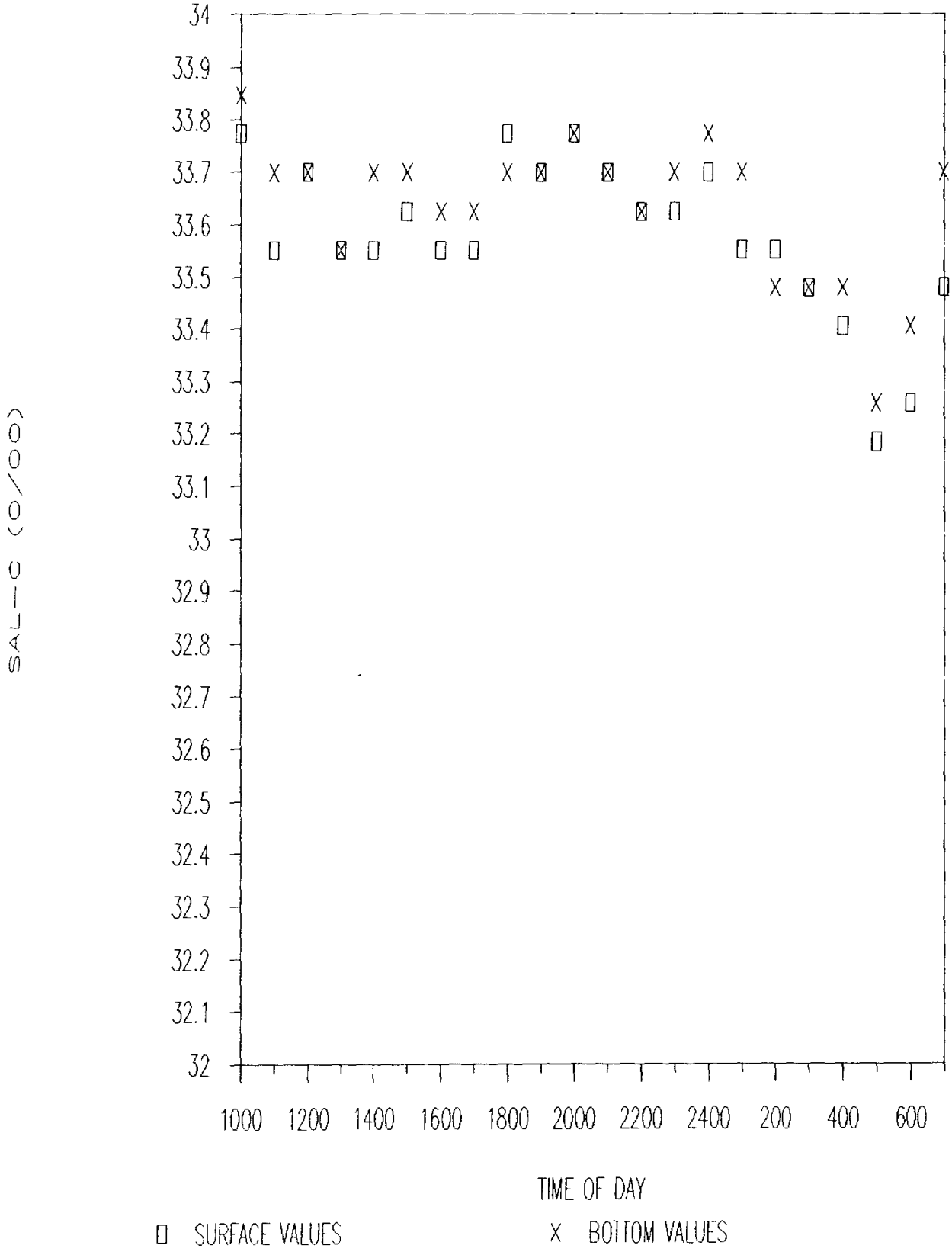

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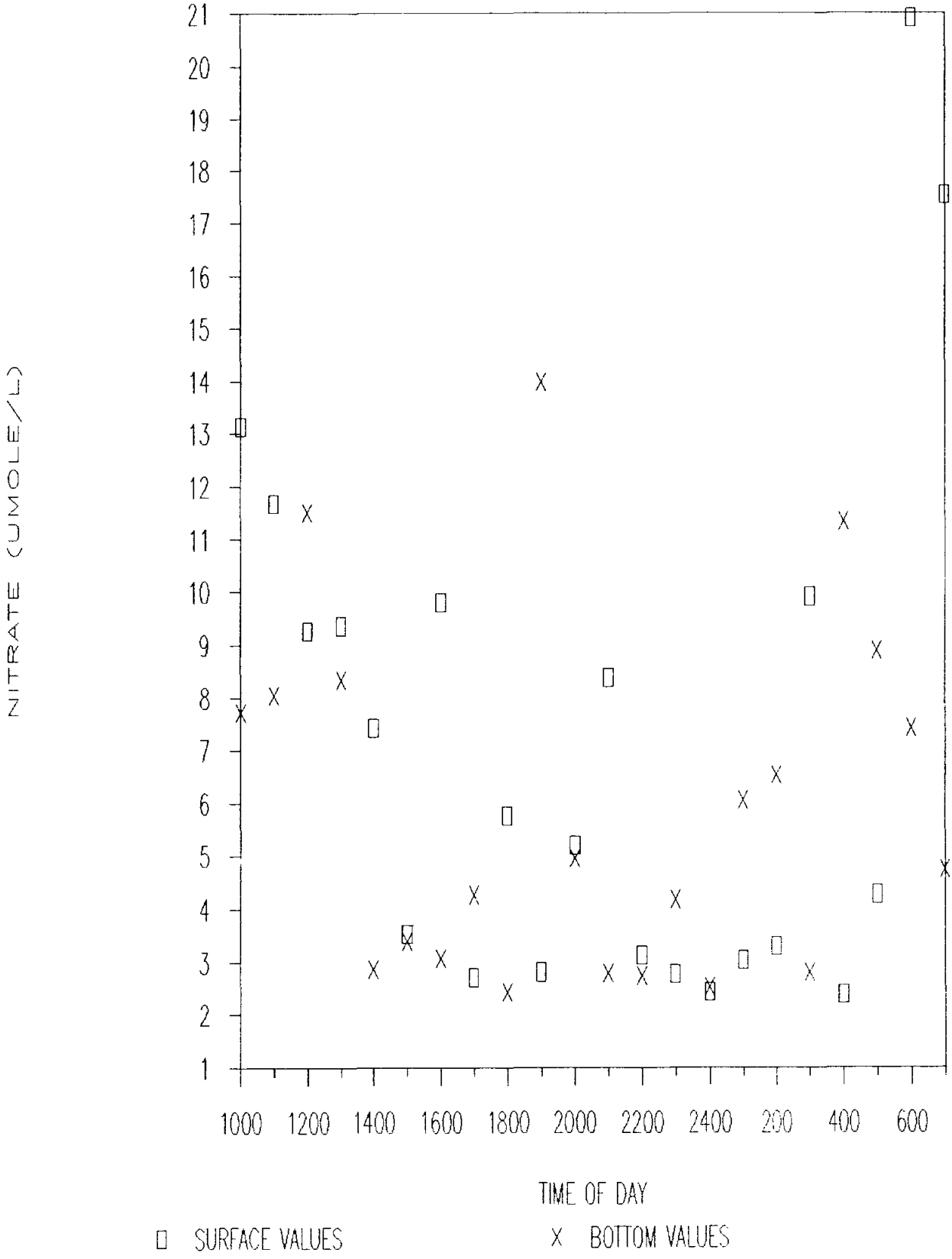

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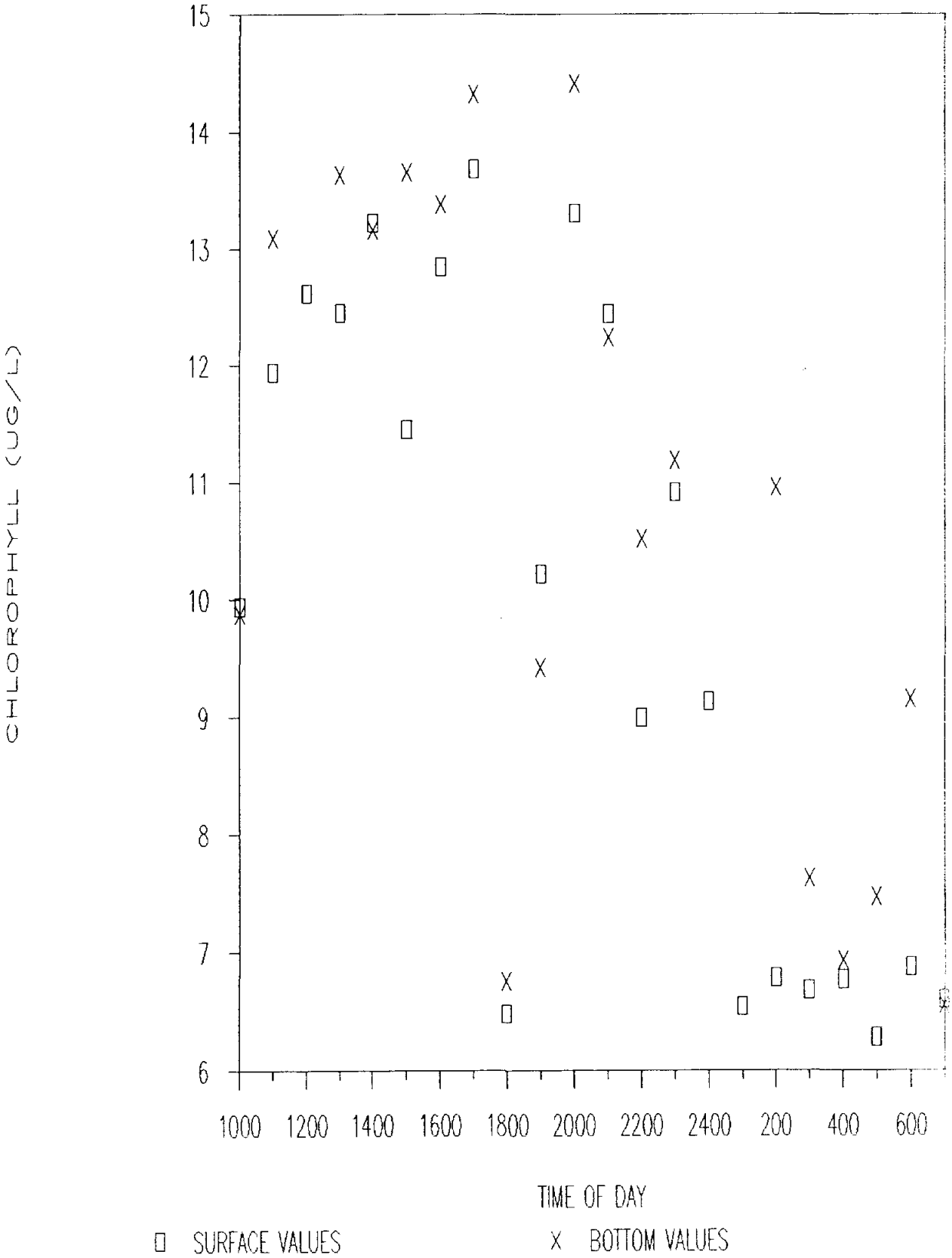

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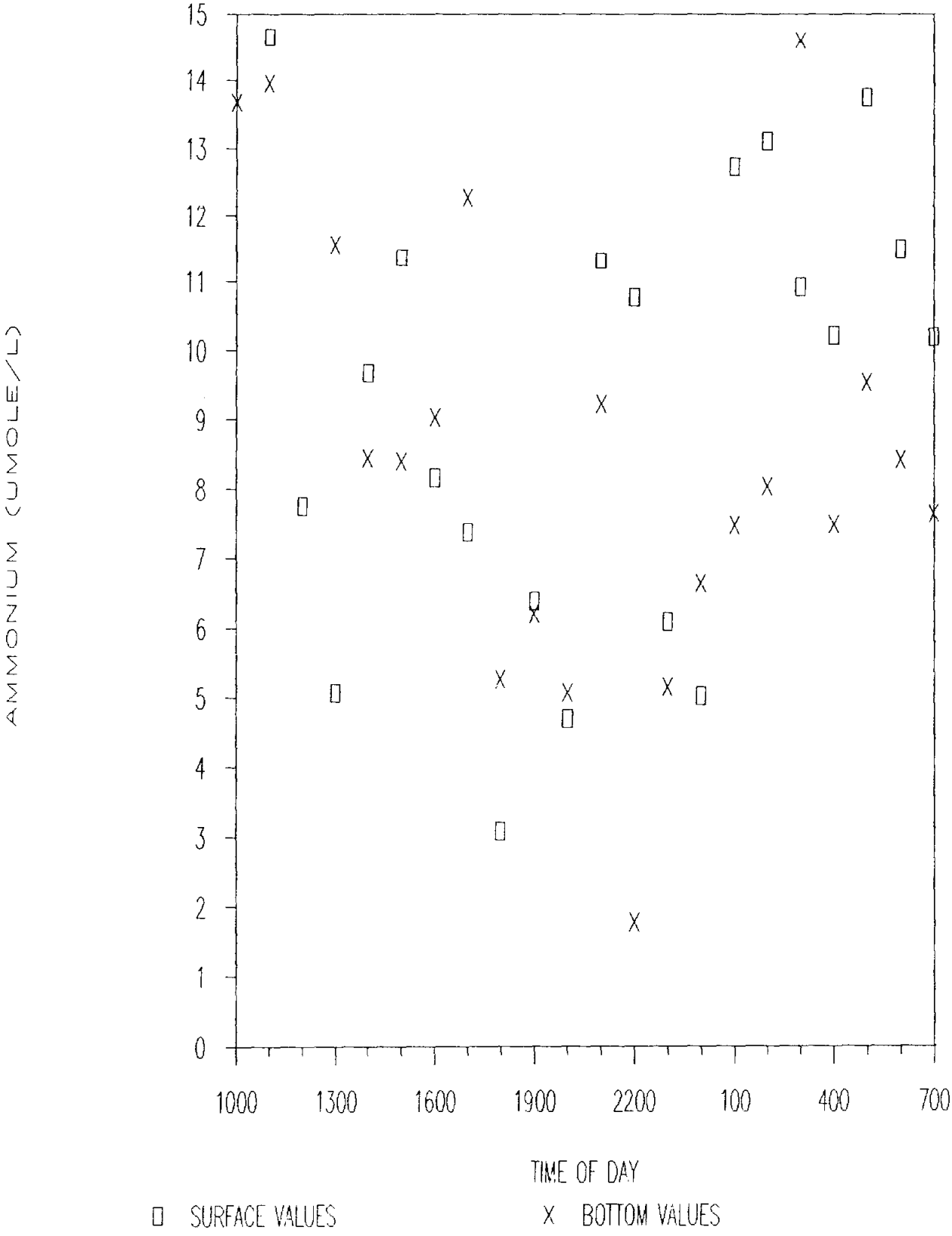

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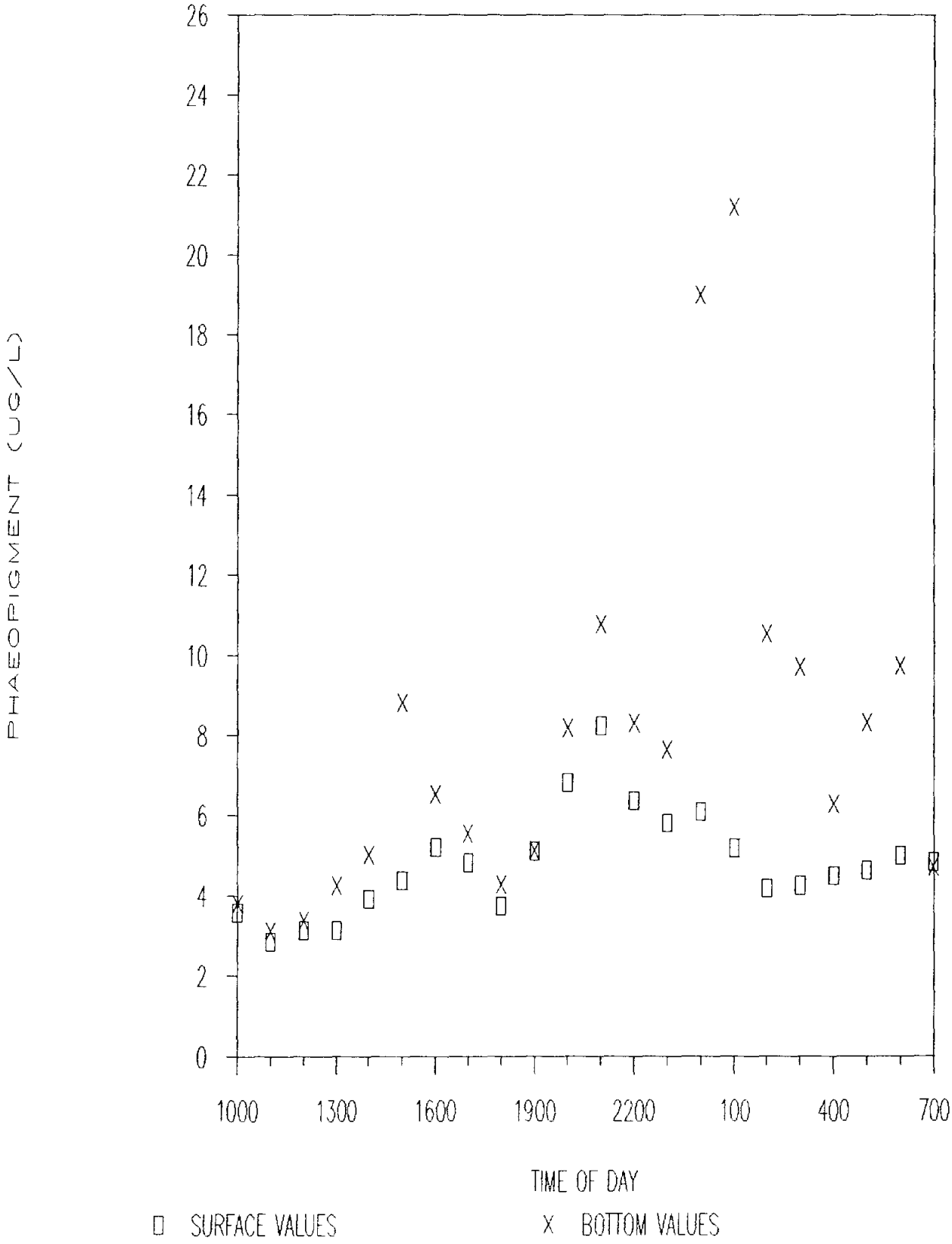

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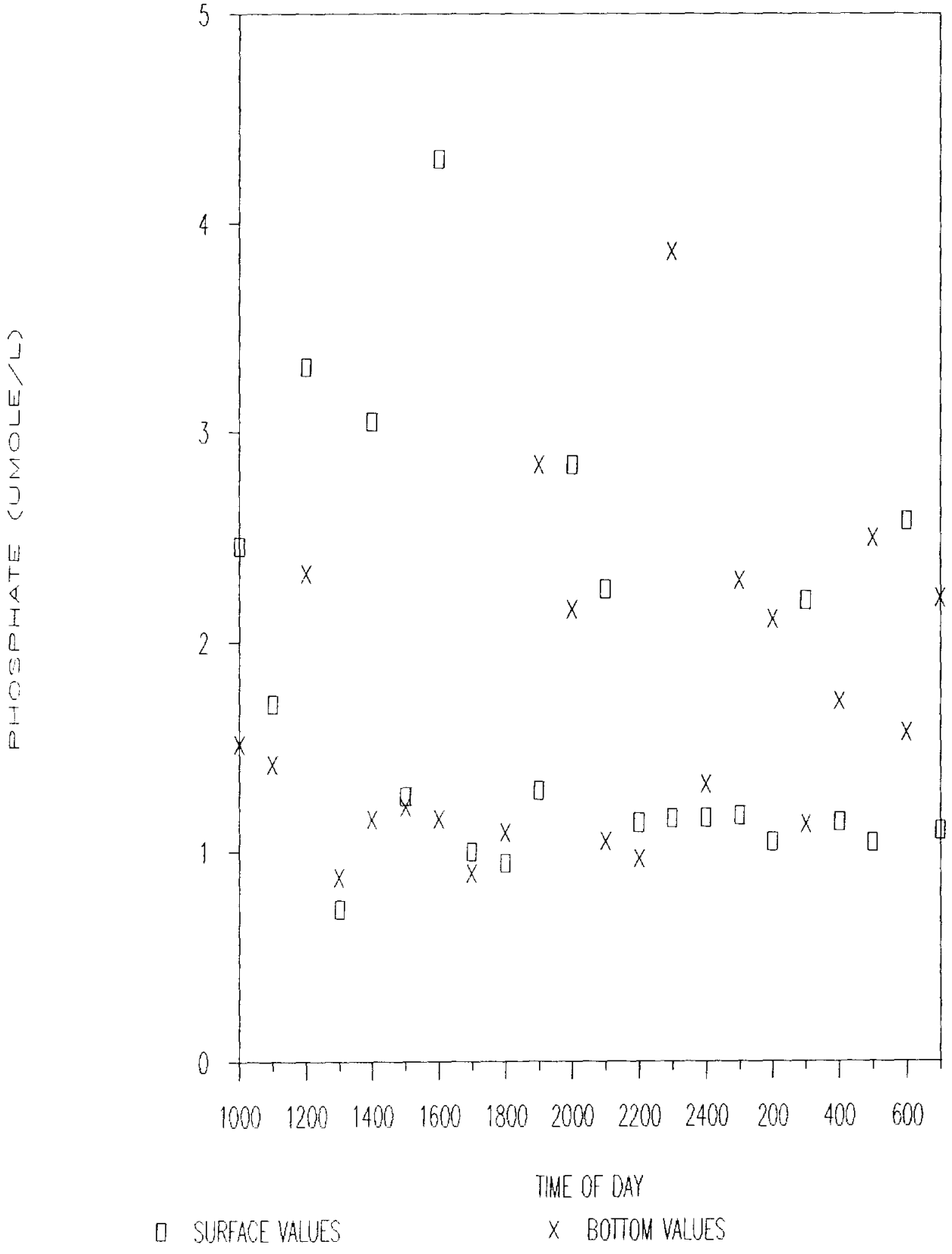

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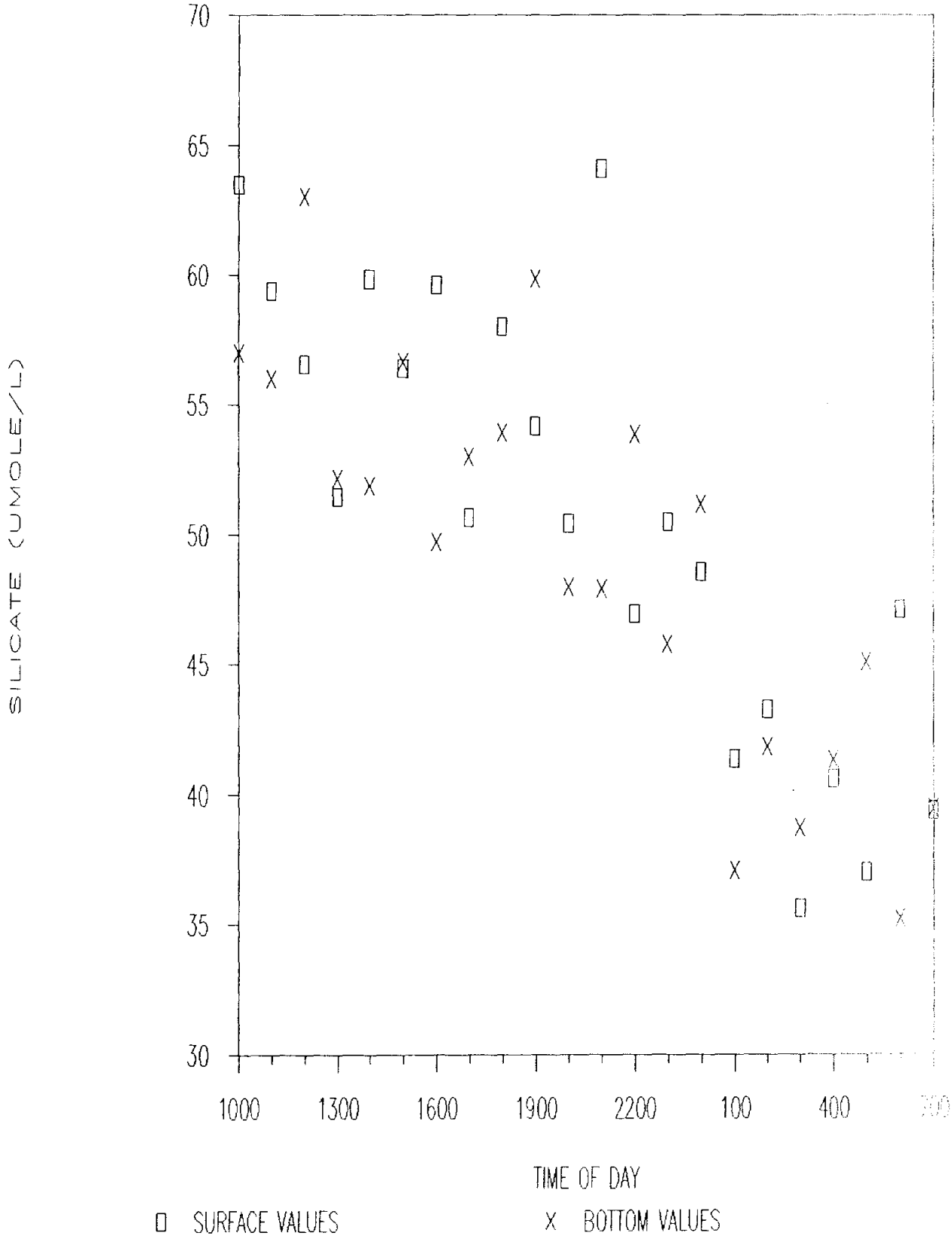

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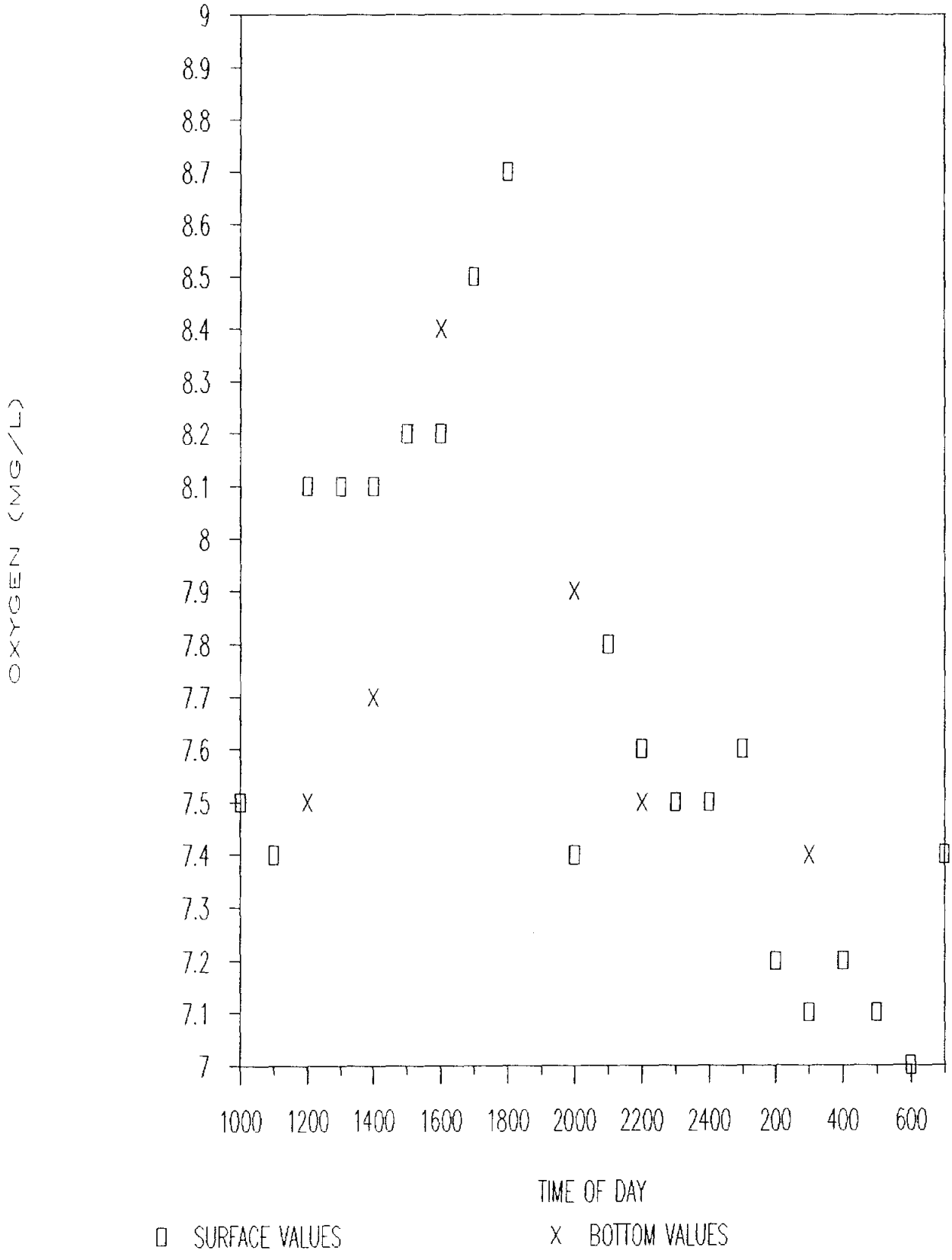

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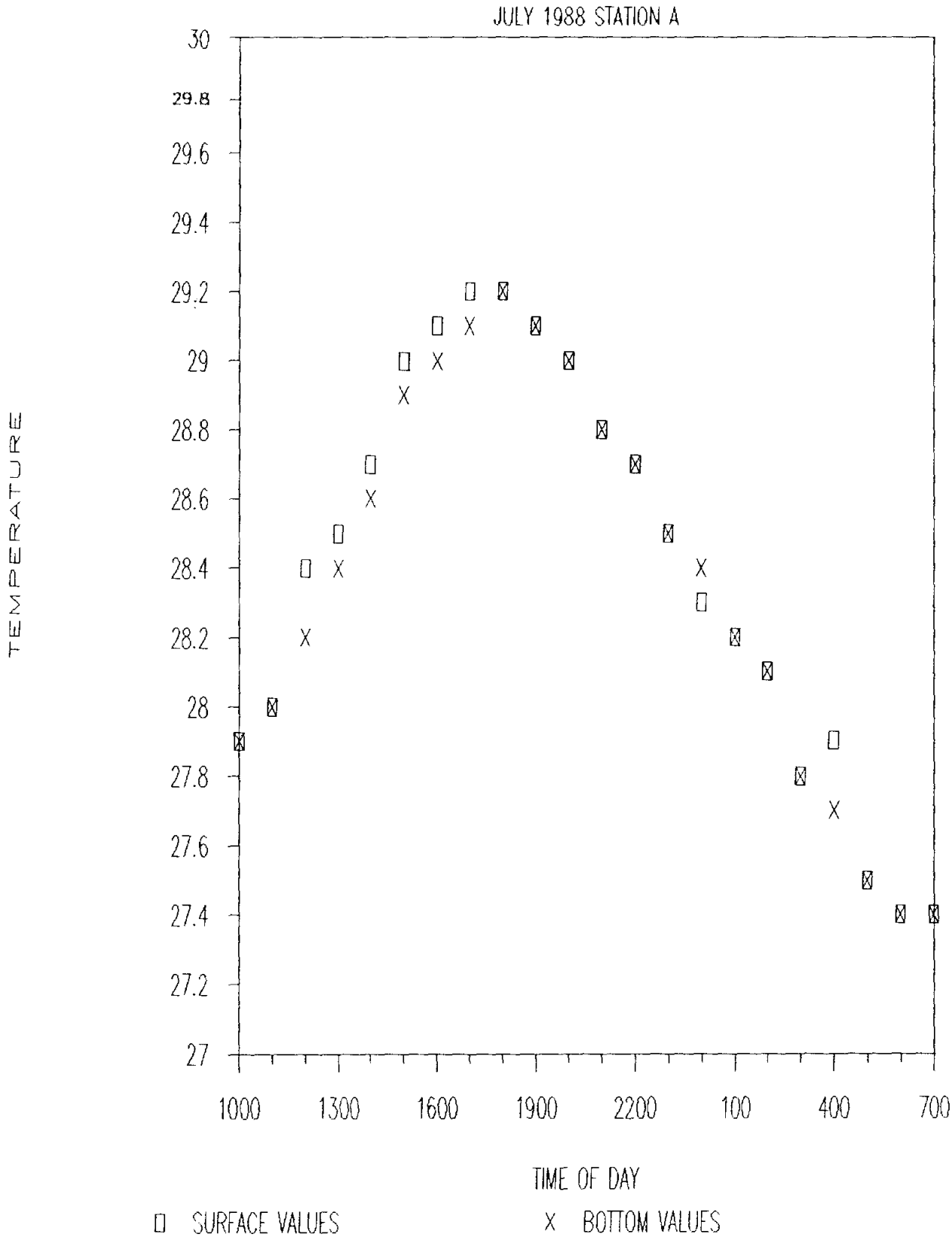

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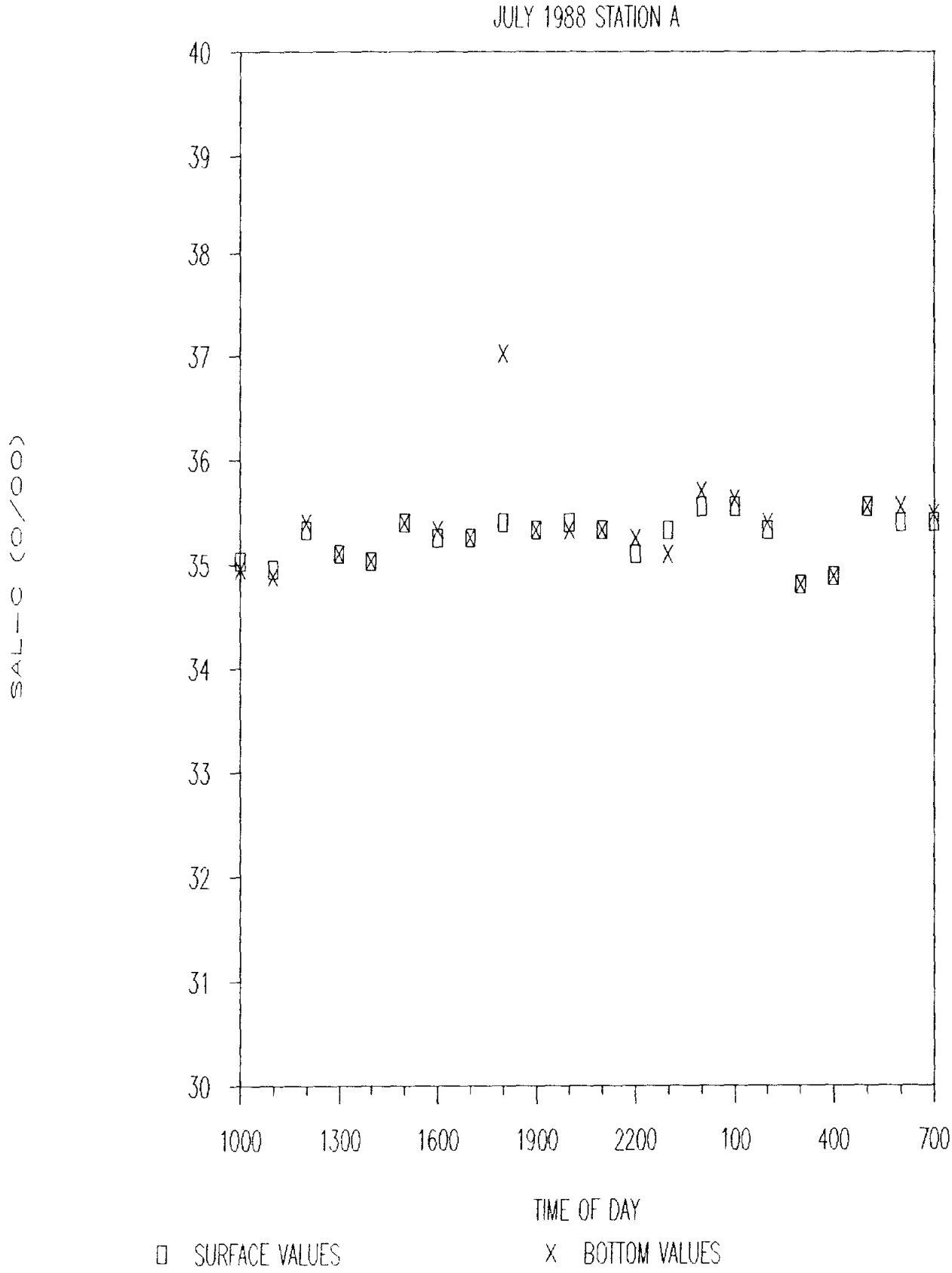

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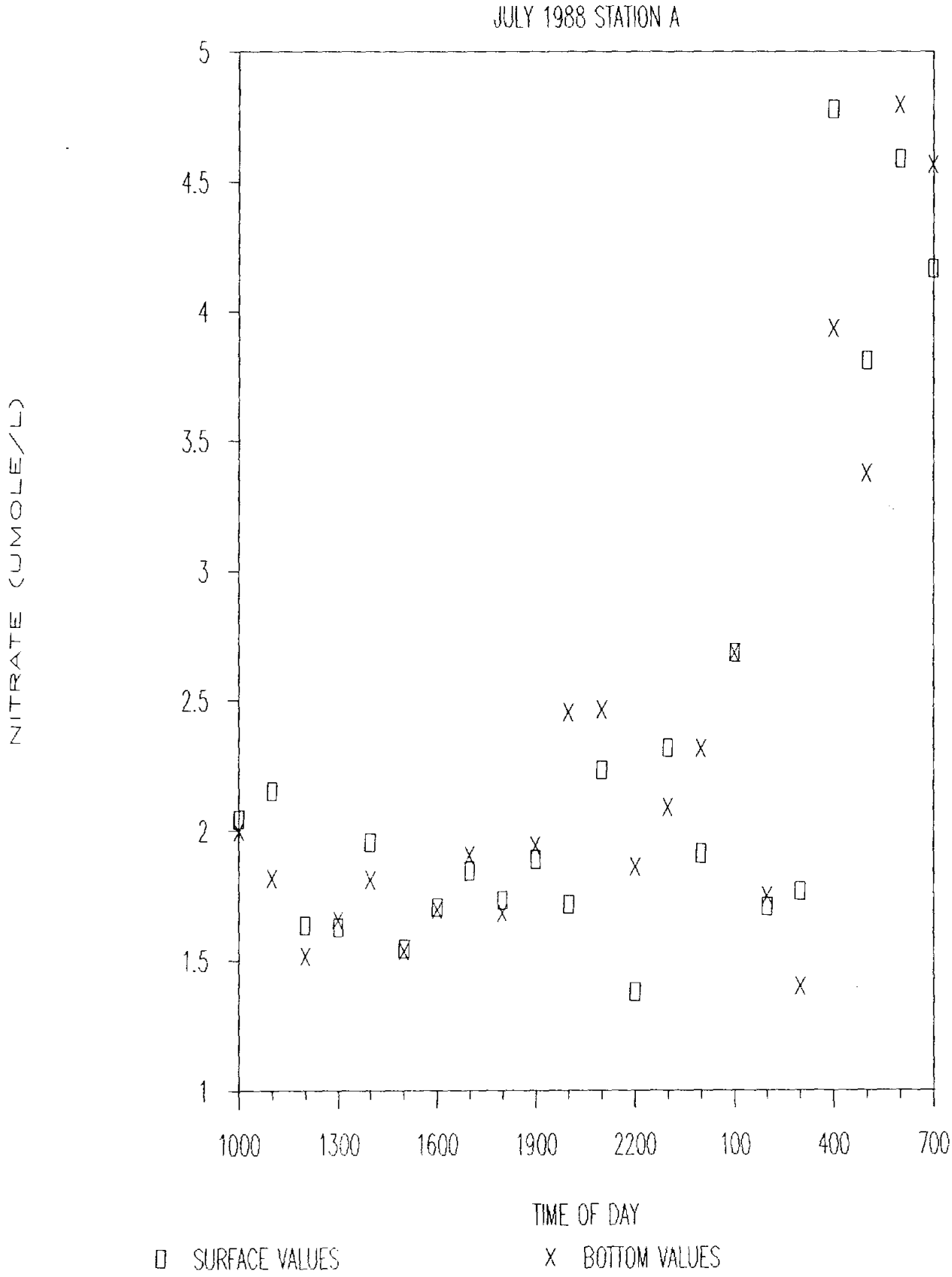

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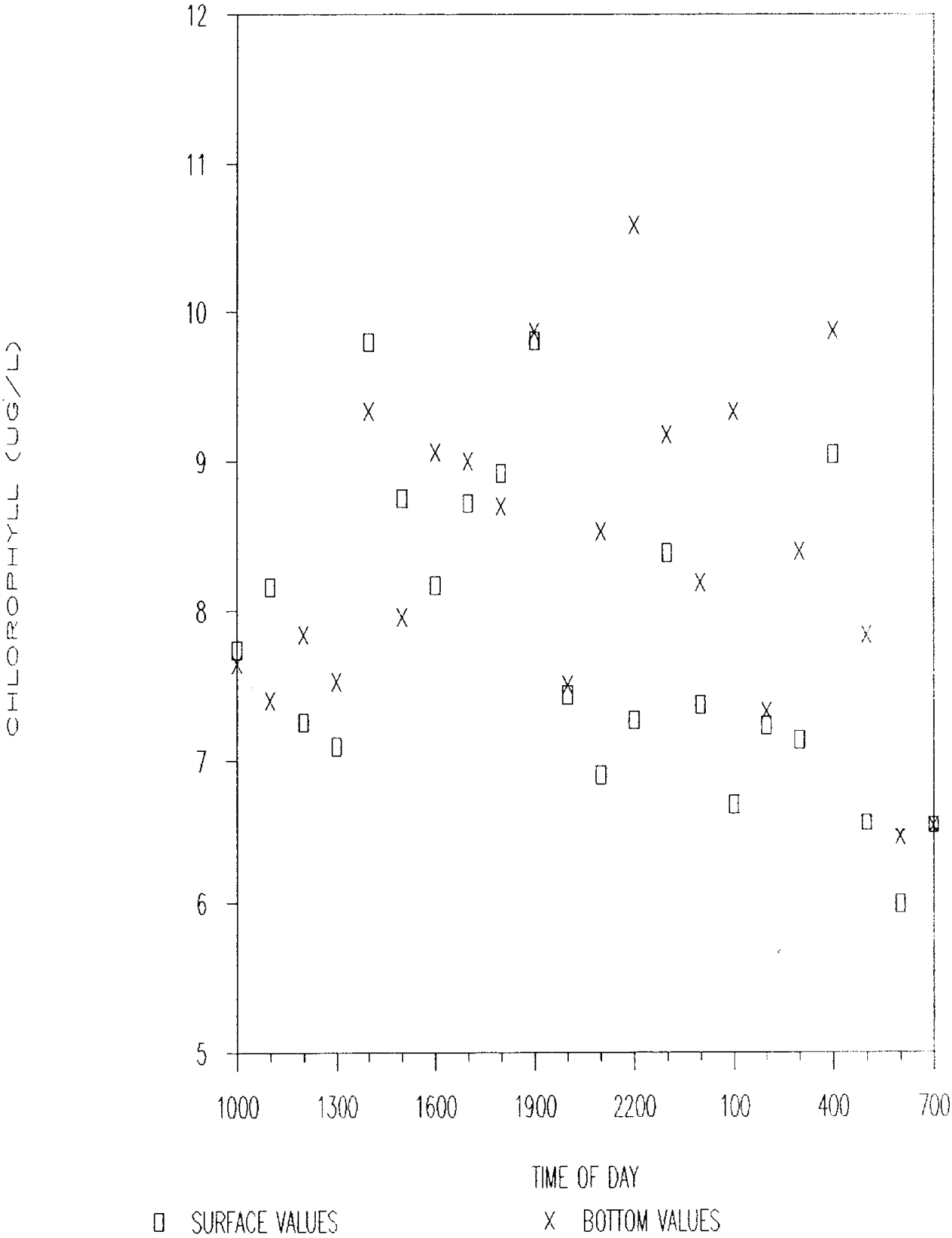

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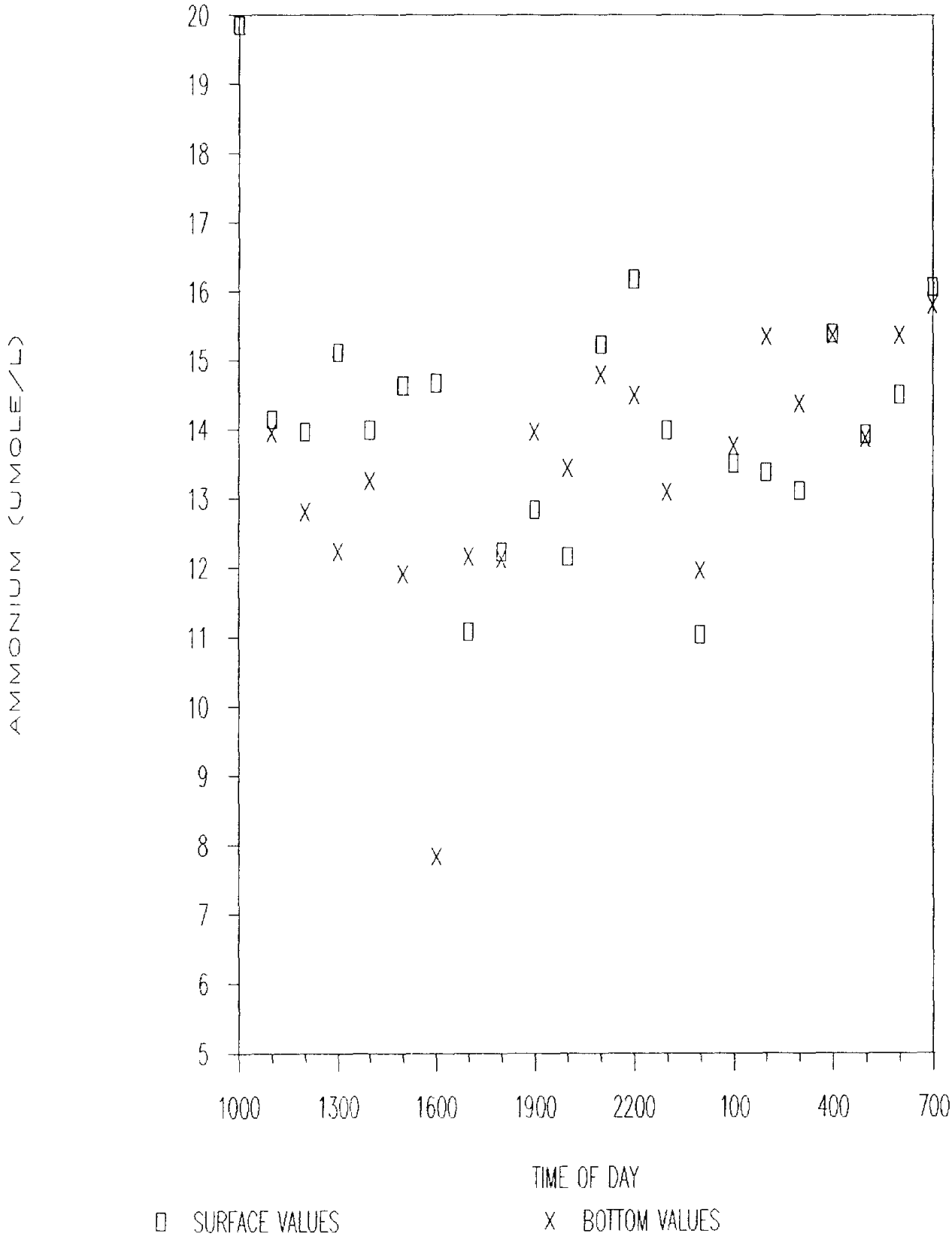

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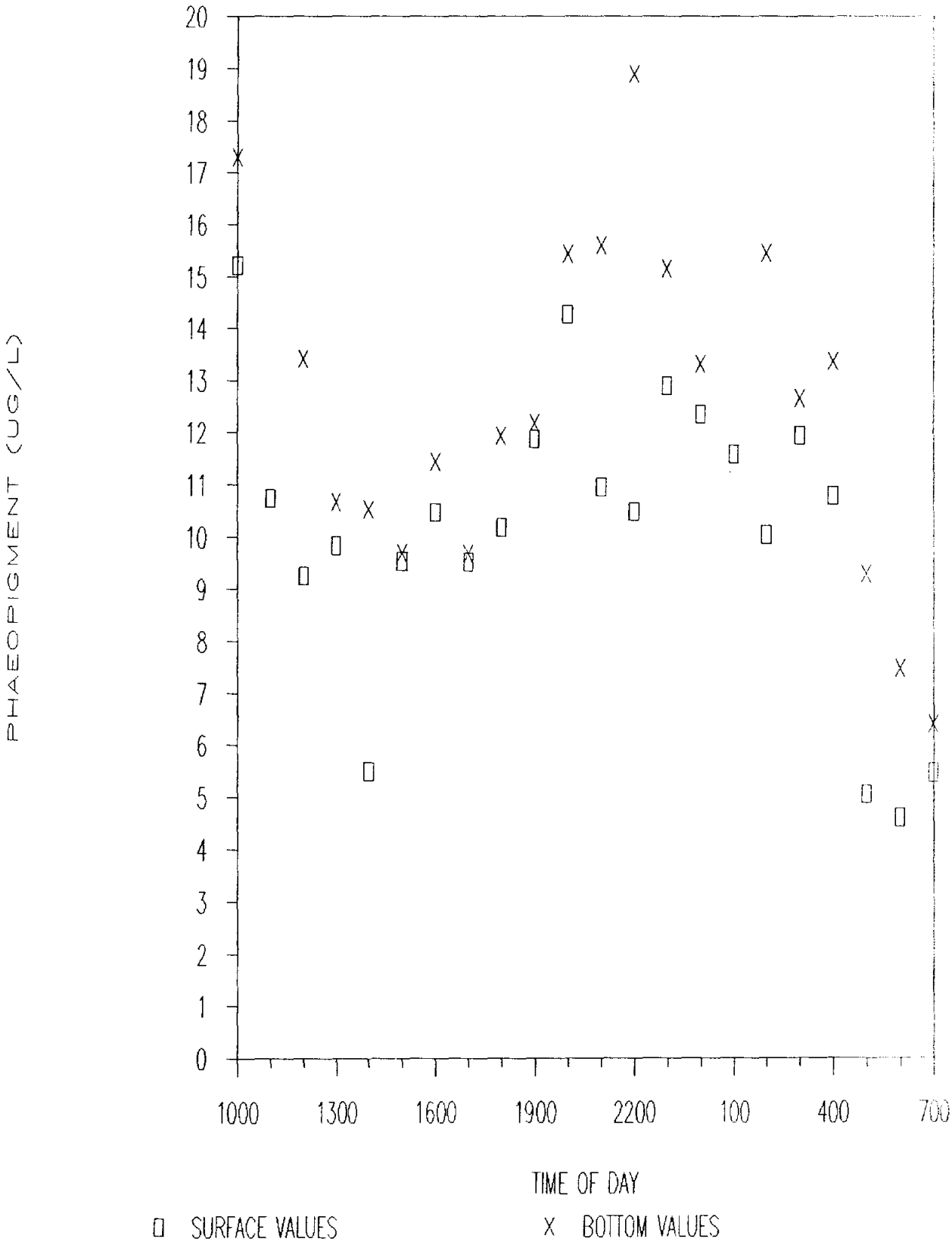

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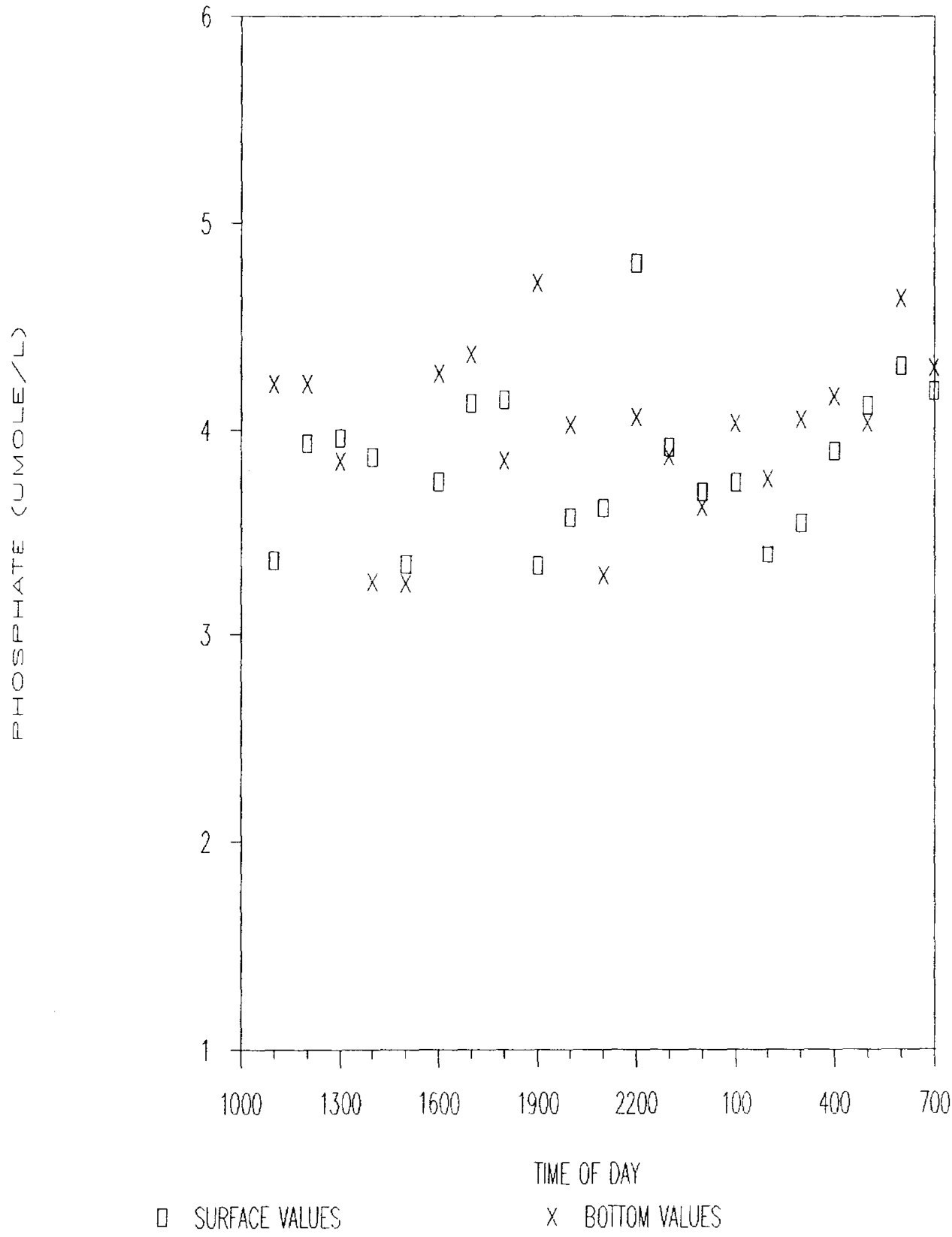

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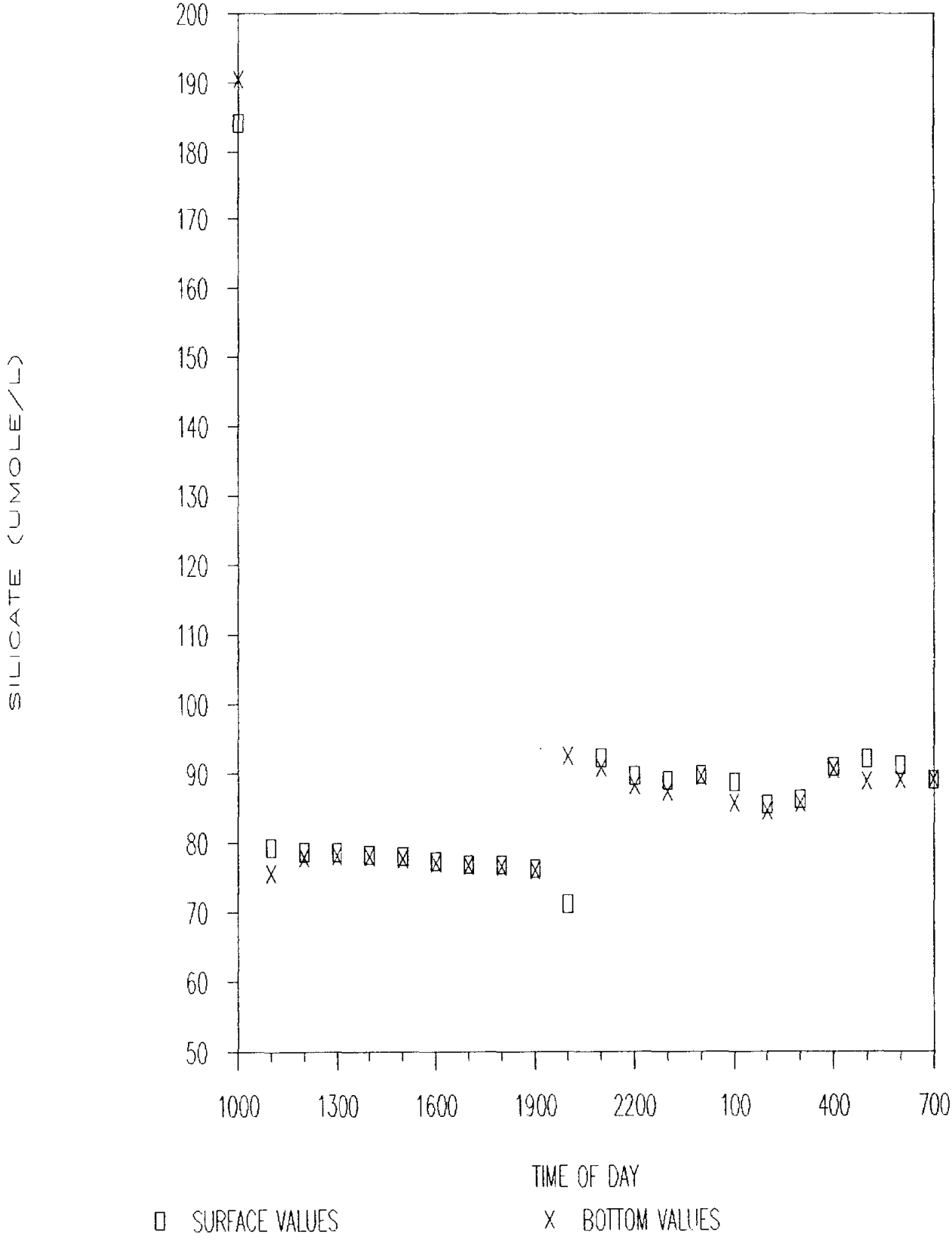

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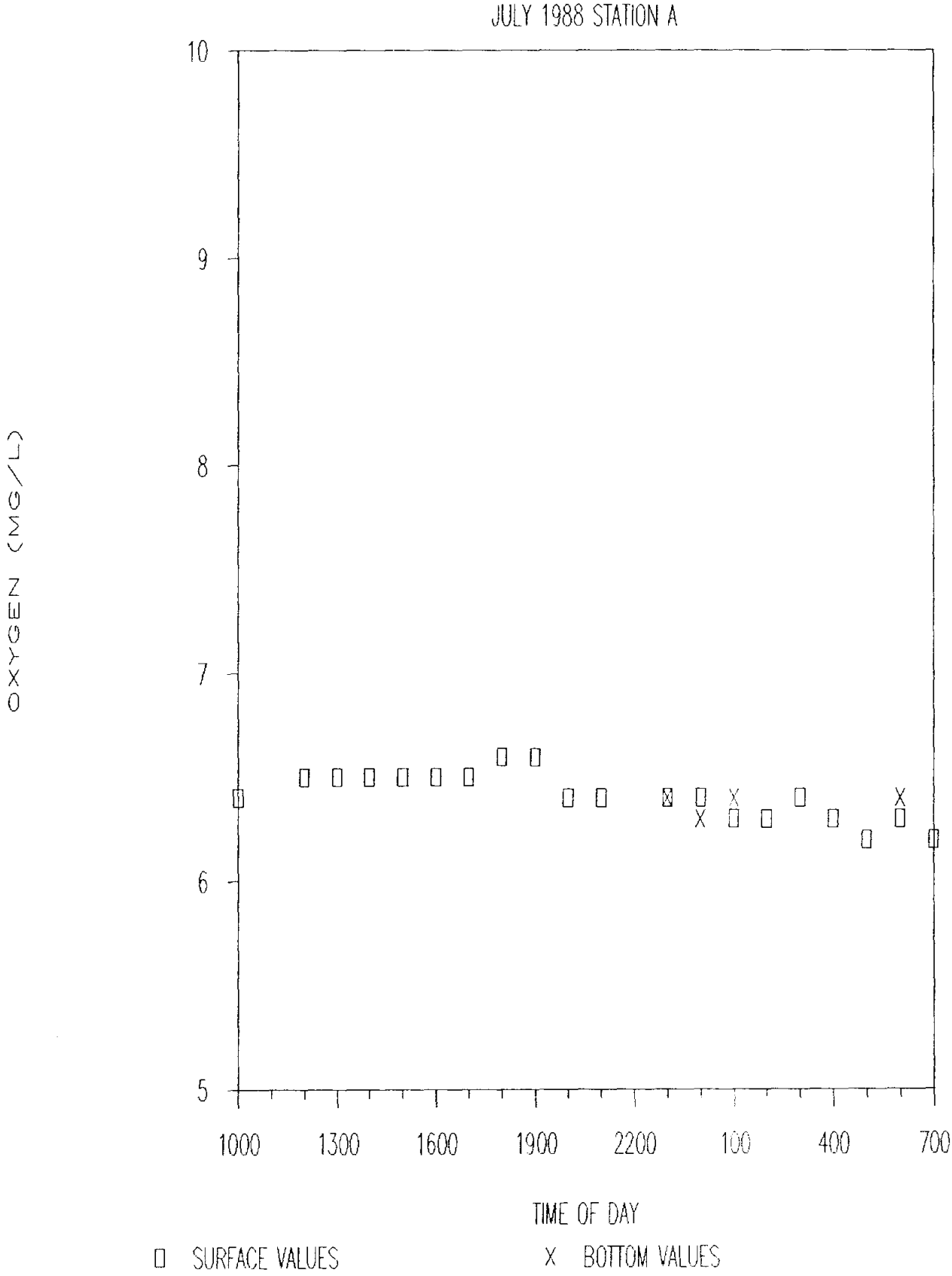
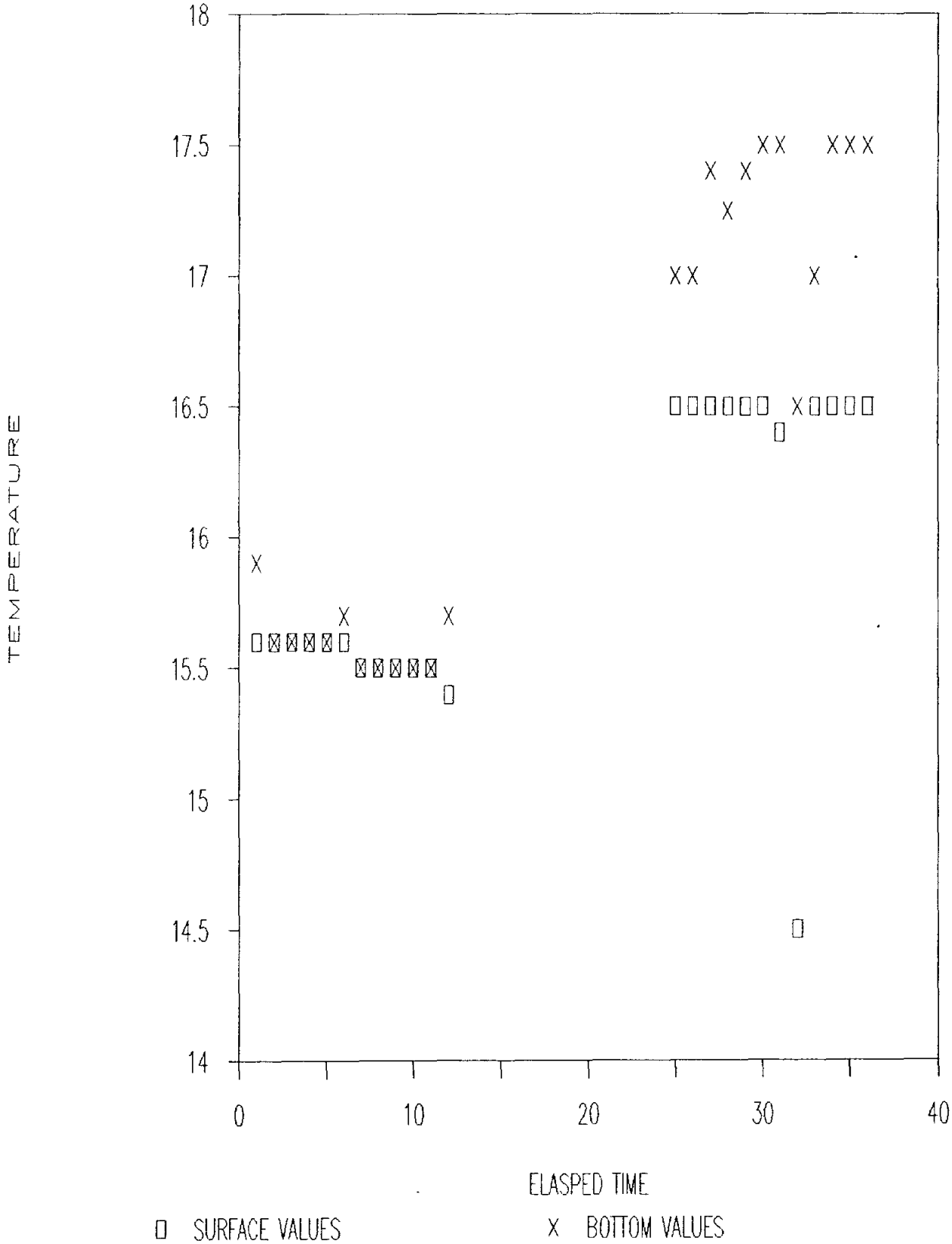


SAN ANTONIO BAY

JAN 1987 STATION C



SAN ANTONIO BAY

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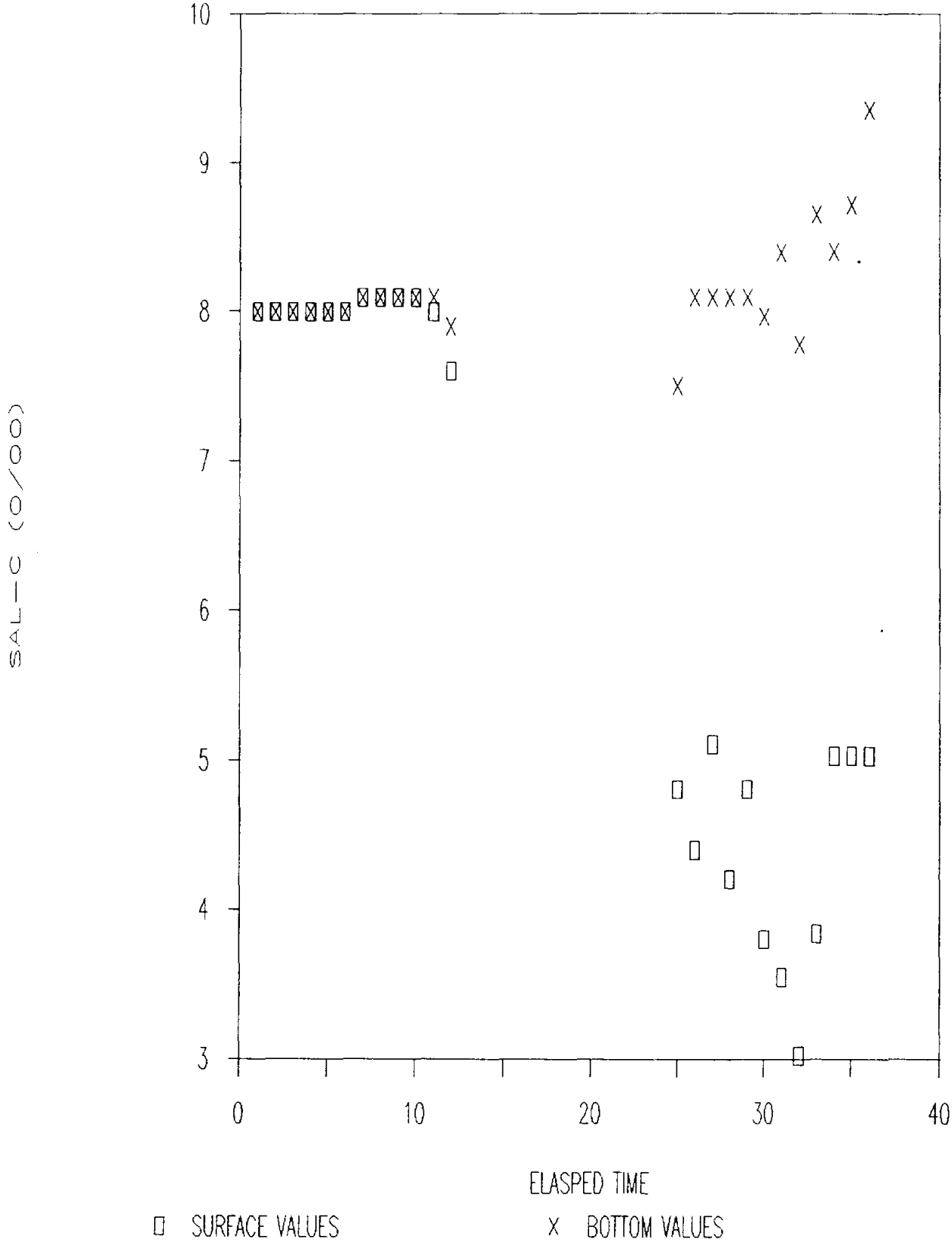

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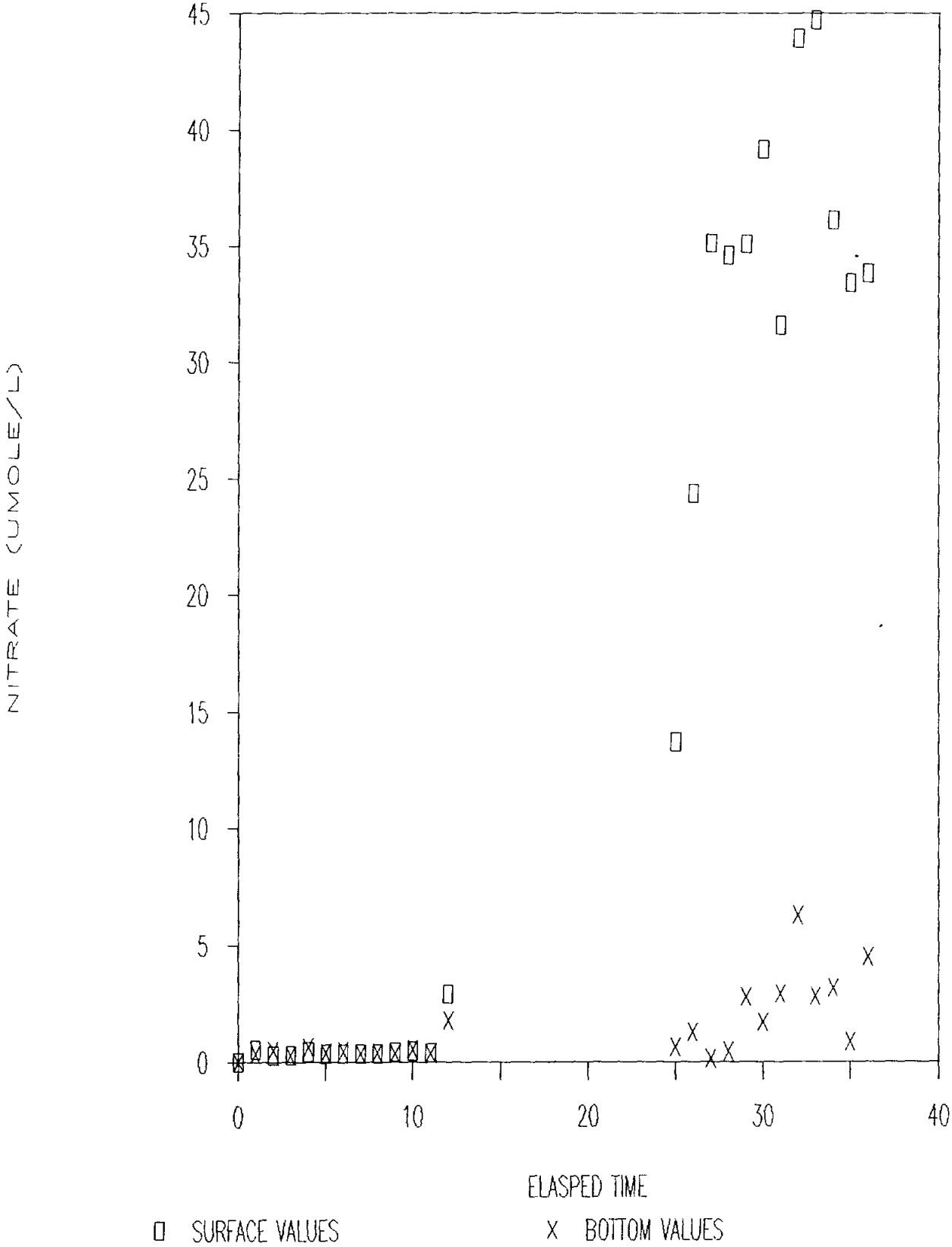

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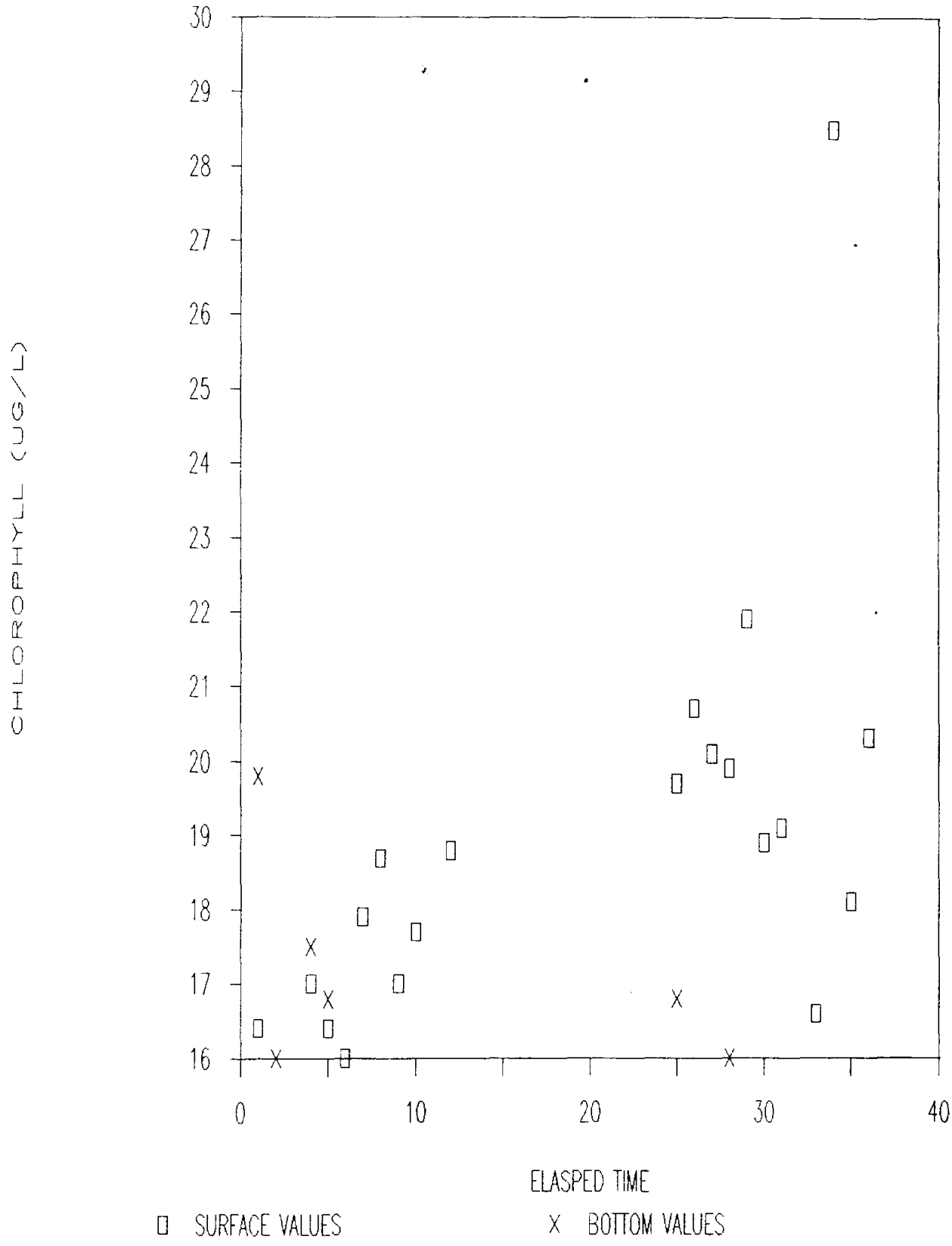

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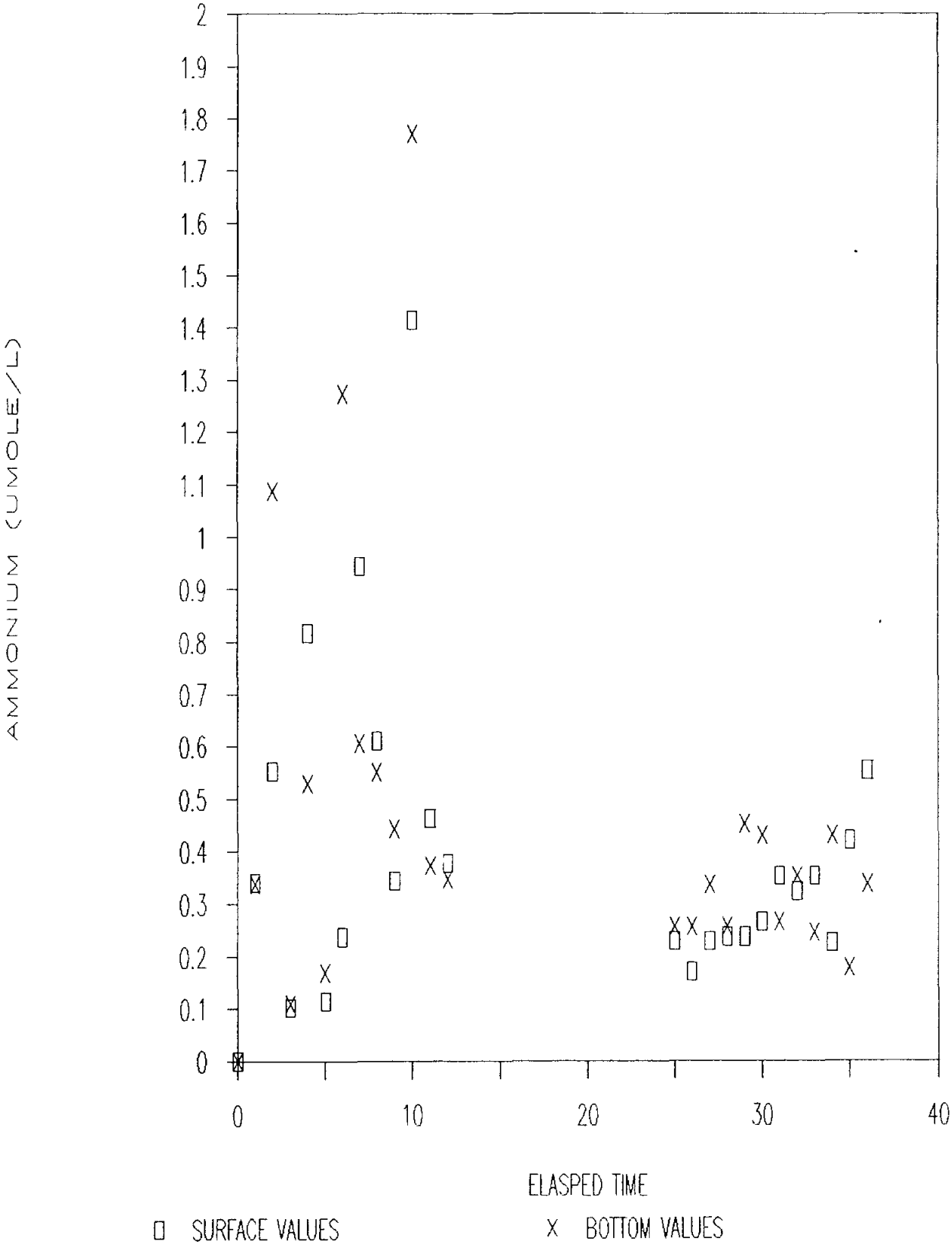

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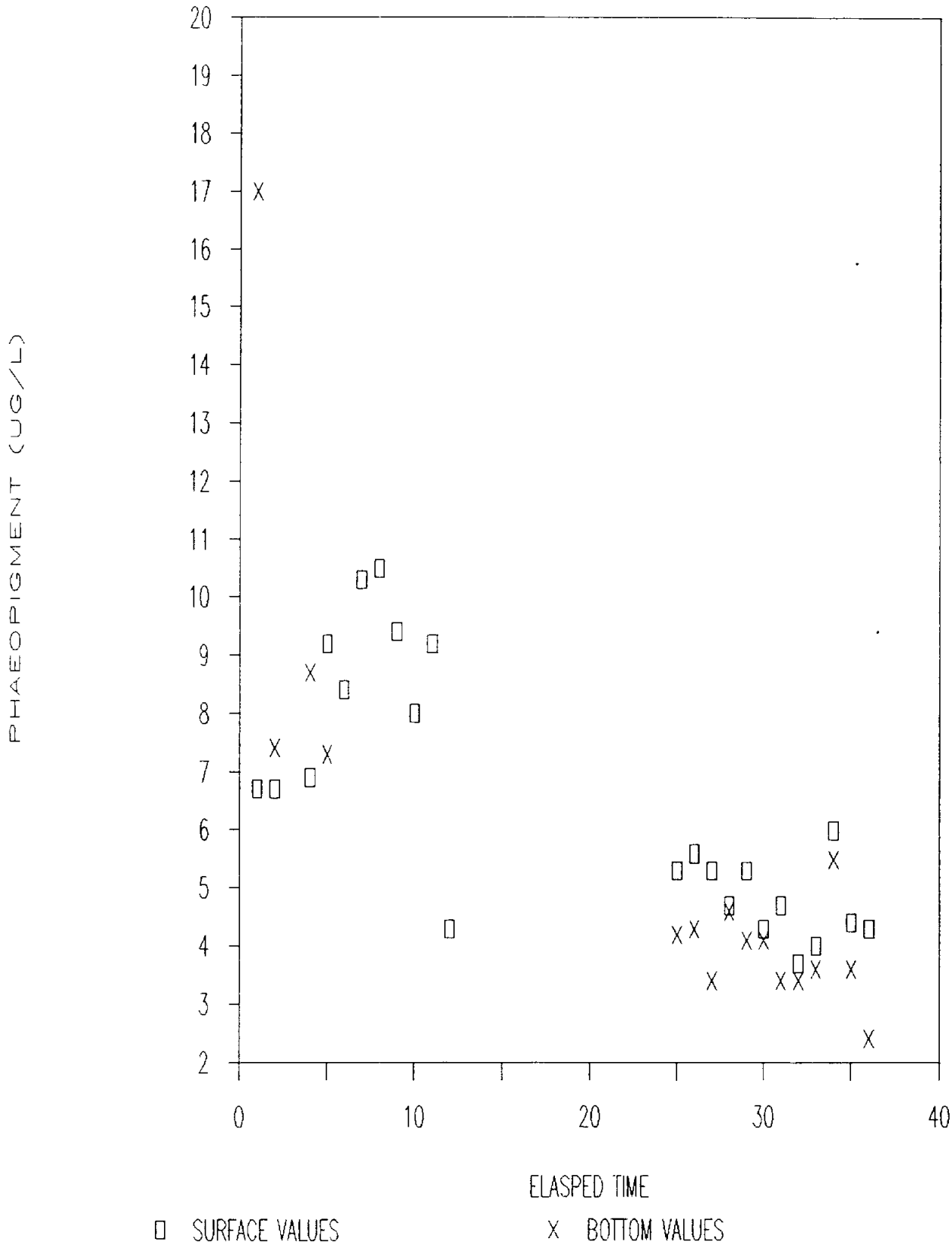

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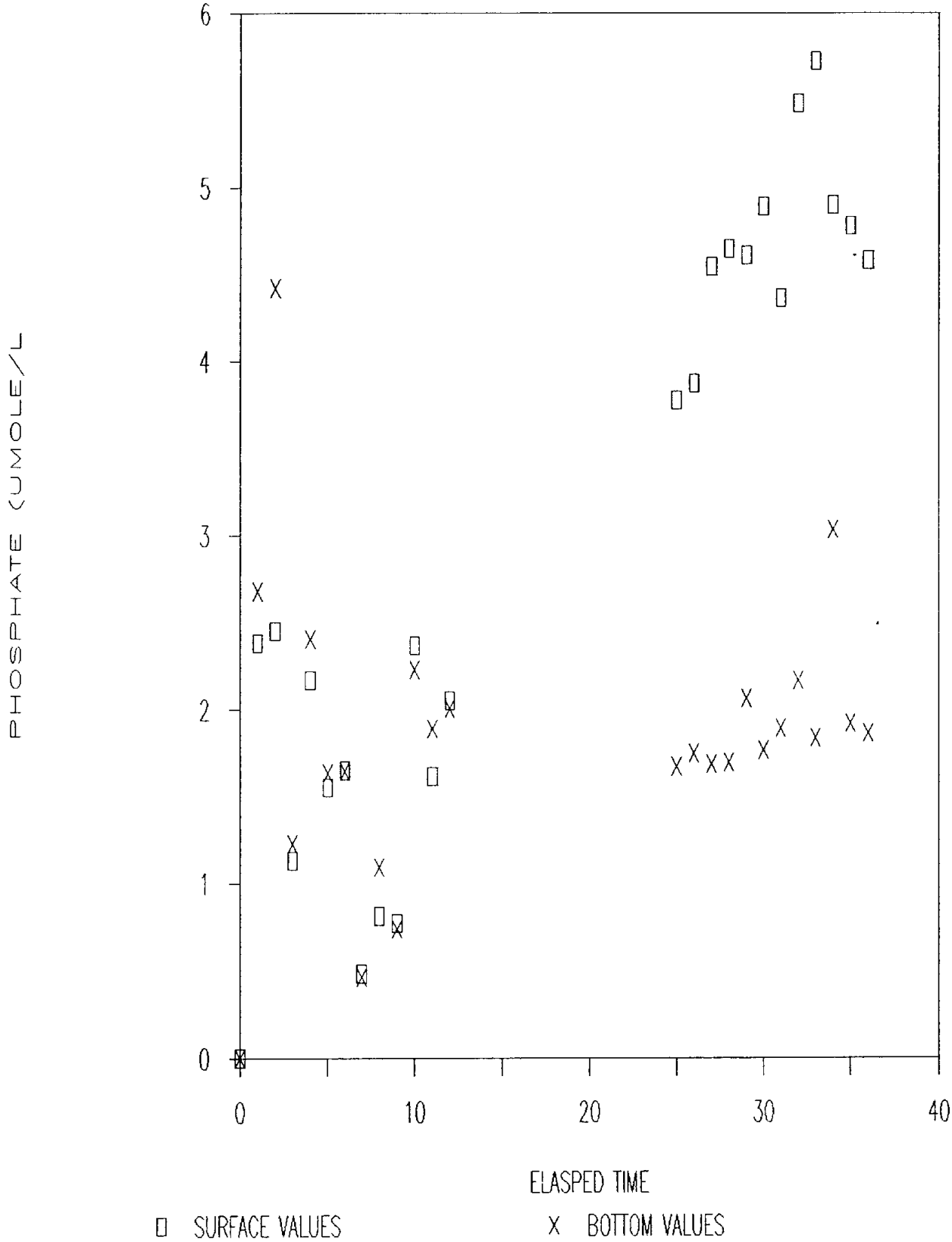

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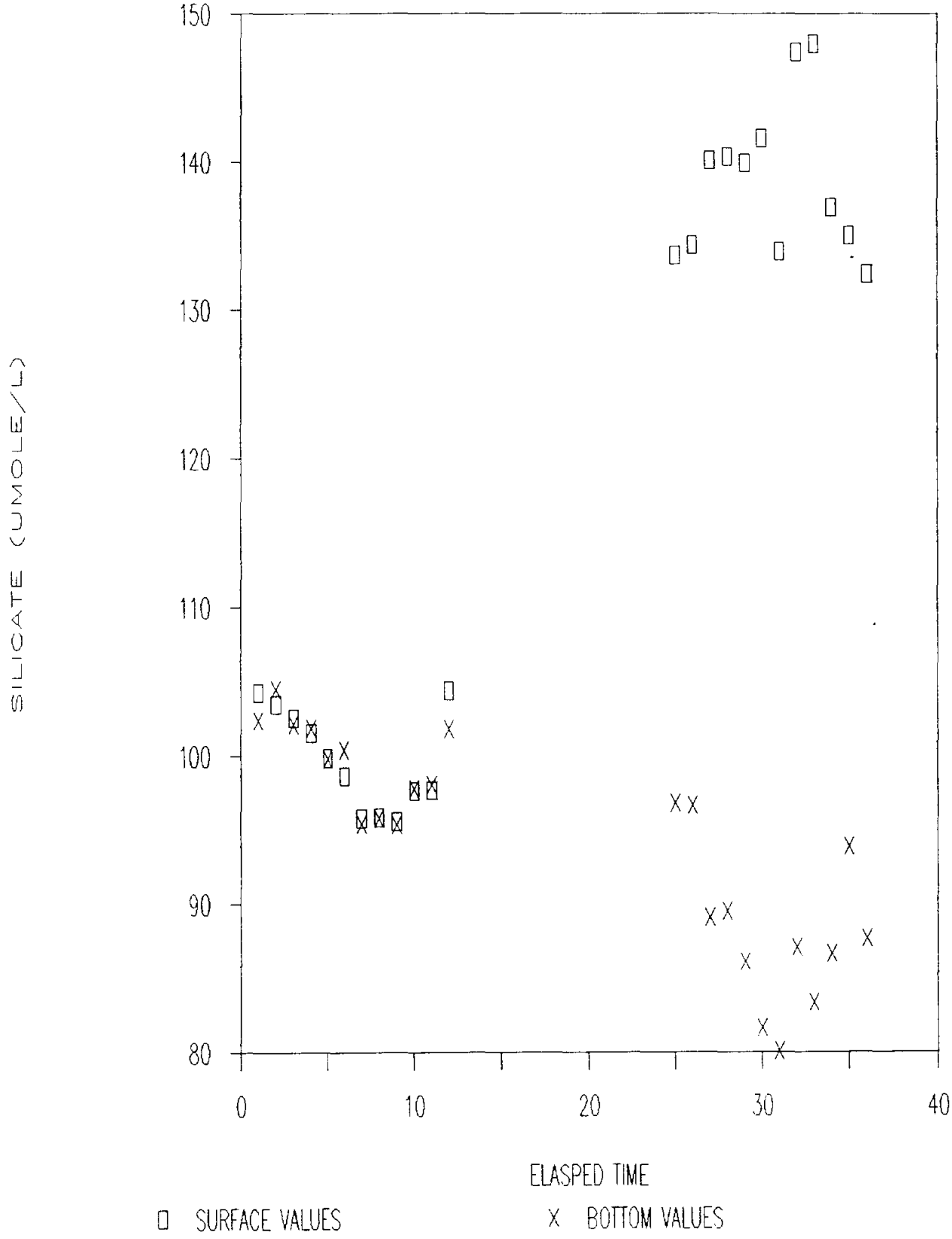

SAN ANTONIO BAY

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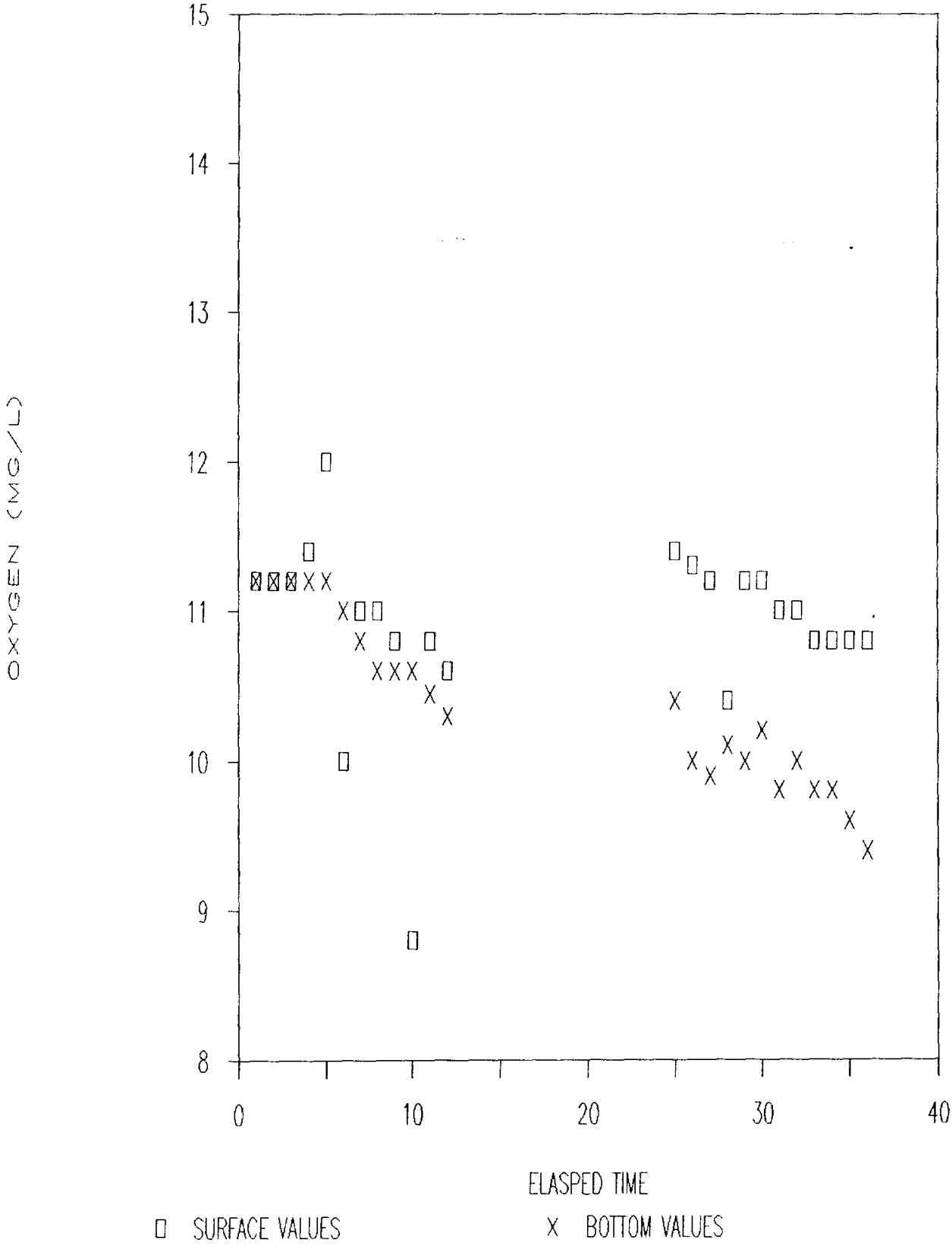

SAN ANTIONIO BAY

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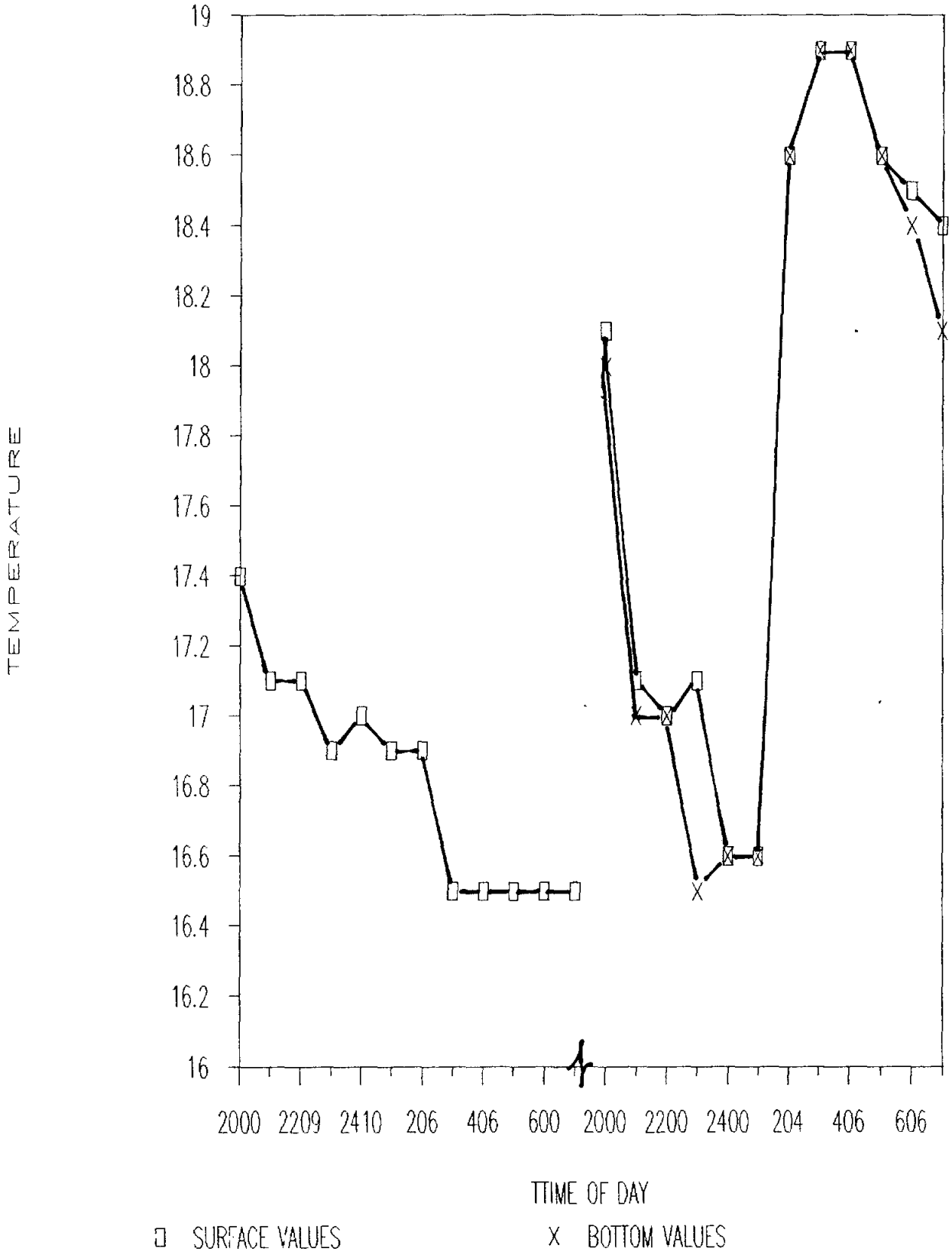
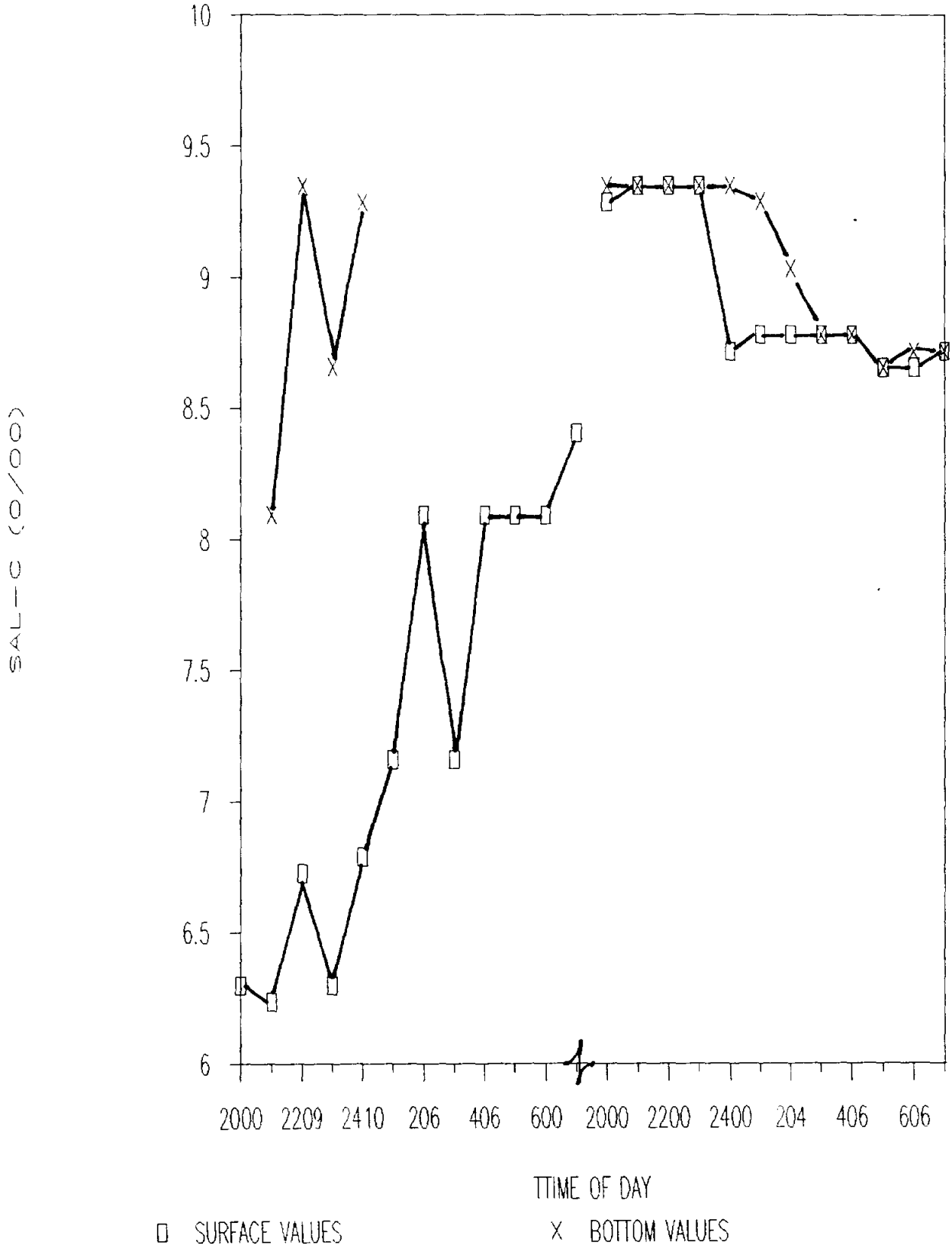


SAN ANTIONIO BAY

APRIL 1987 STATION C



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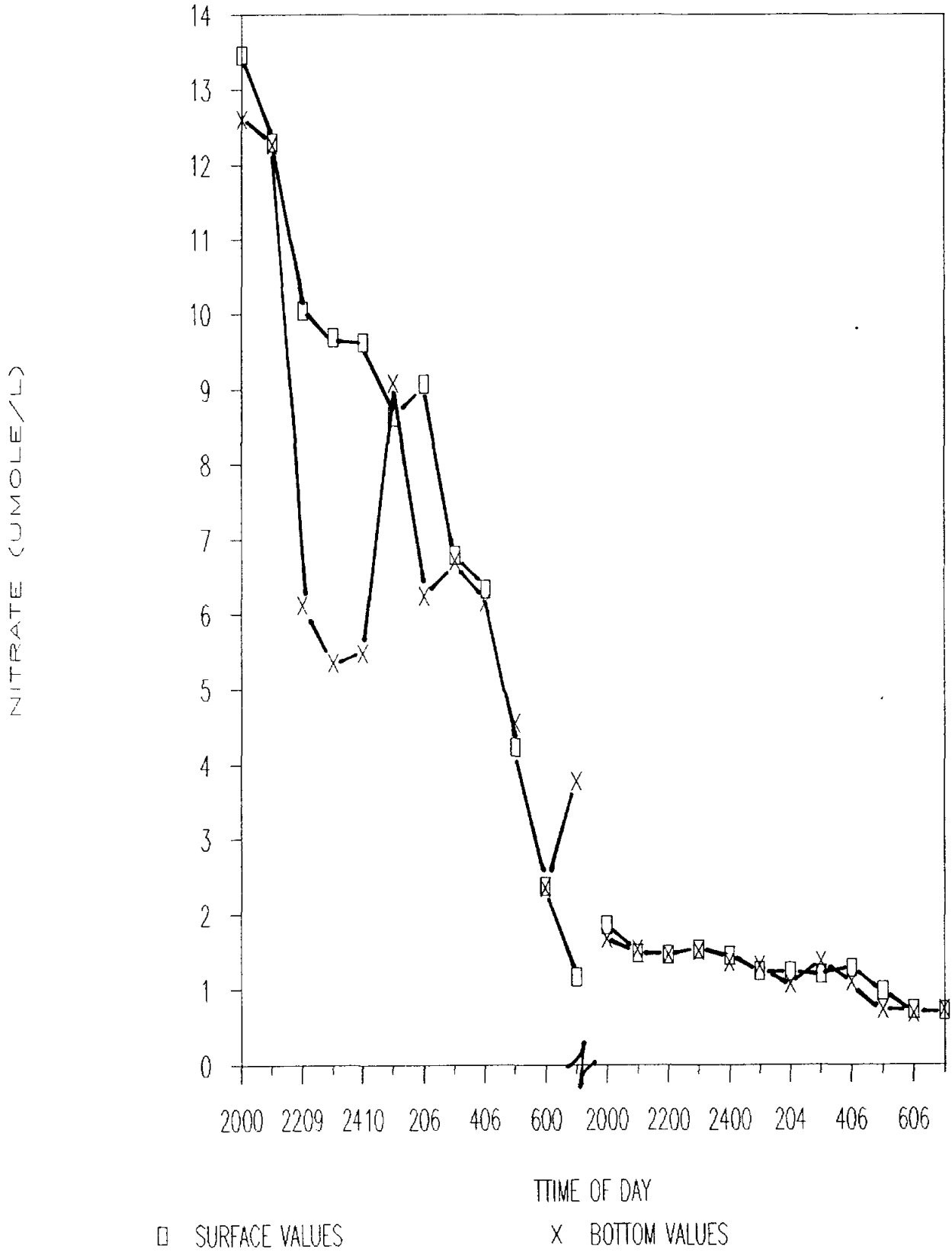

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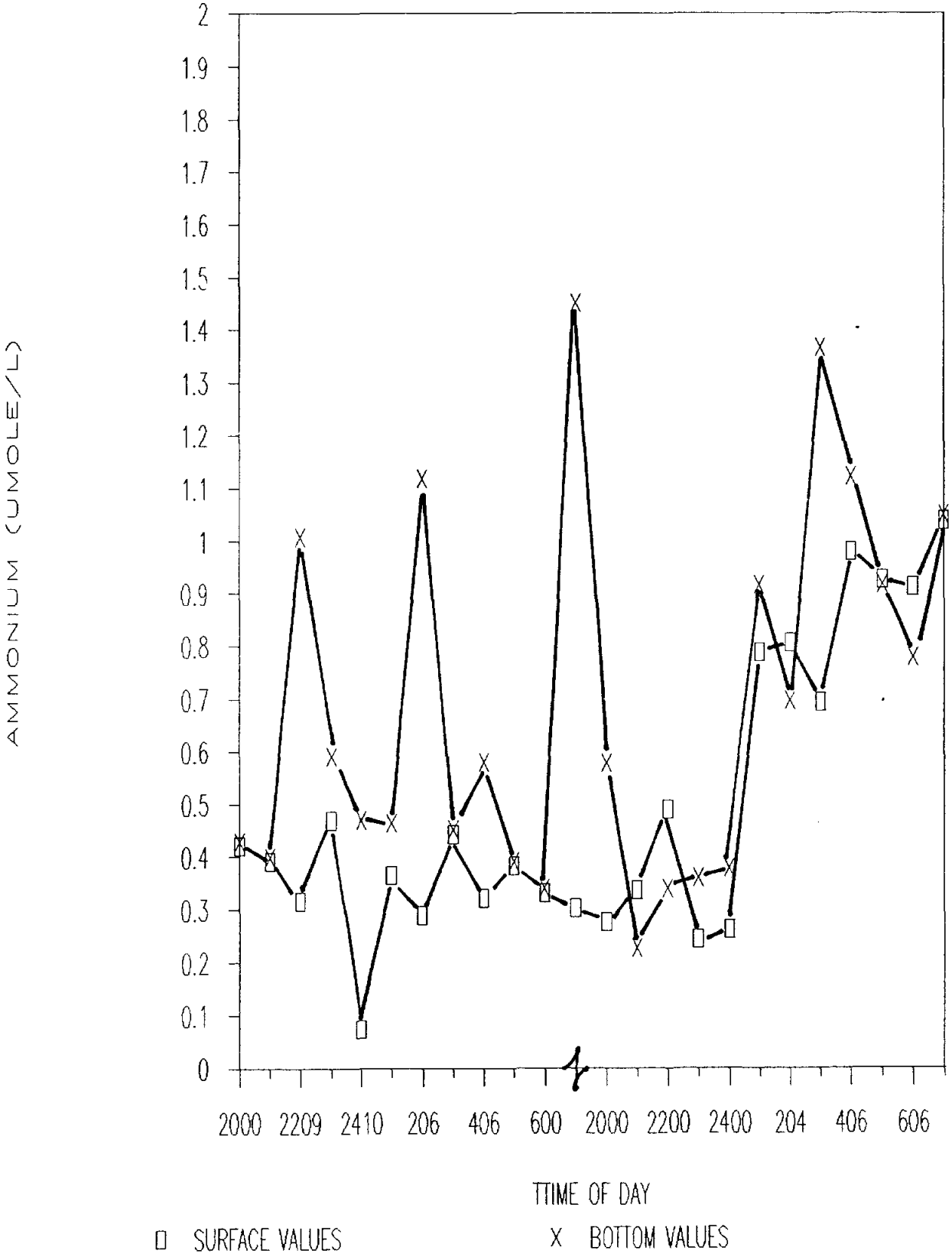

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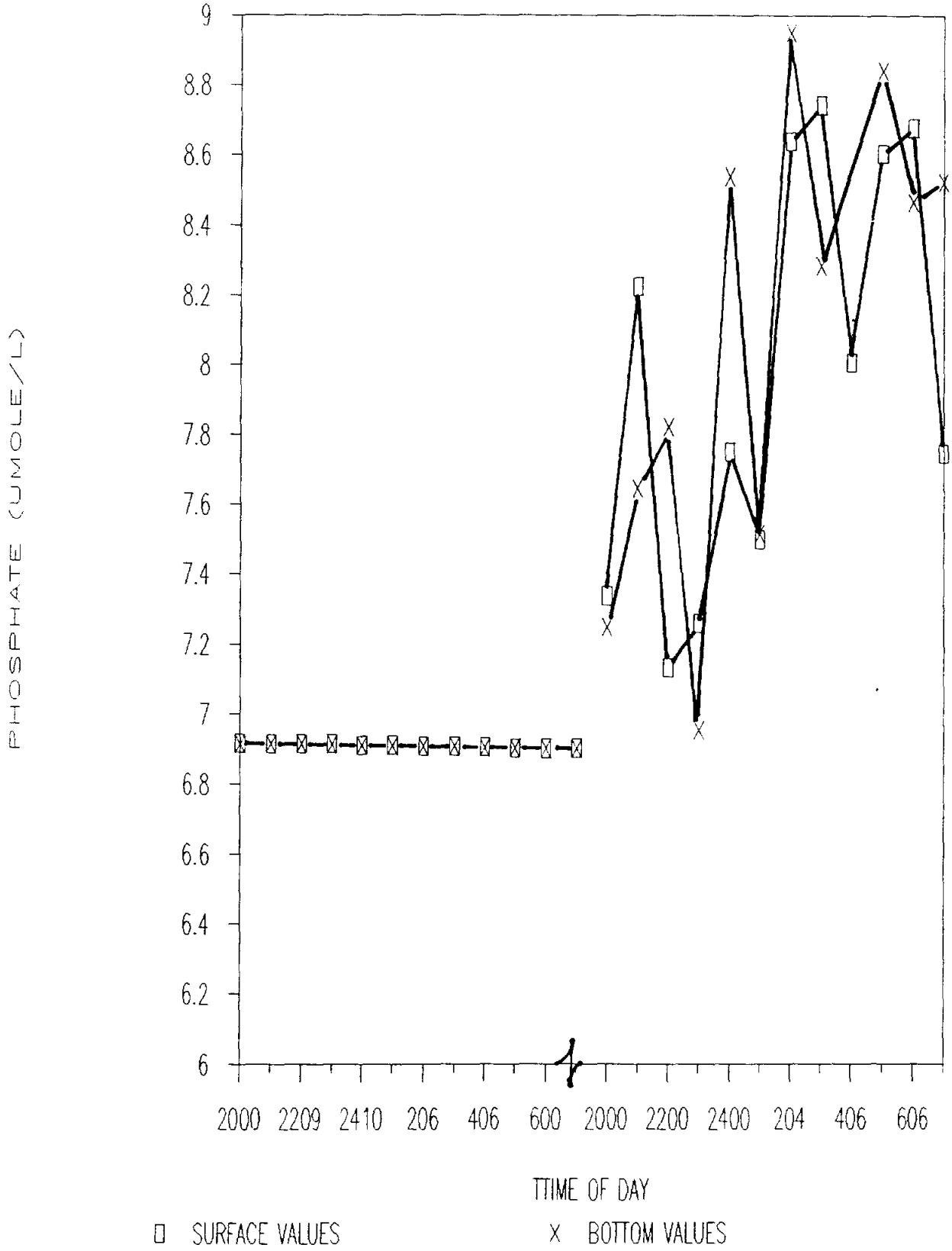

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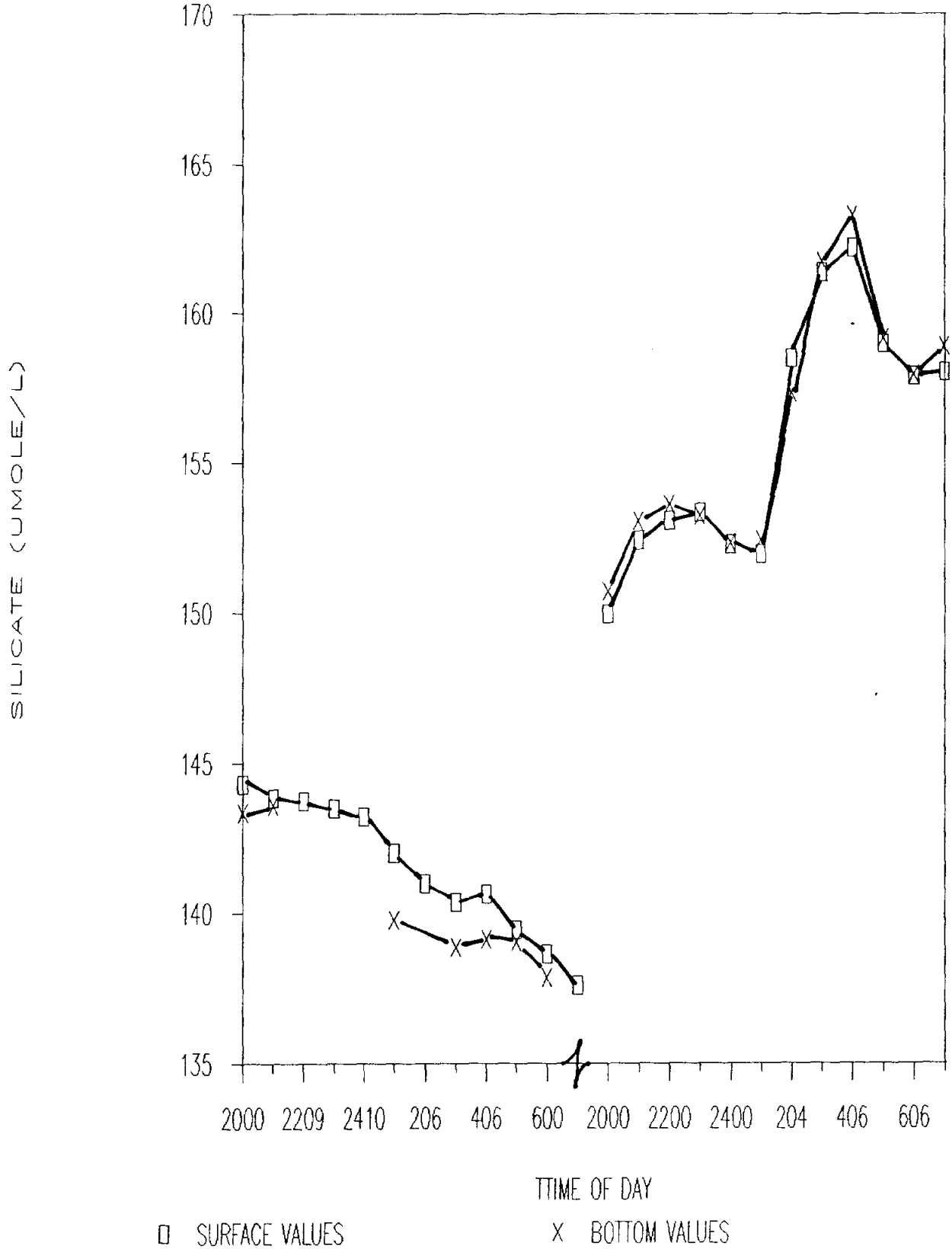

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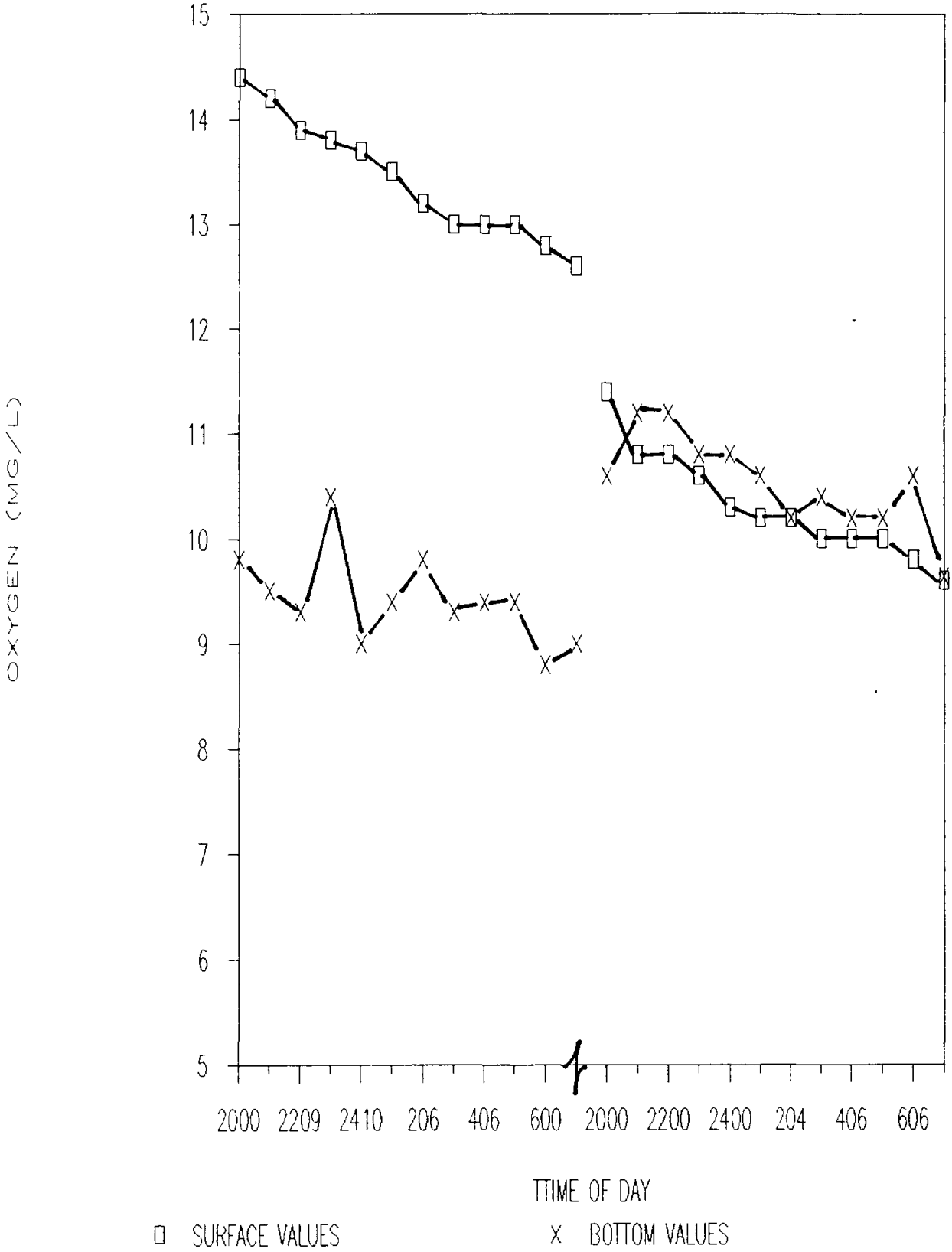

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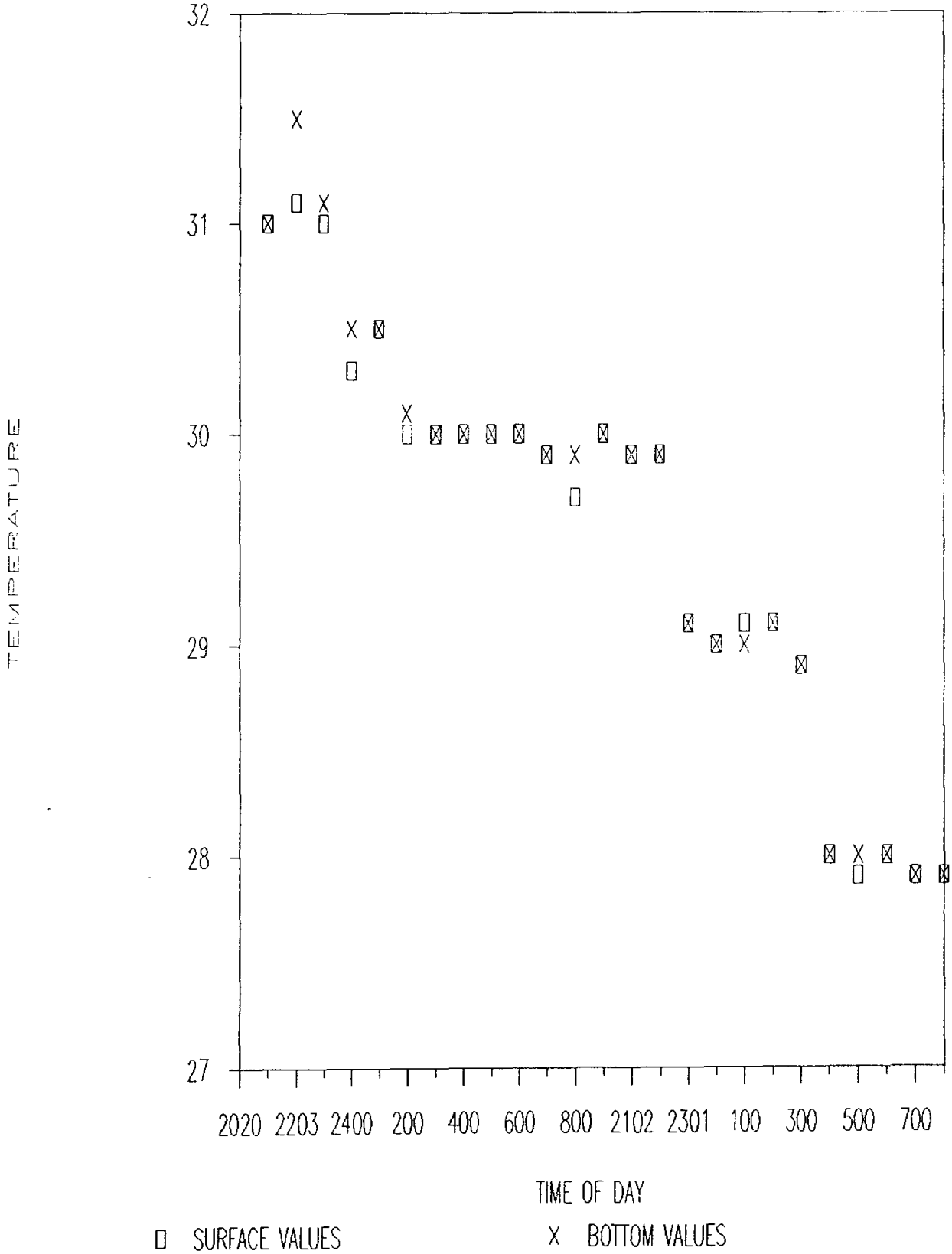

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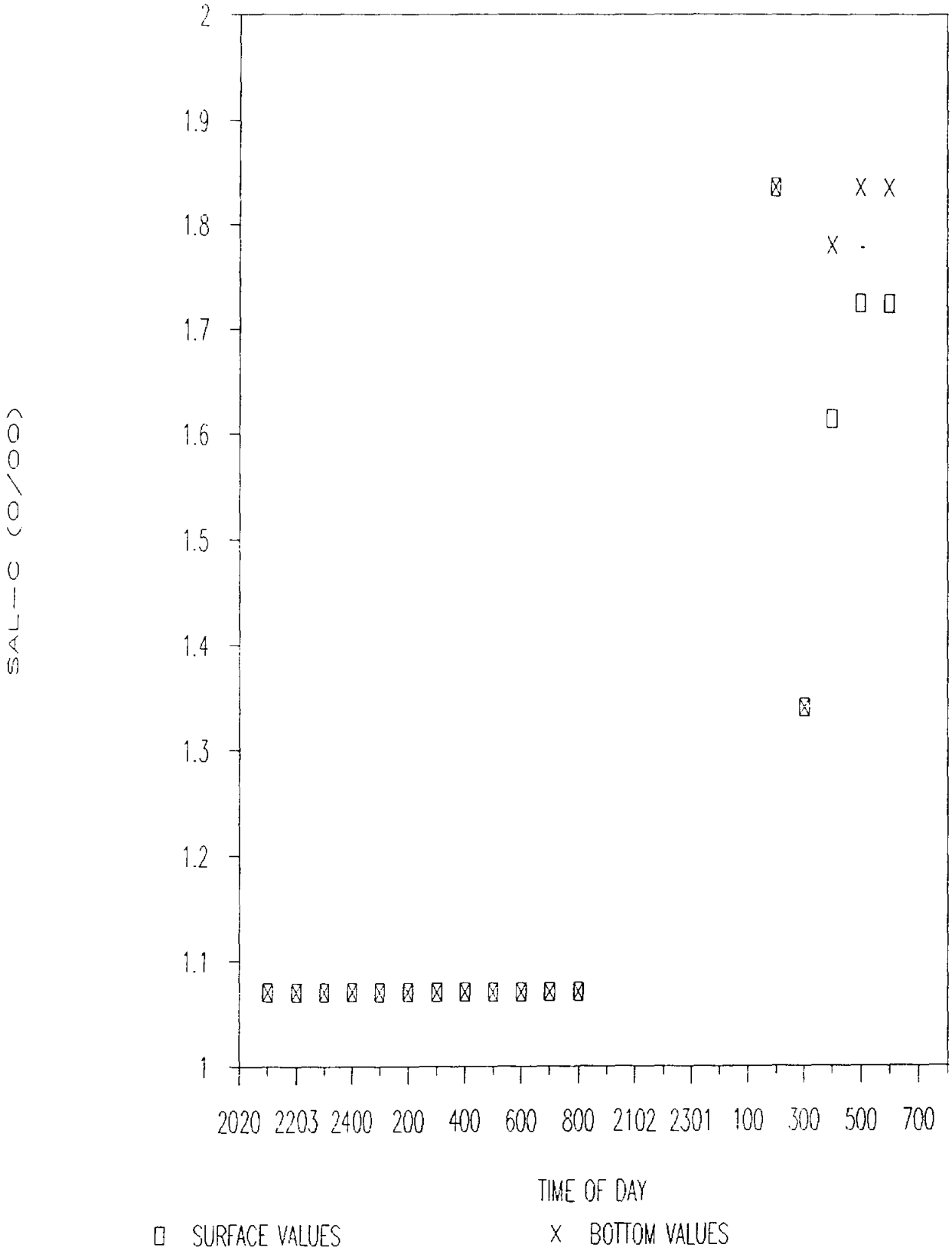

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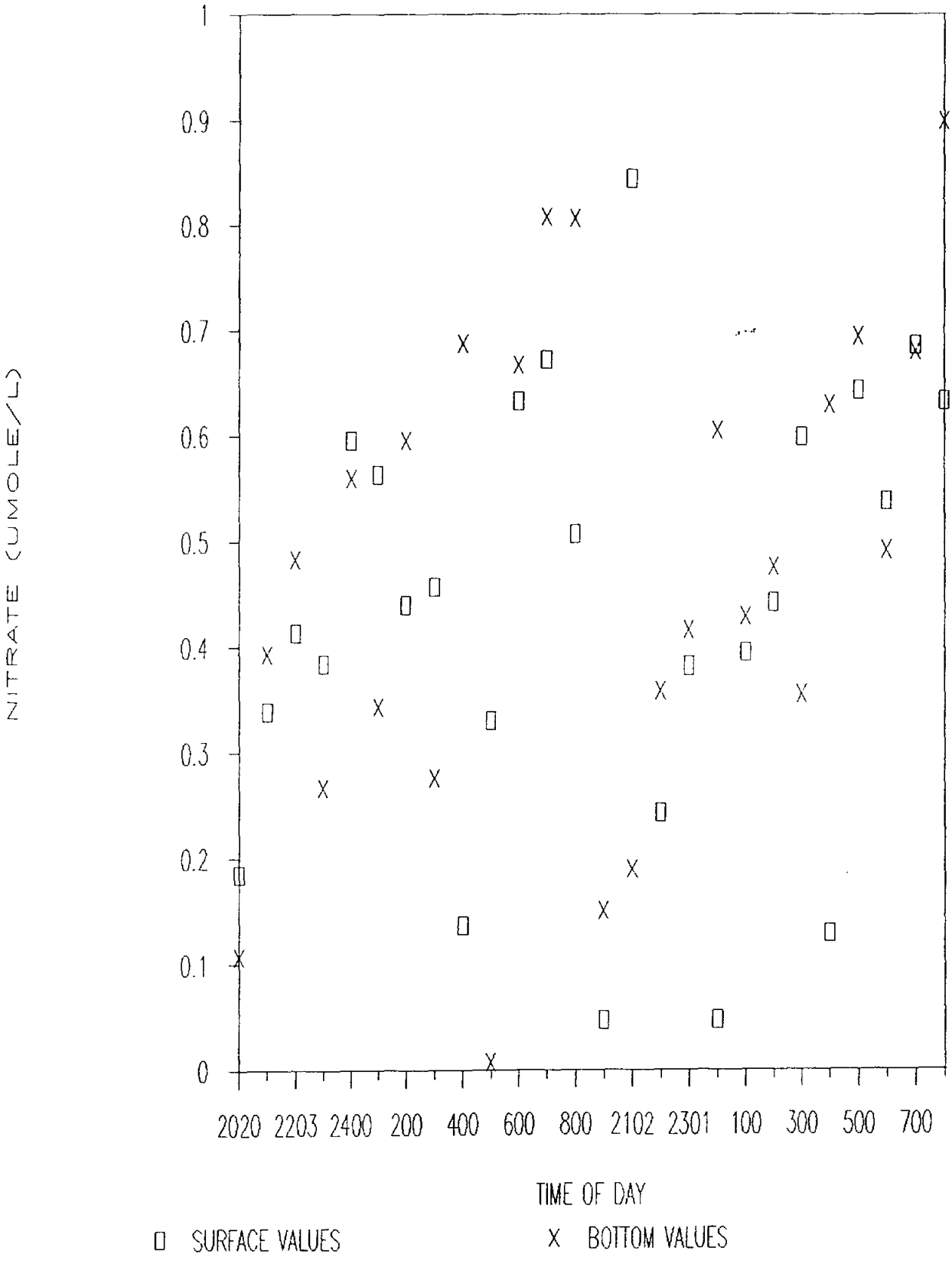

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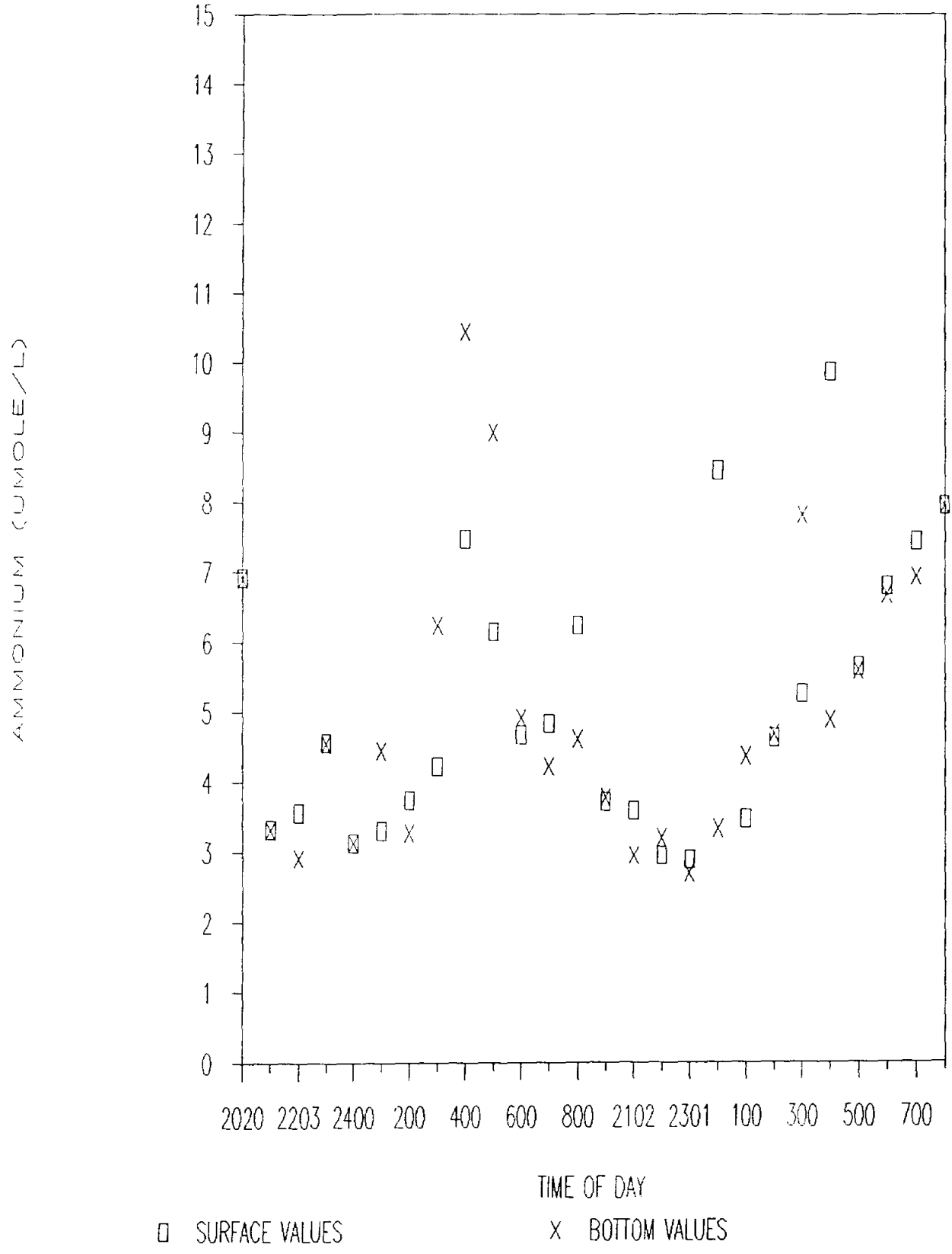

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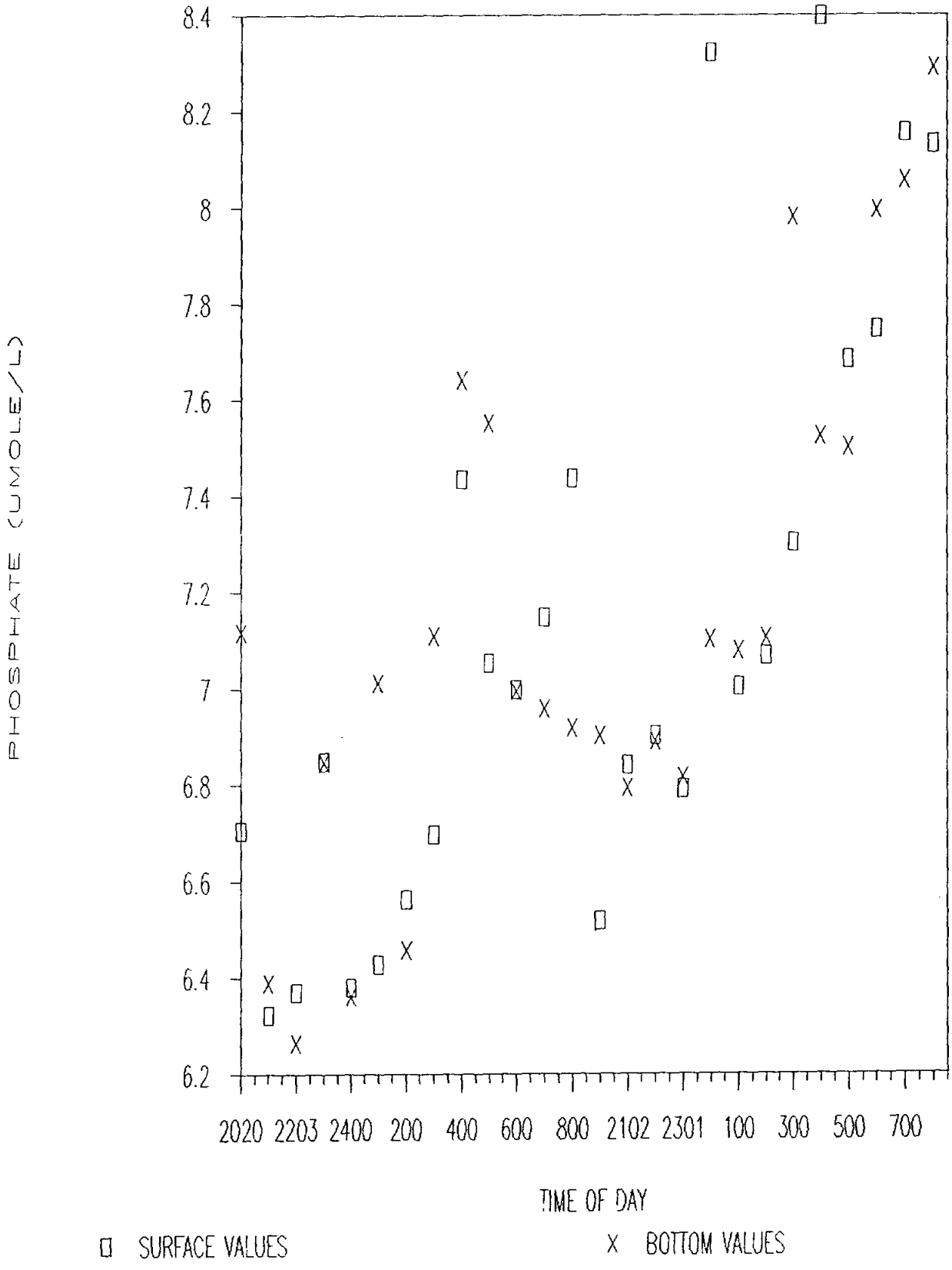

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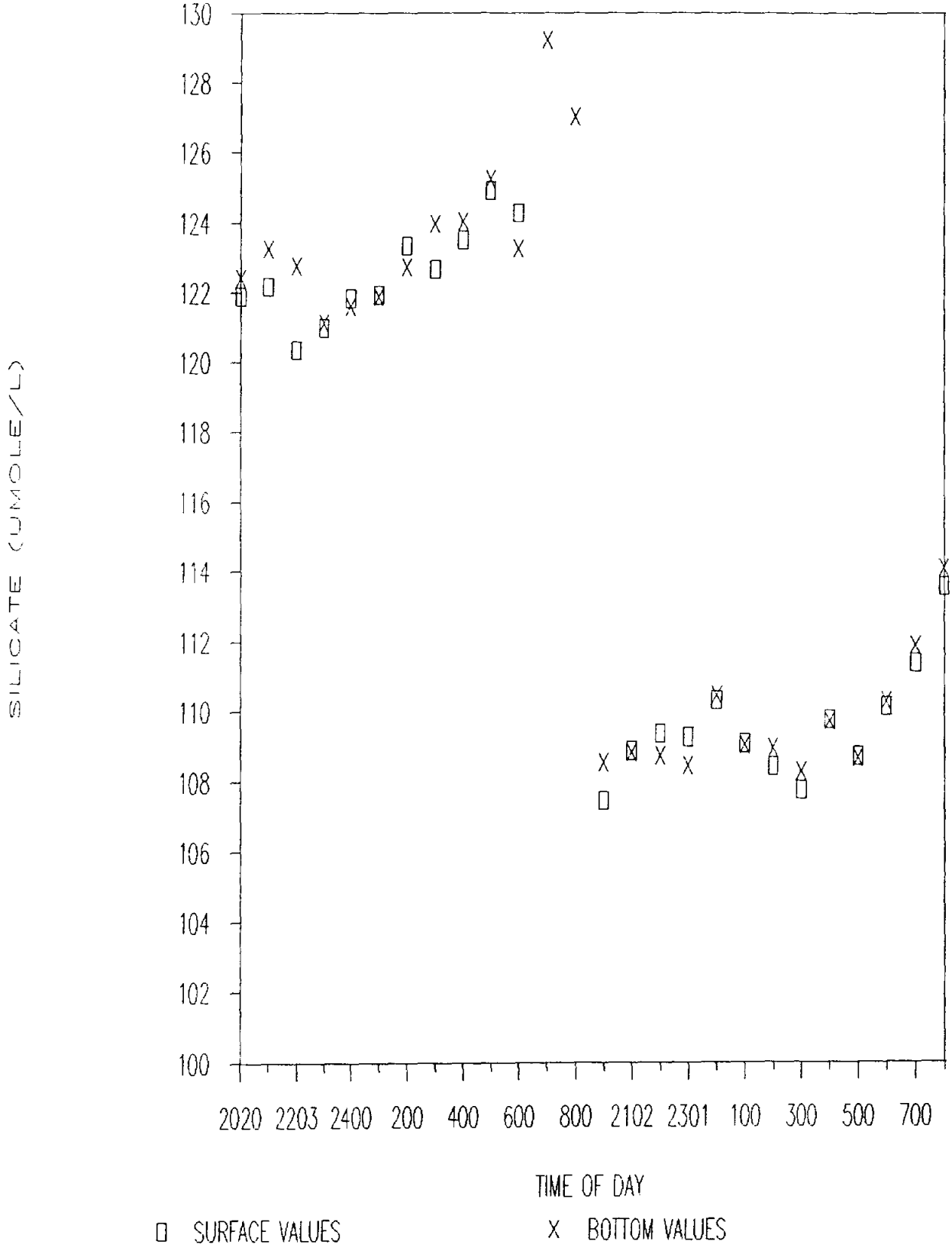

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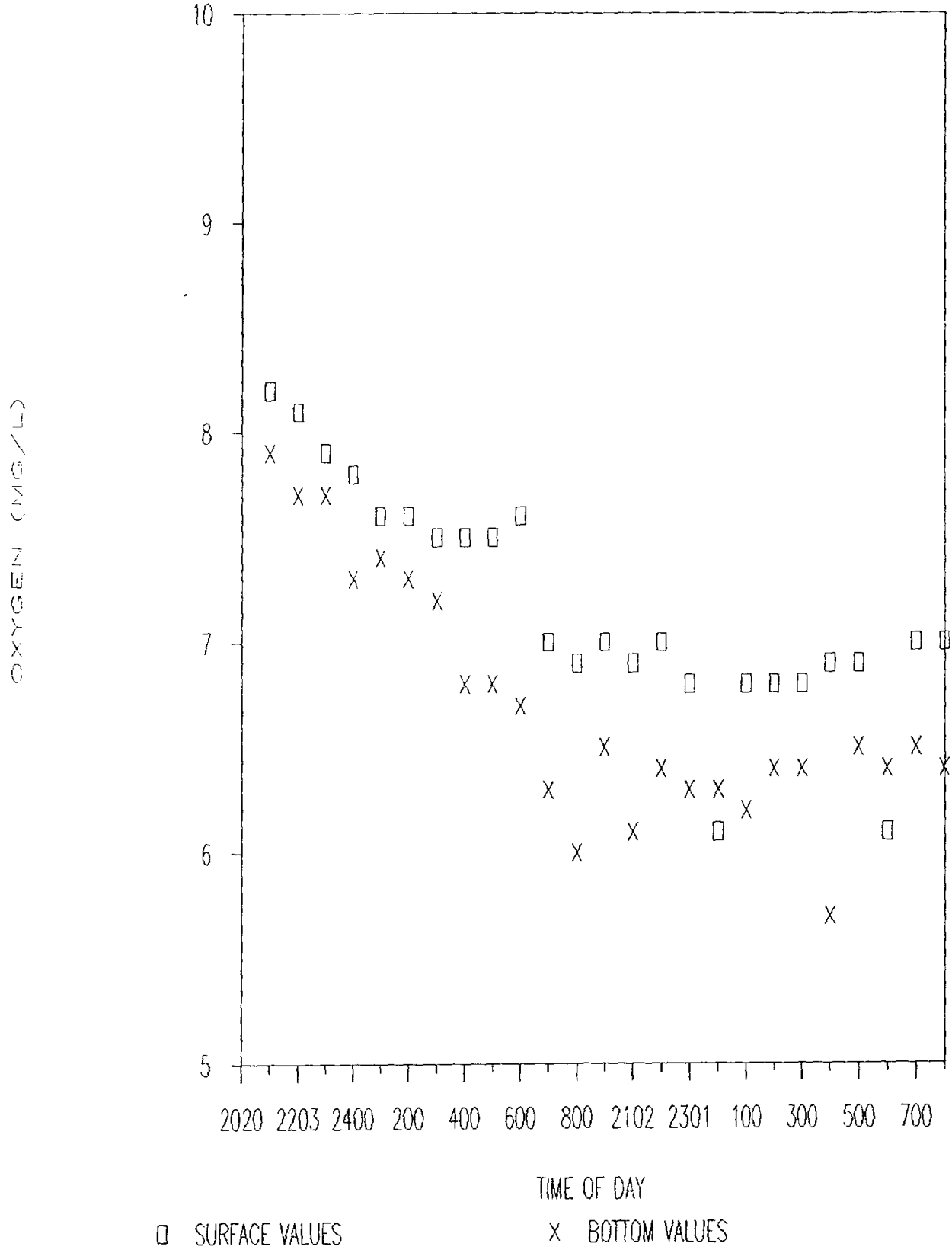

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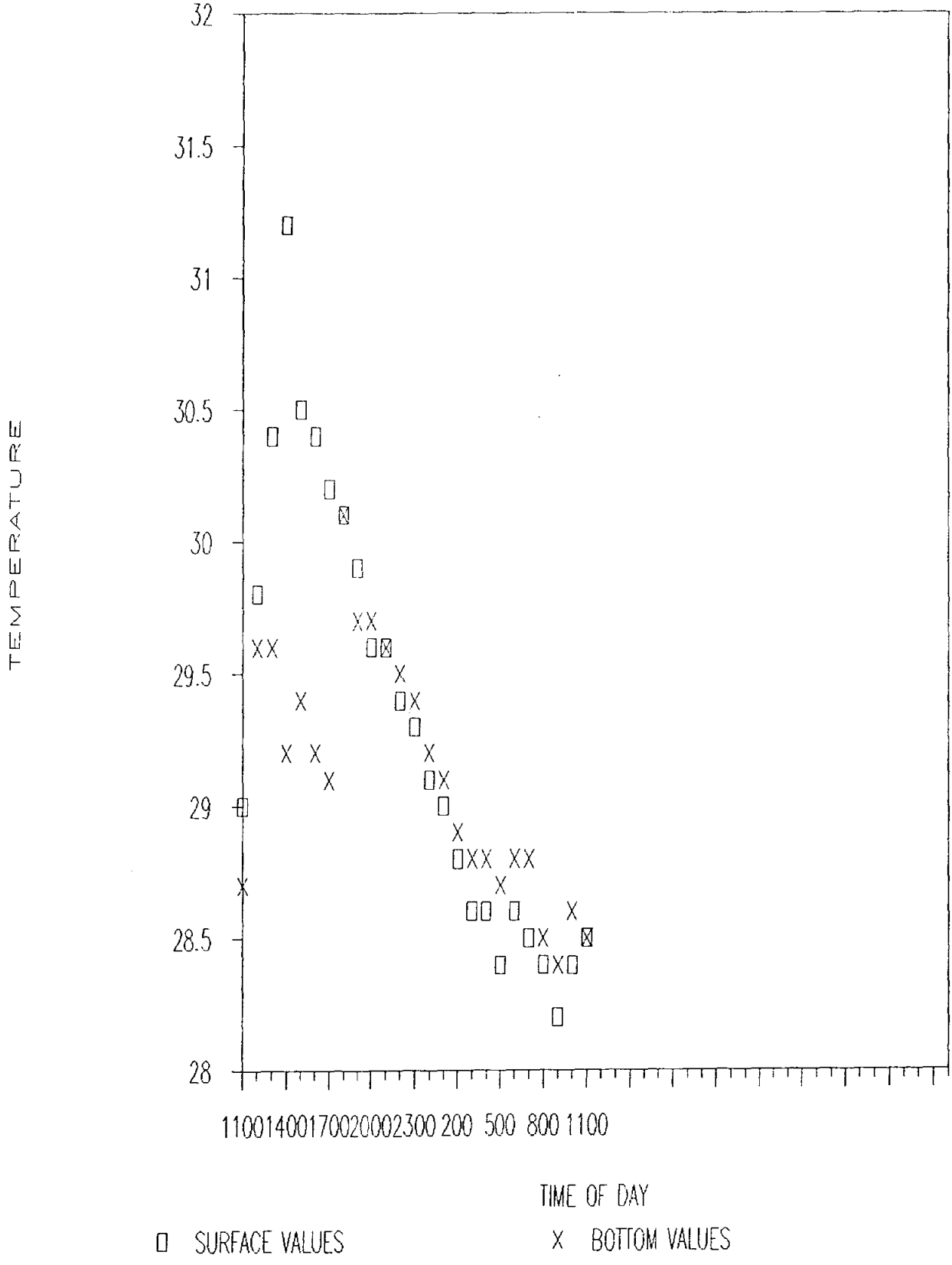

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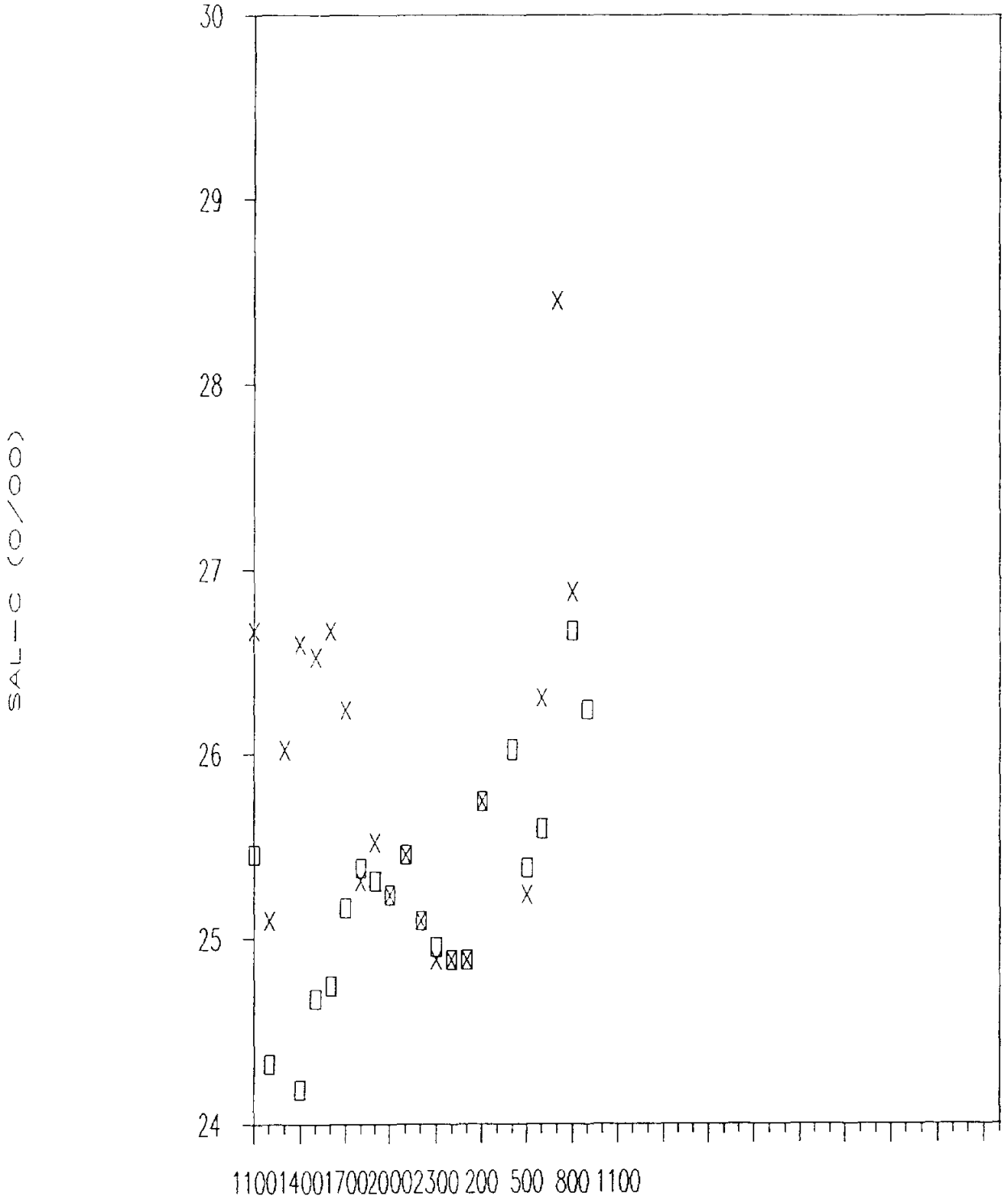

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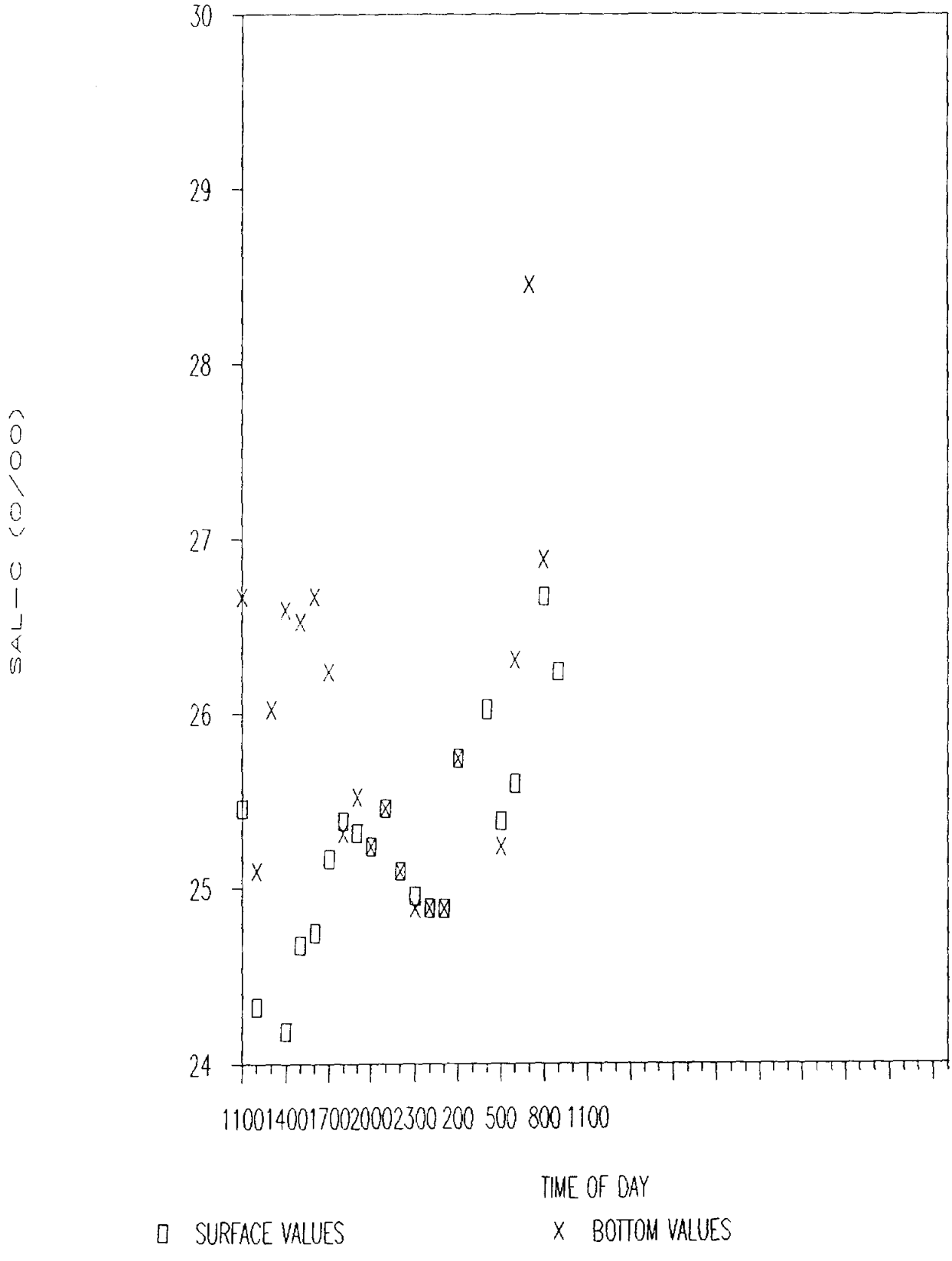

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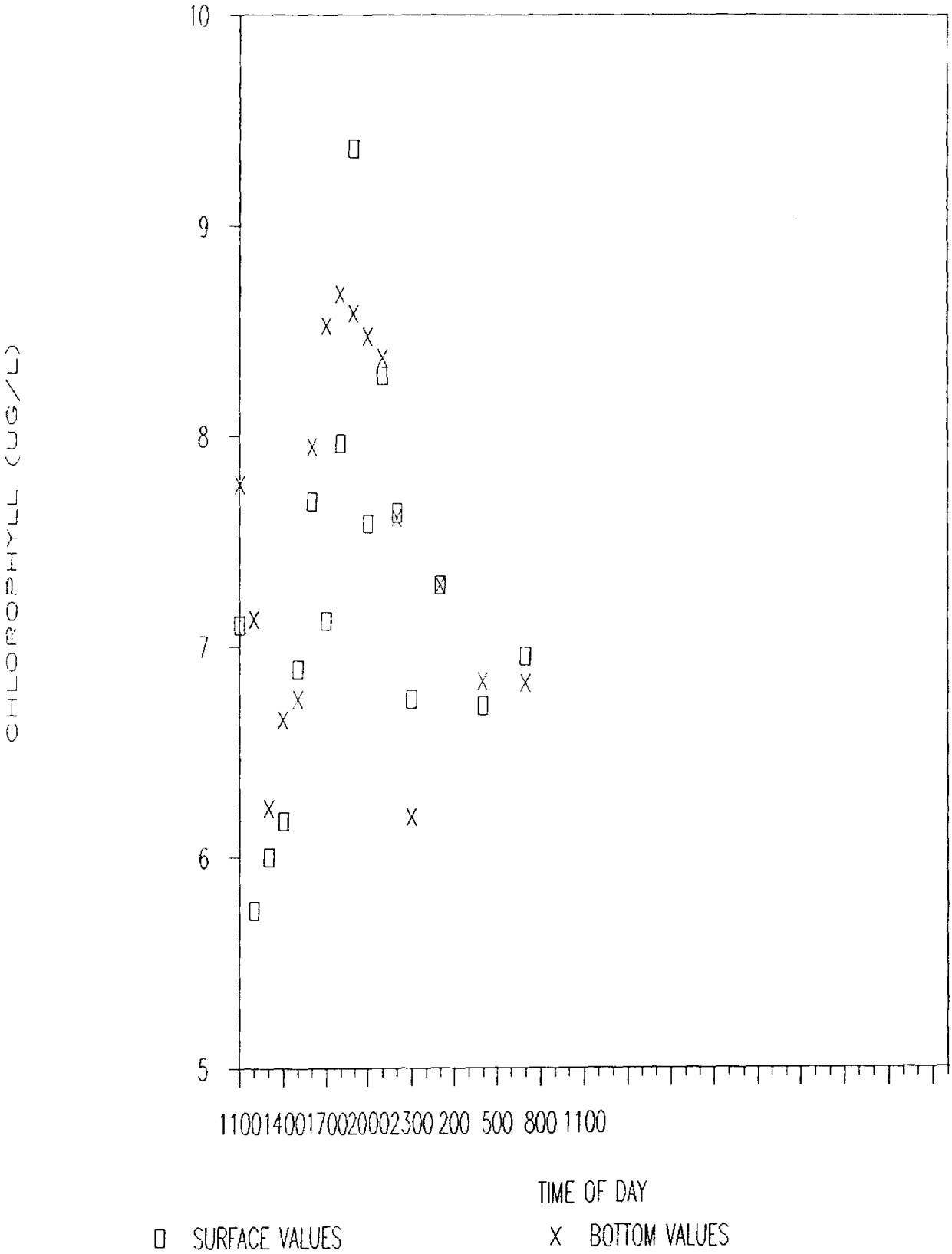

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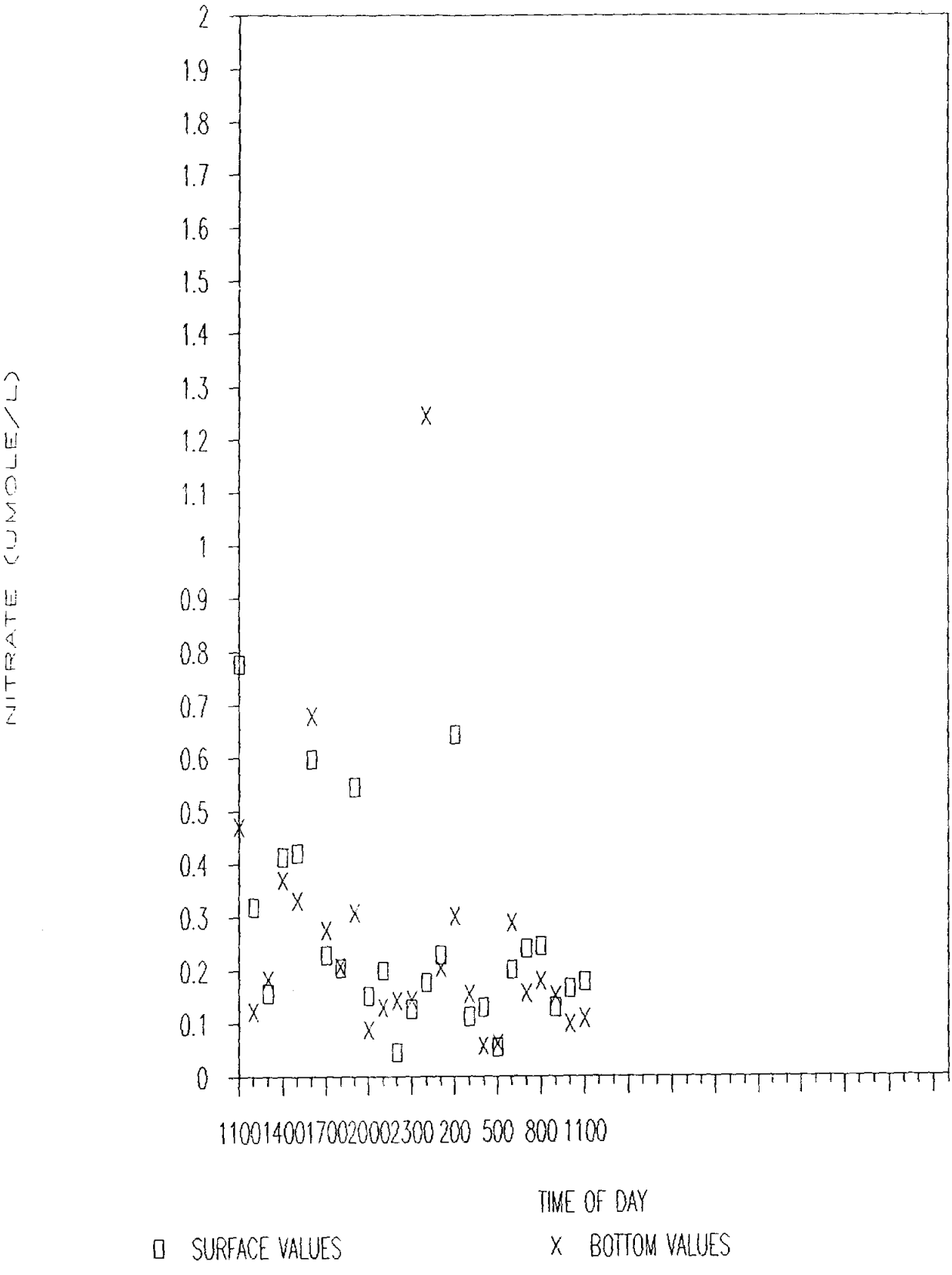

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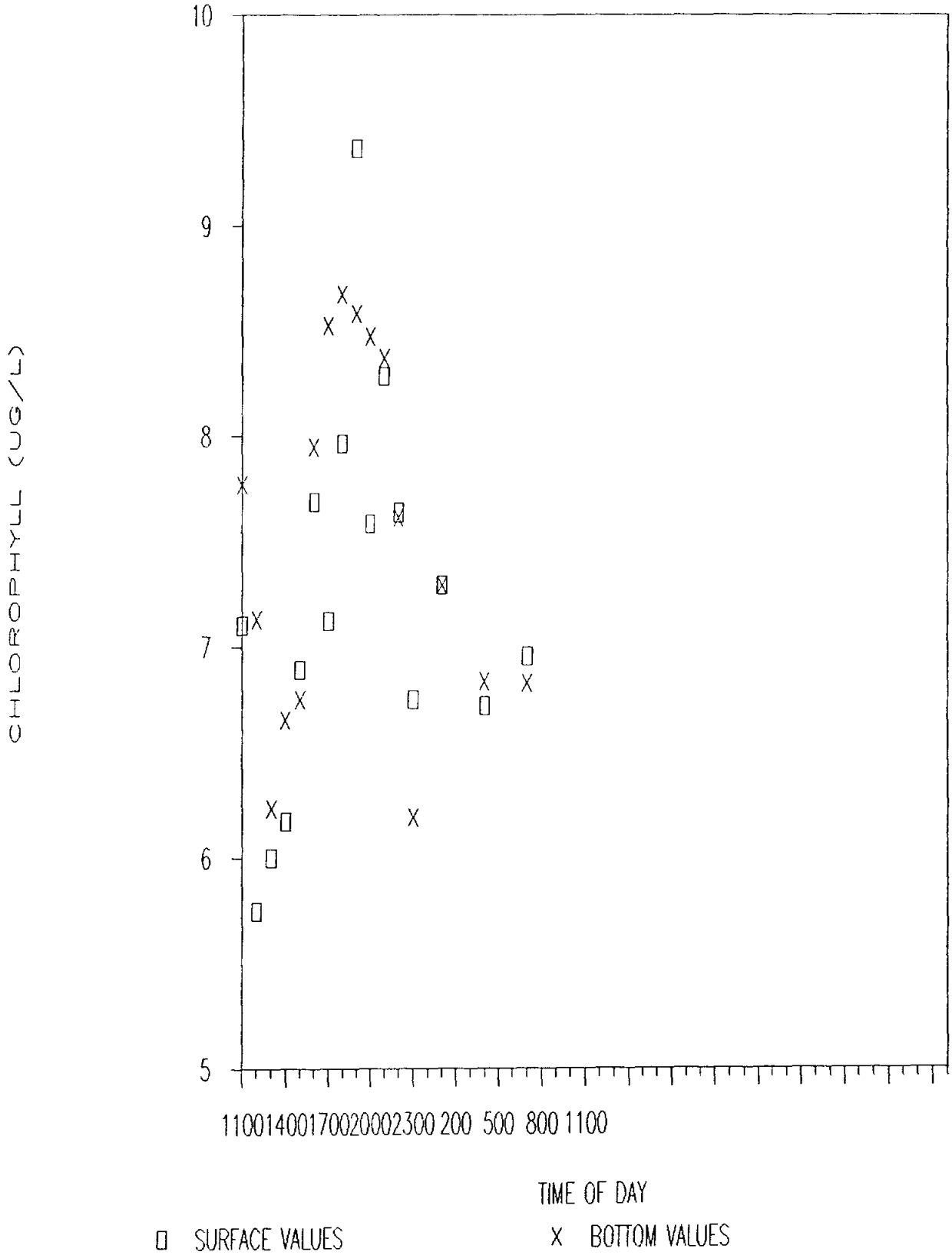

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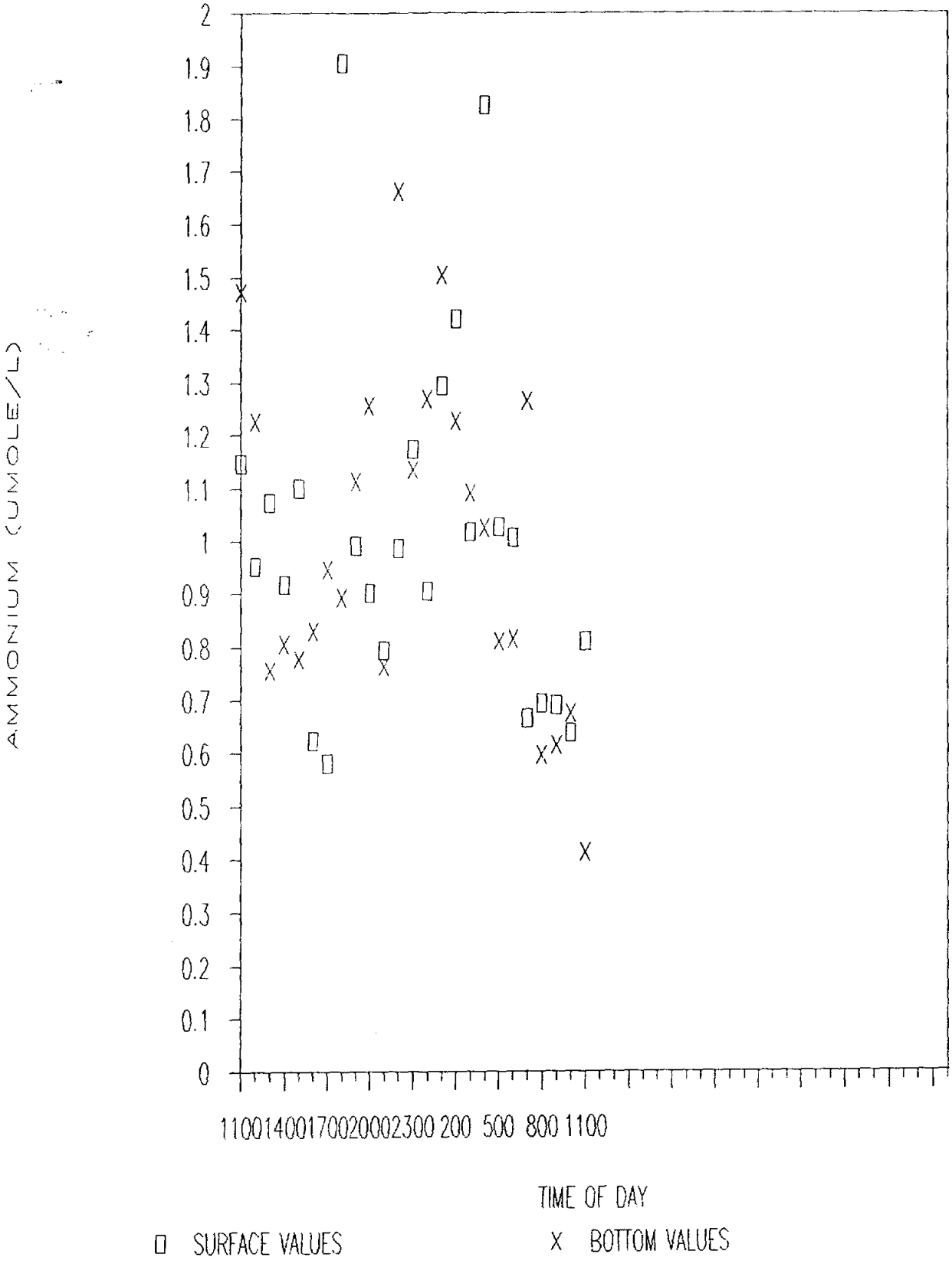

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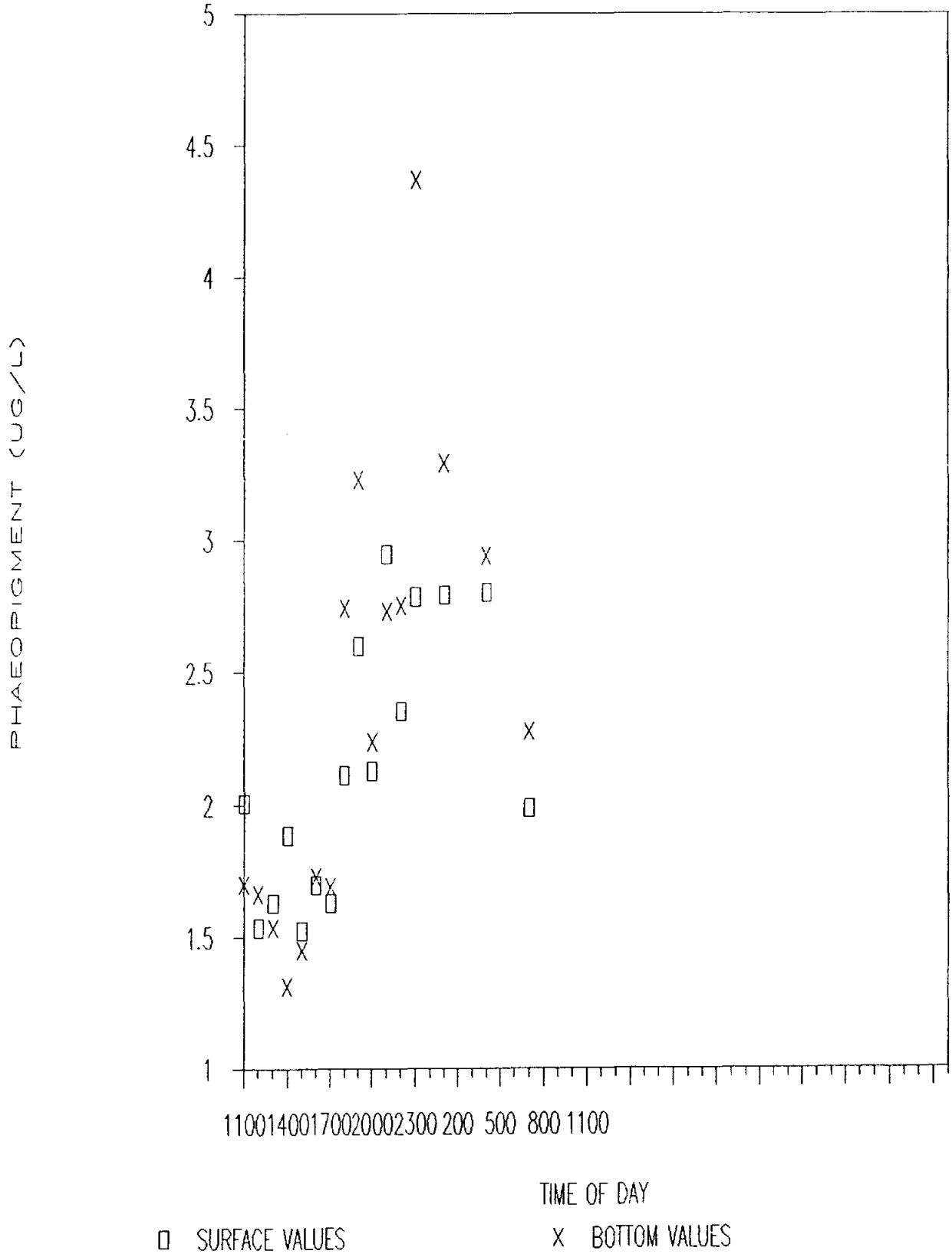

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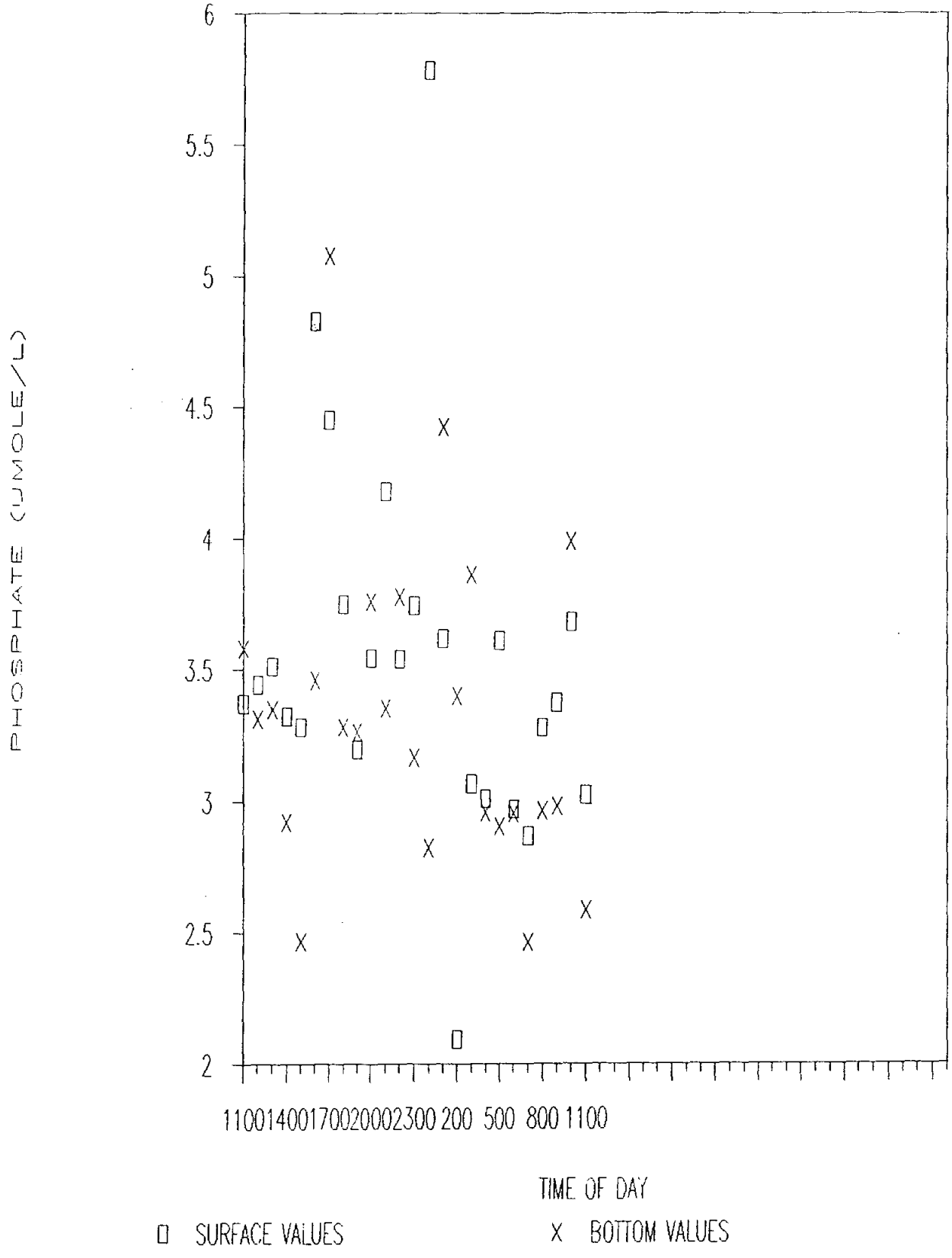

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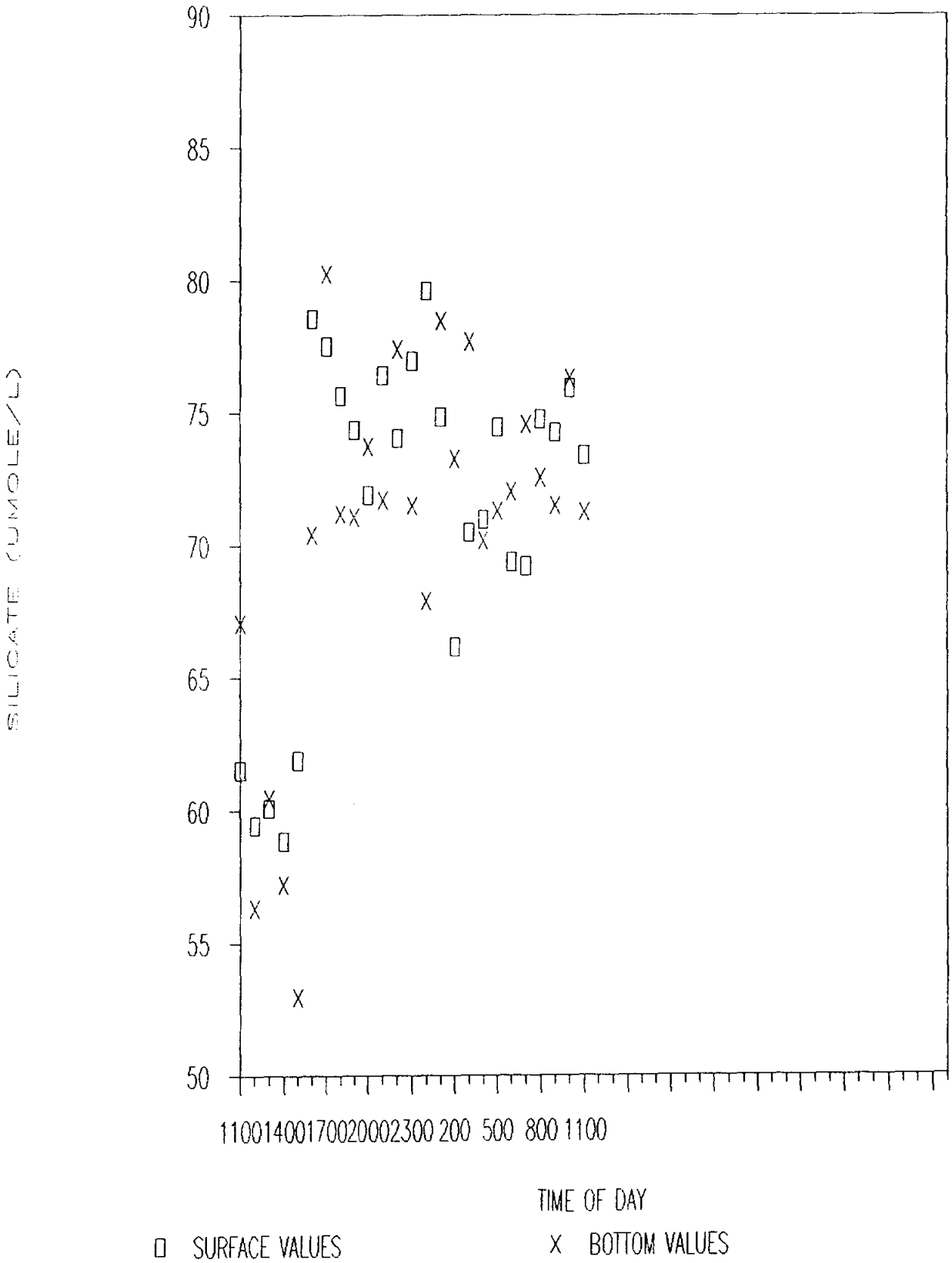

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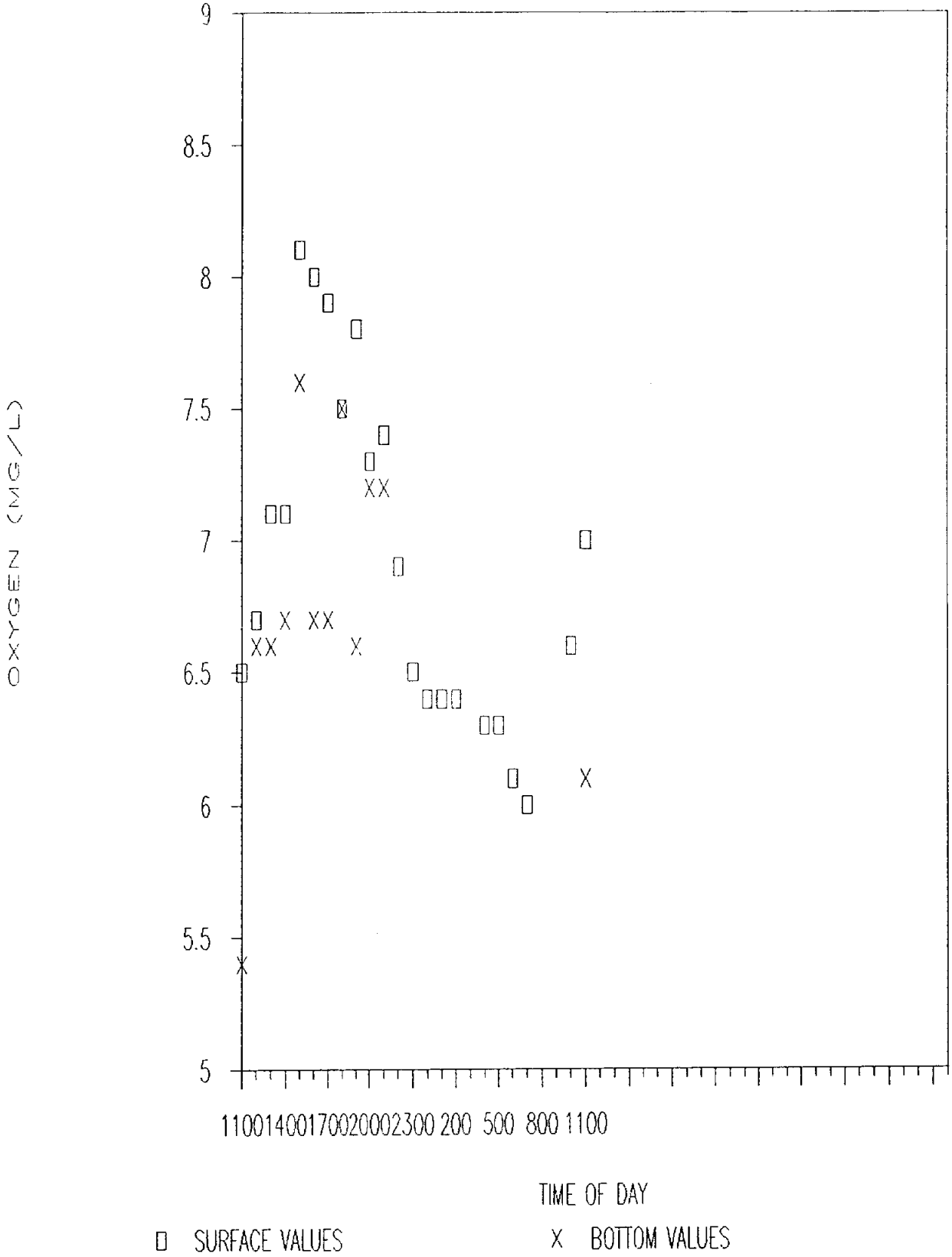

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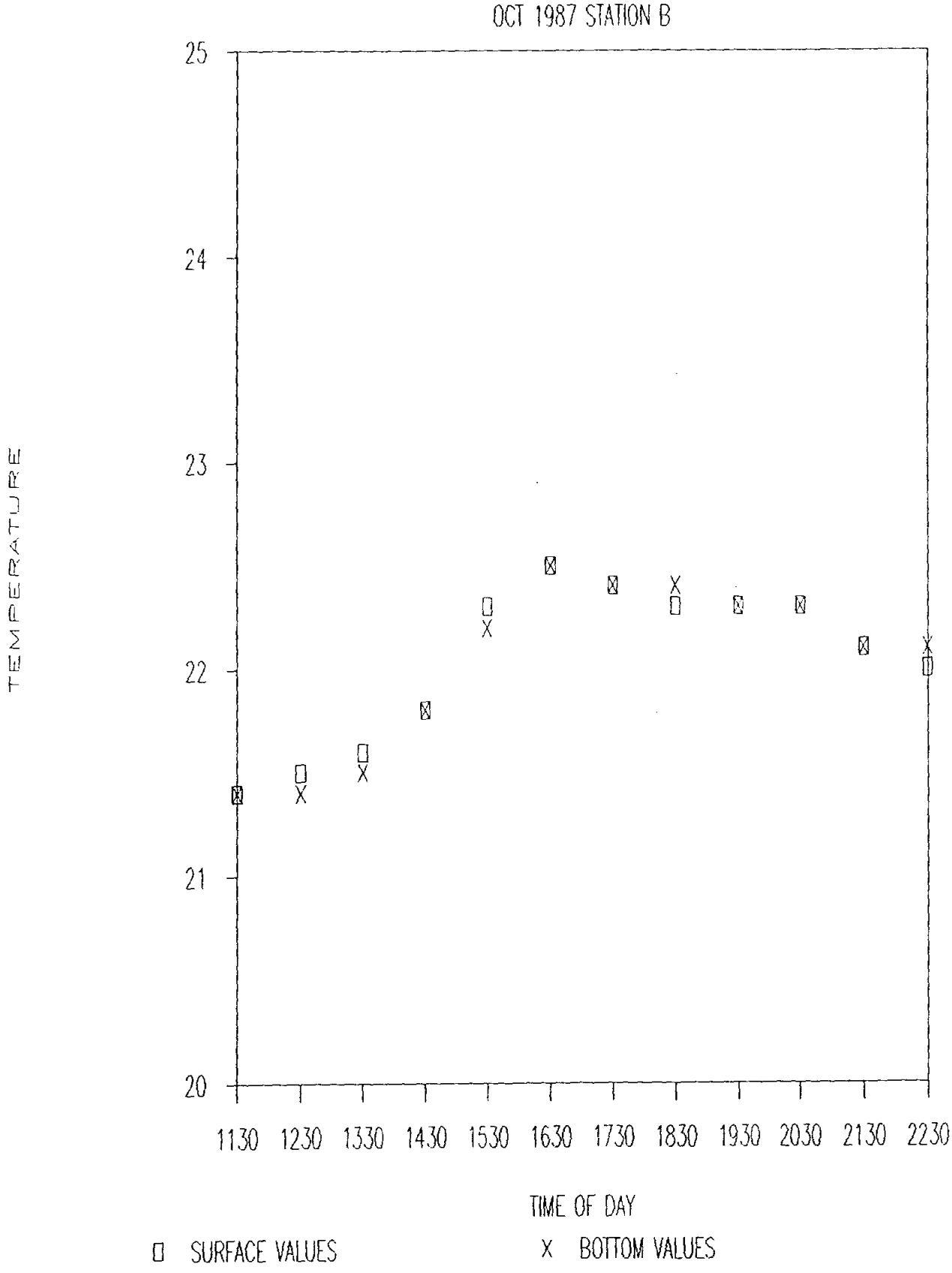

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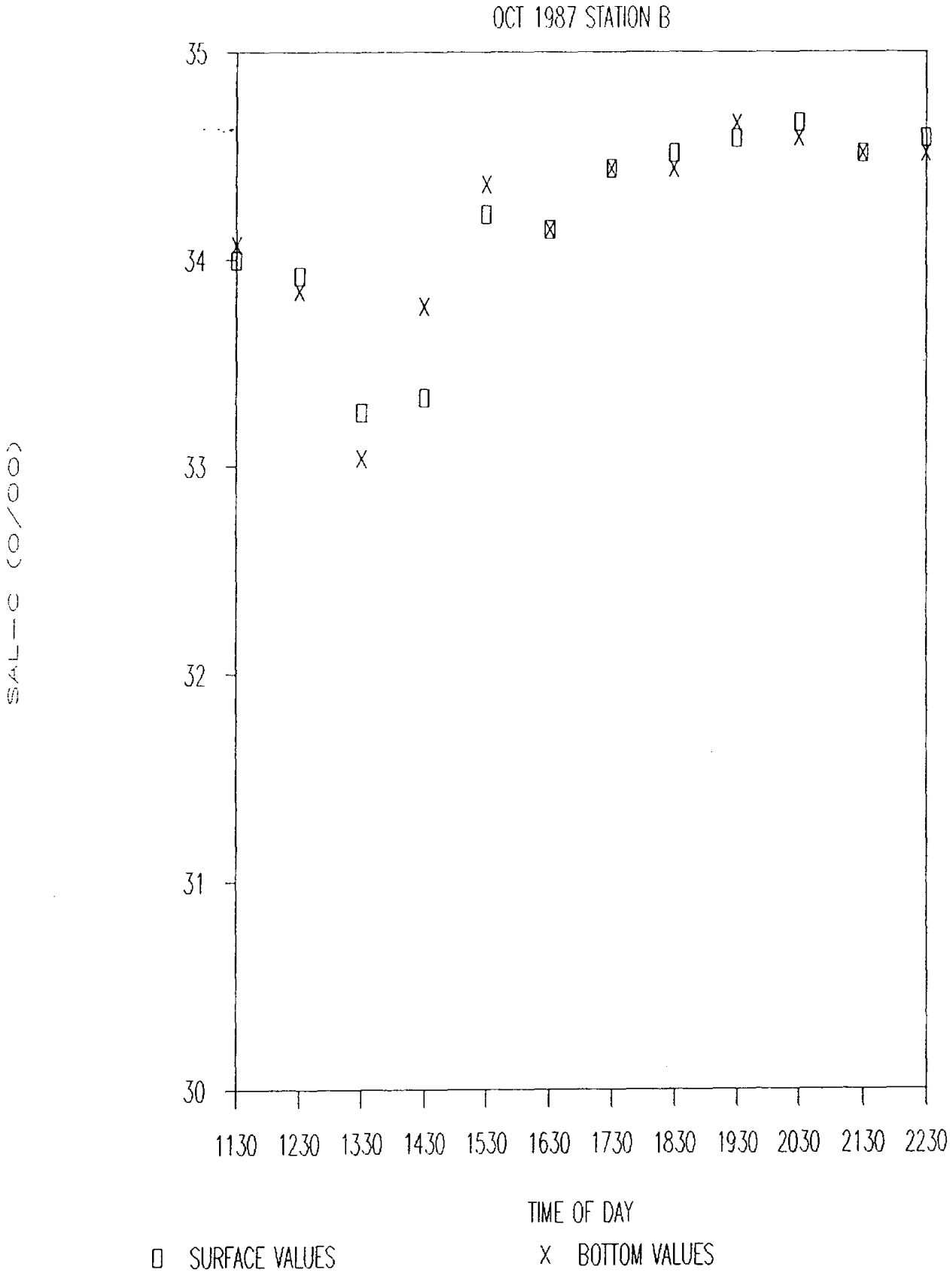

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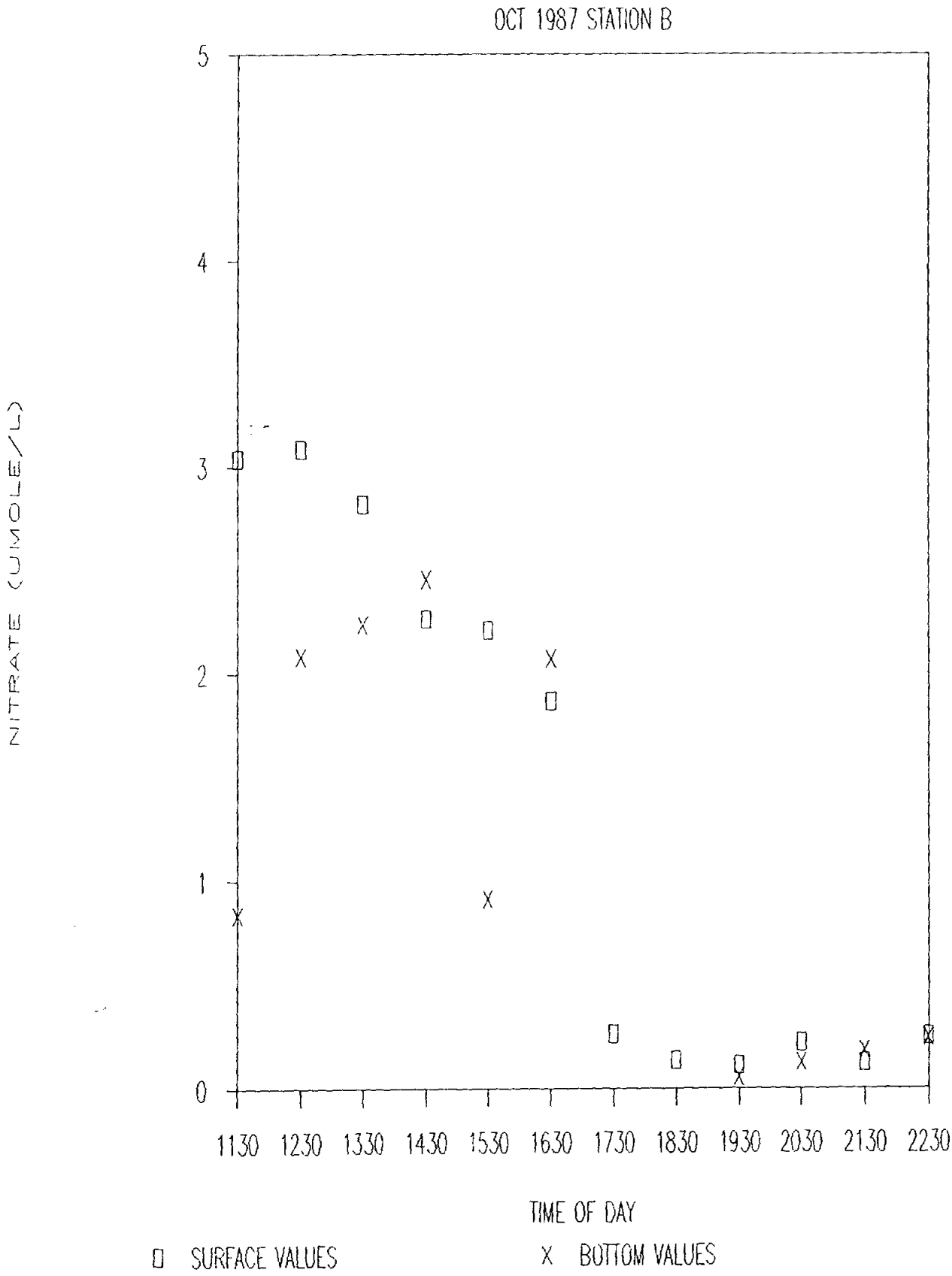

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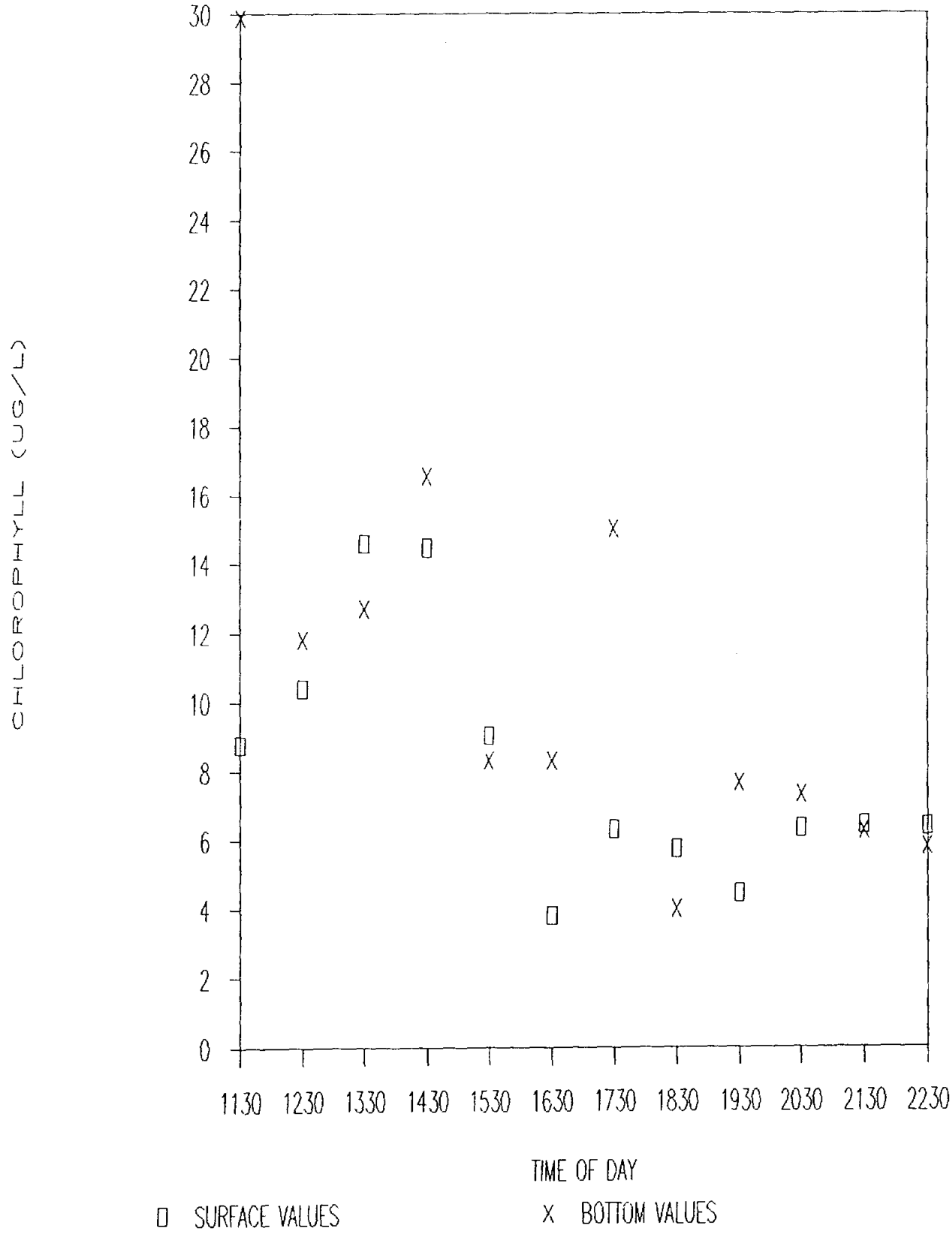

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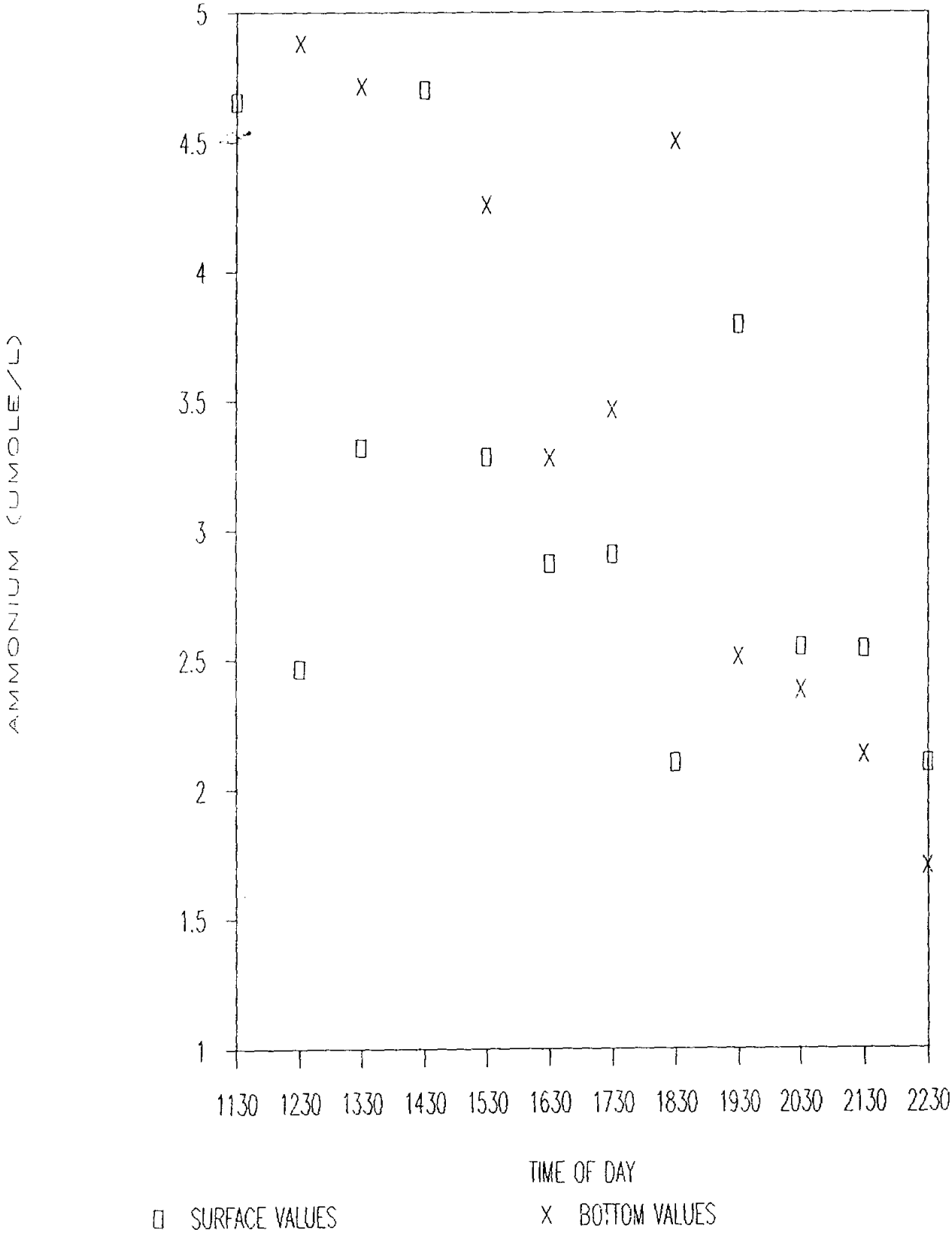

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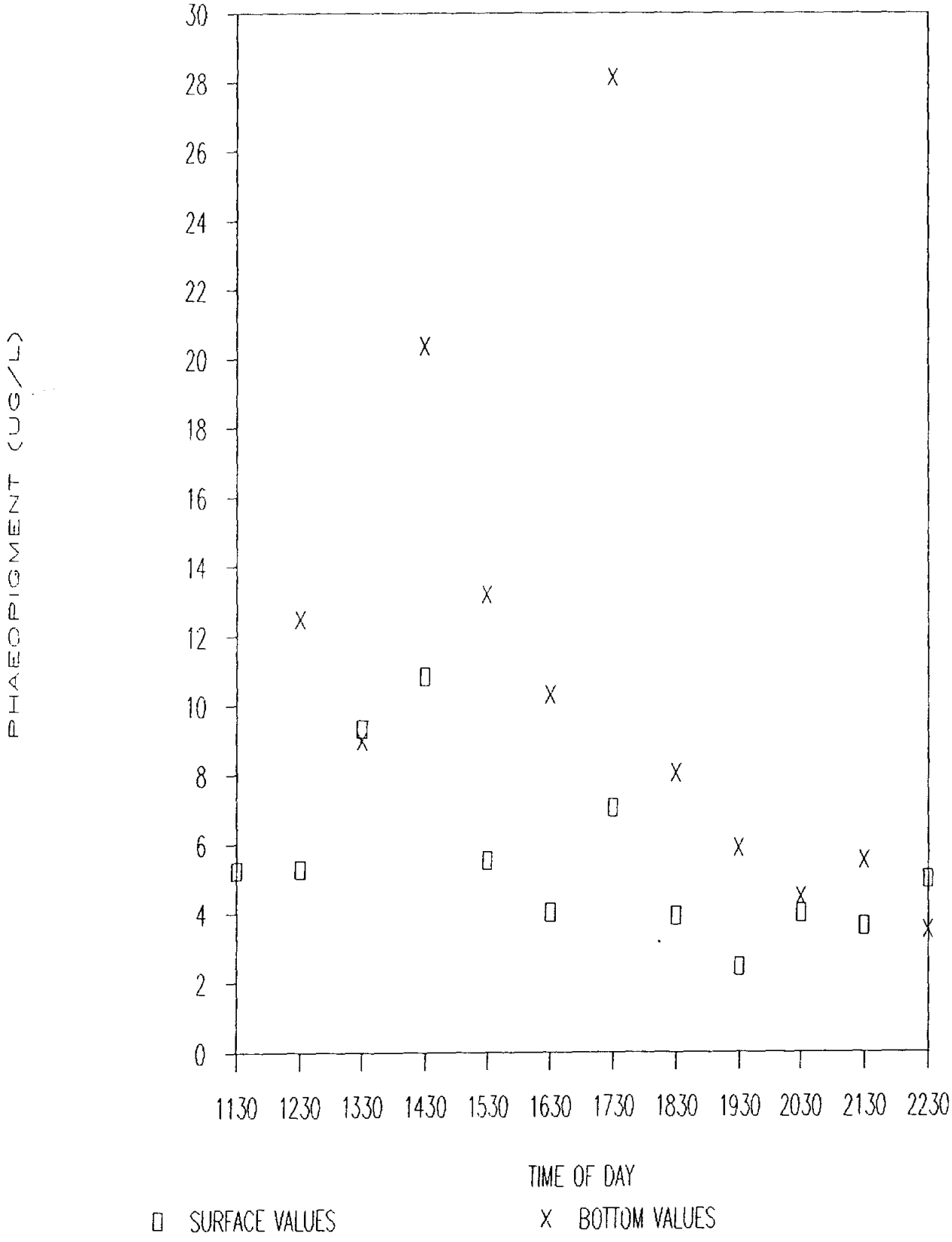

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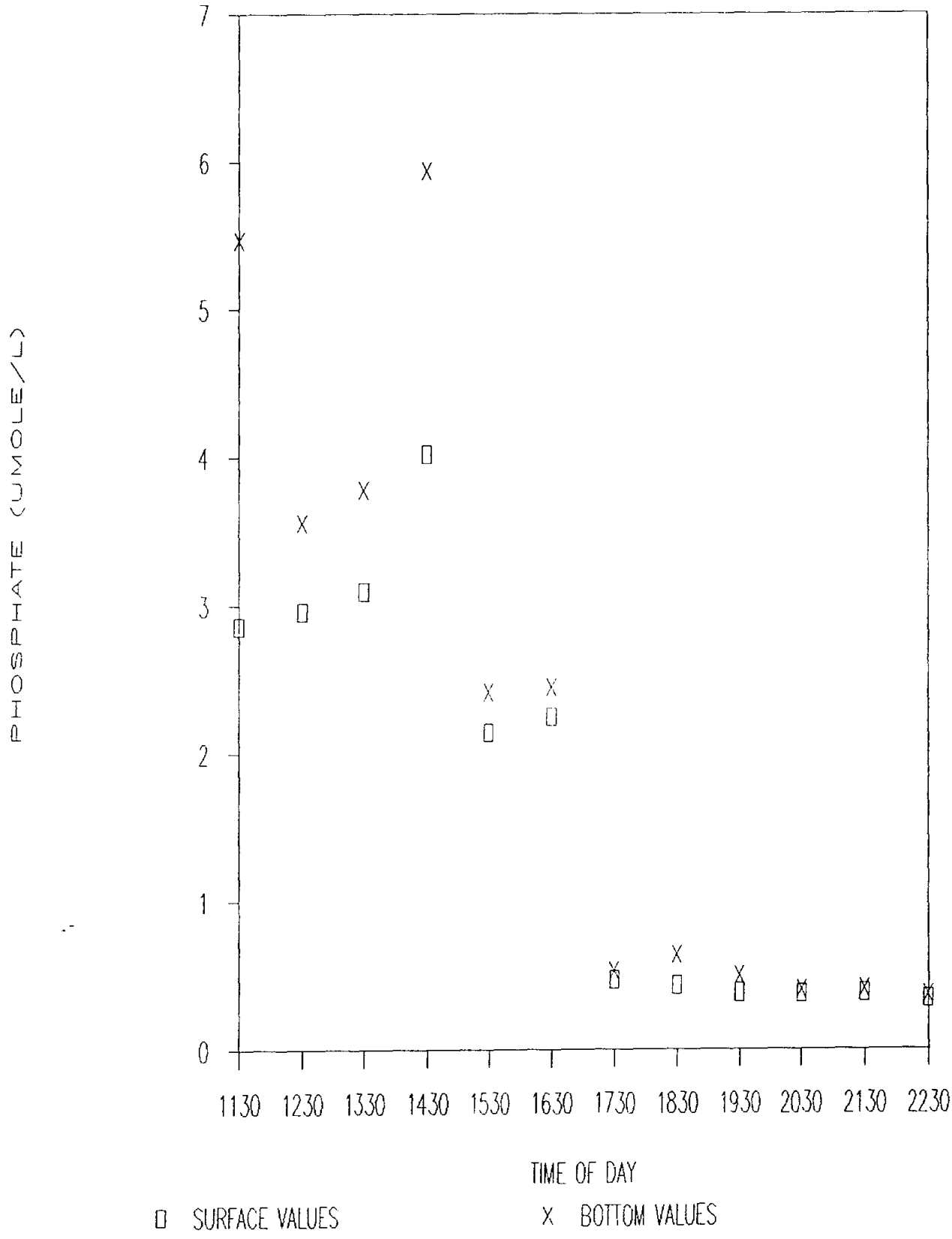

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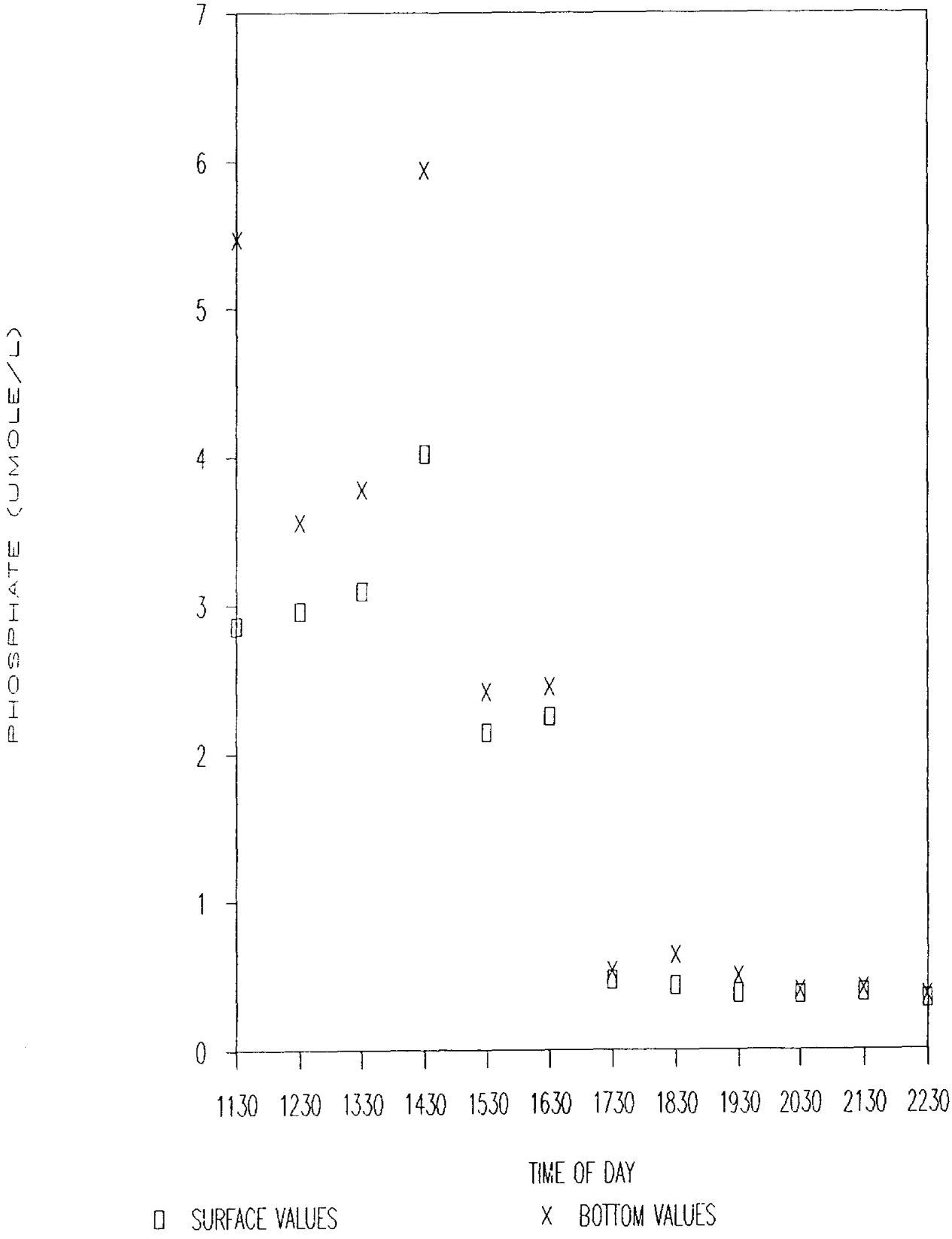

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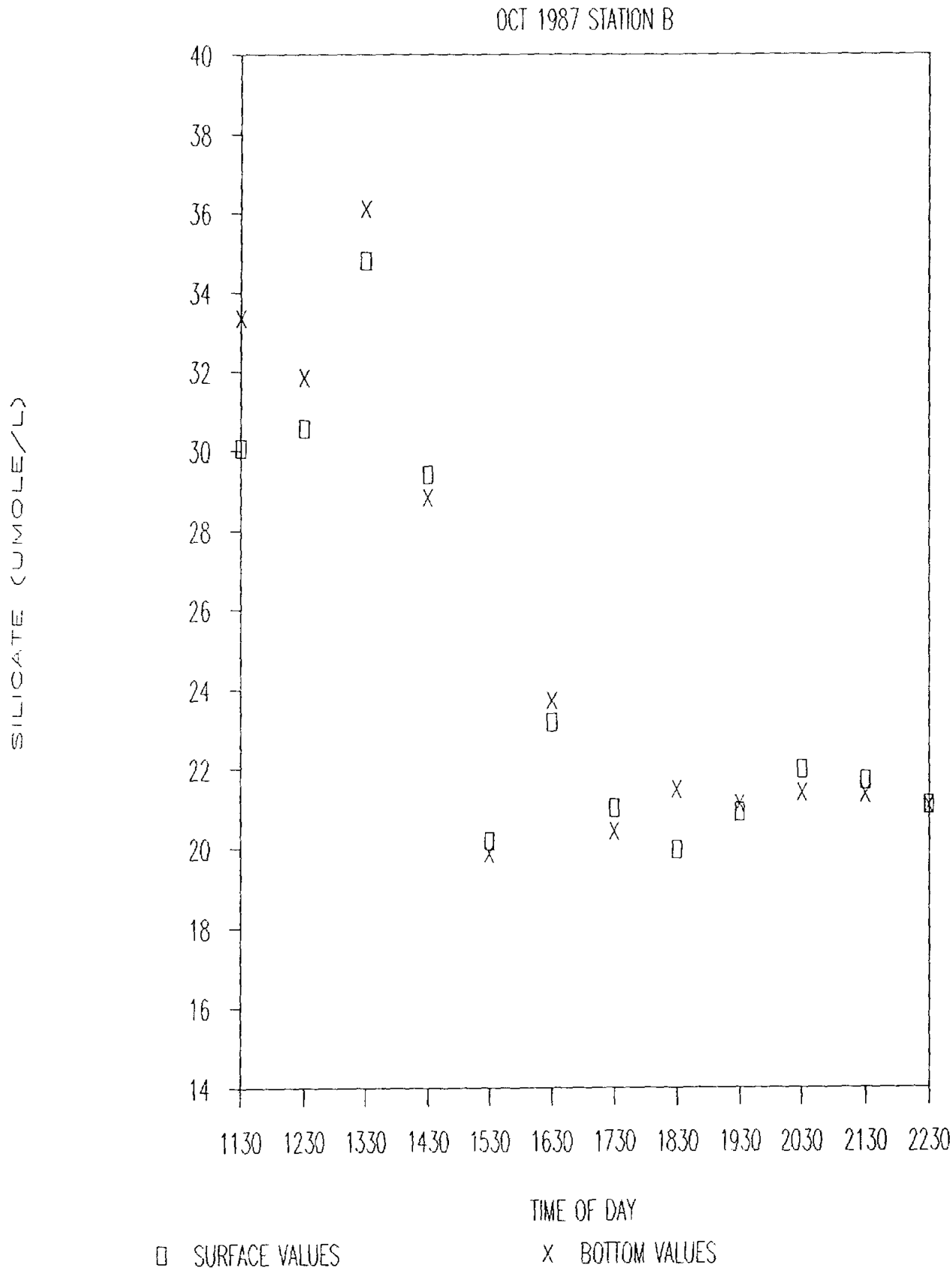

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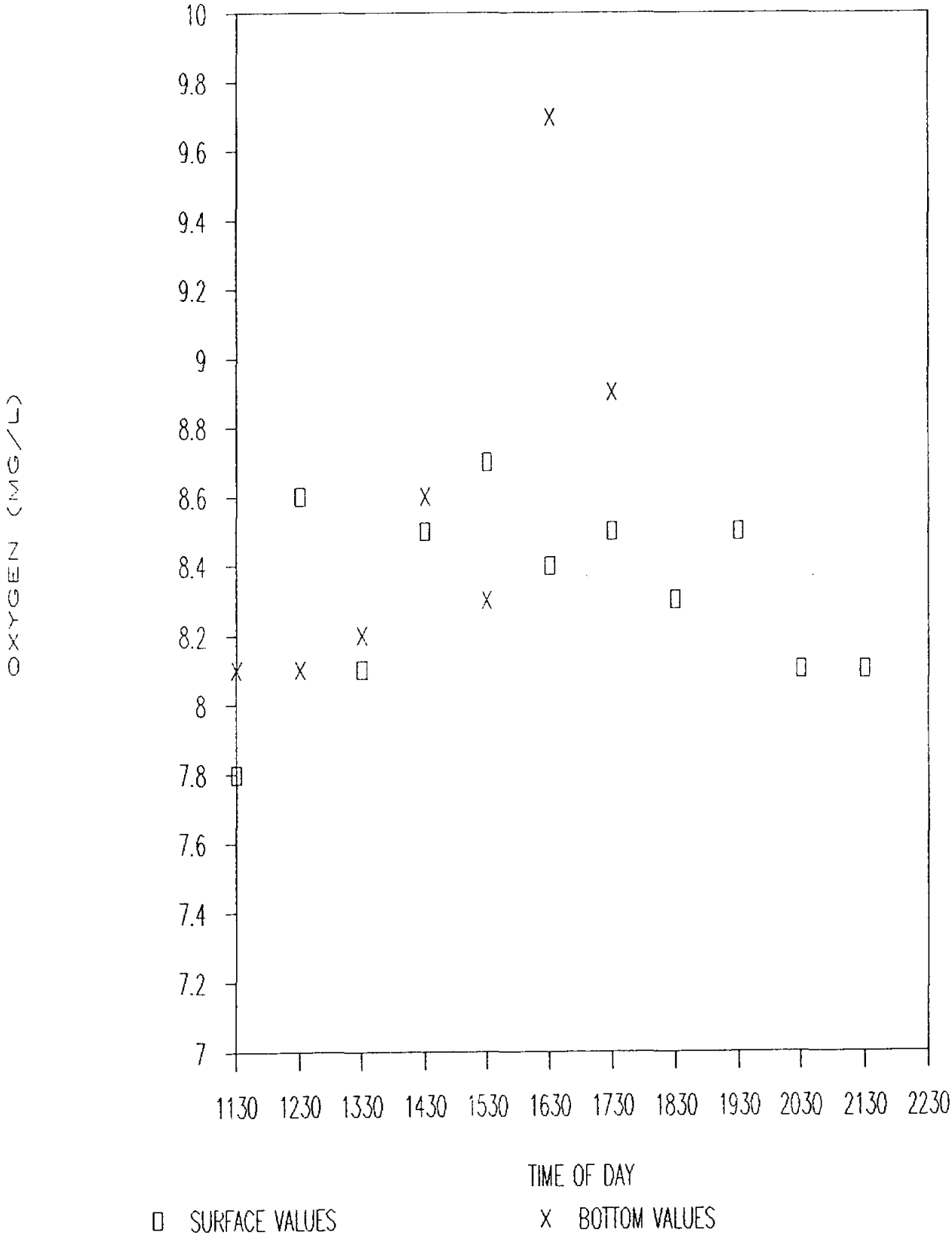

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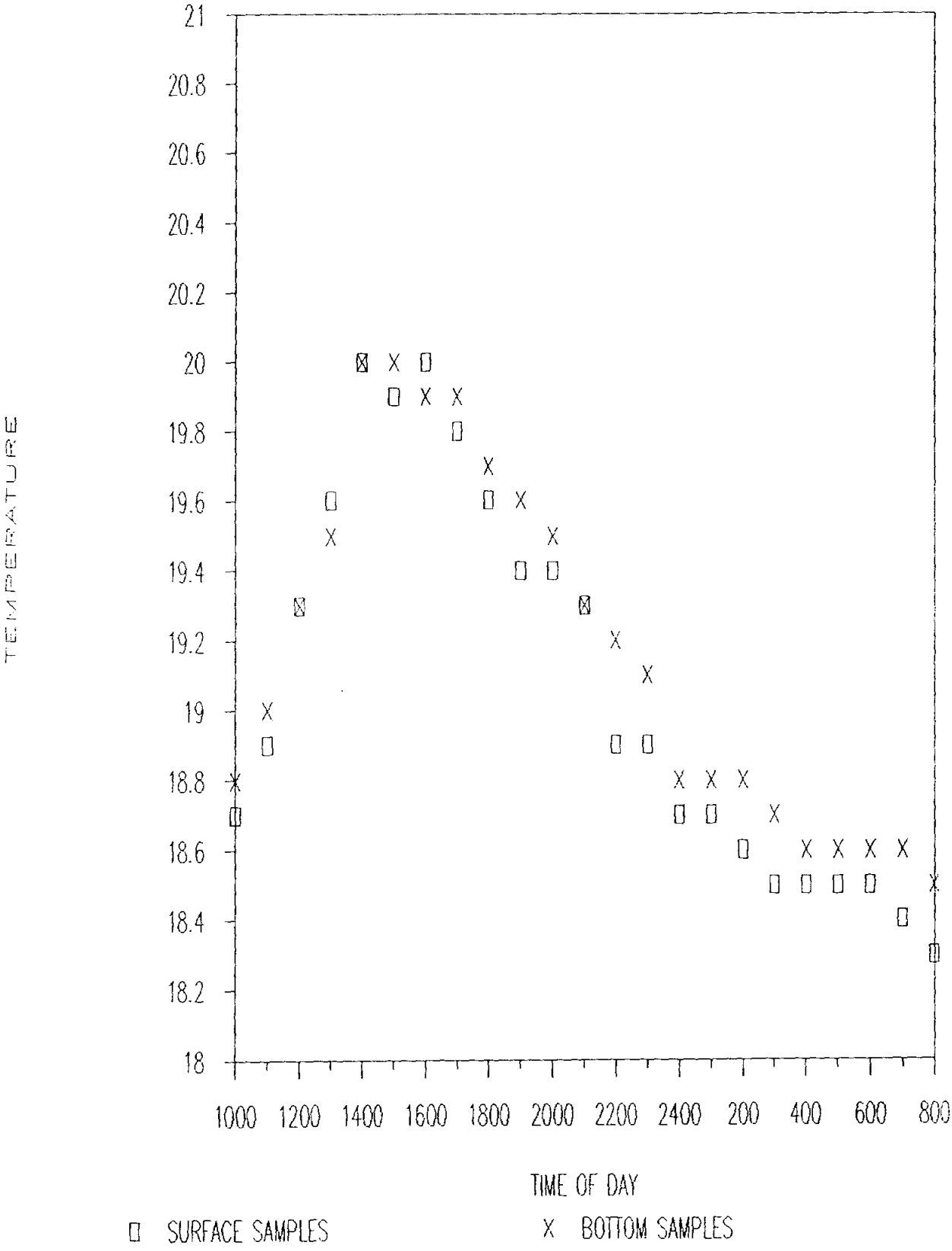

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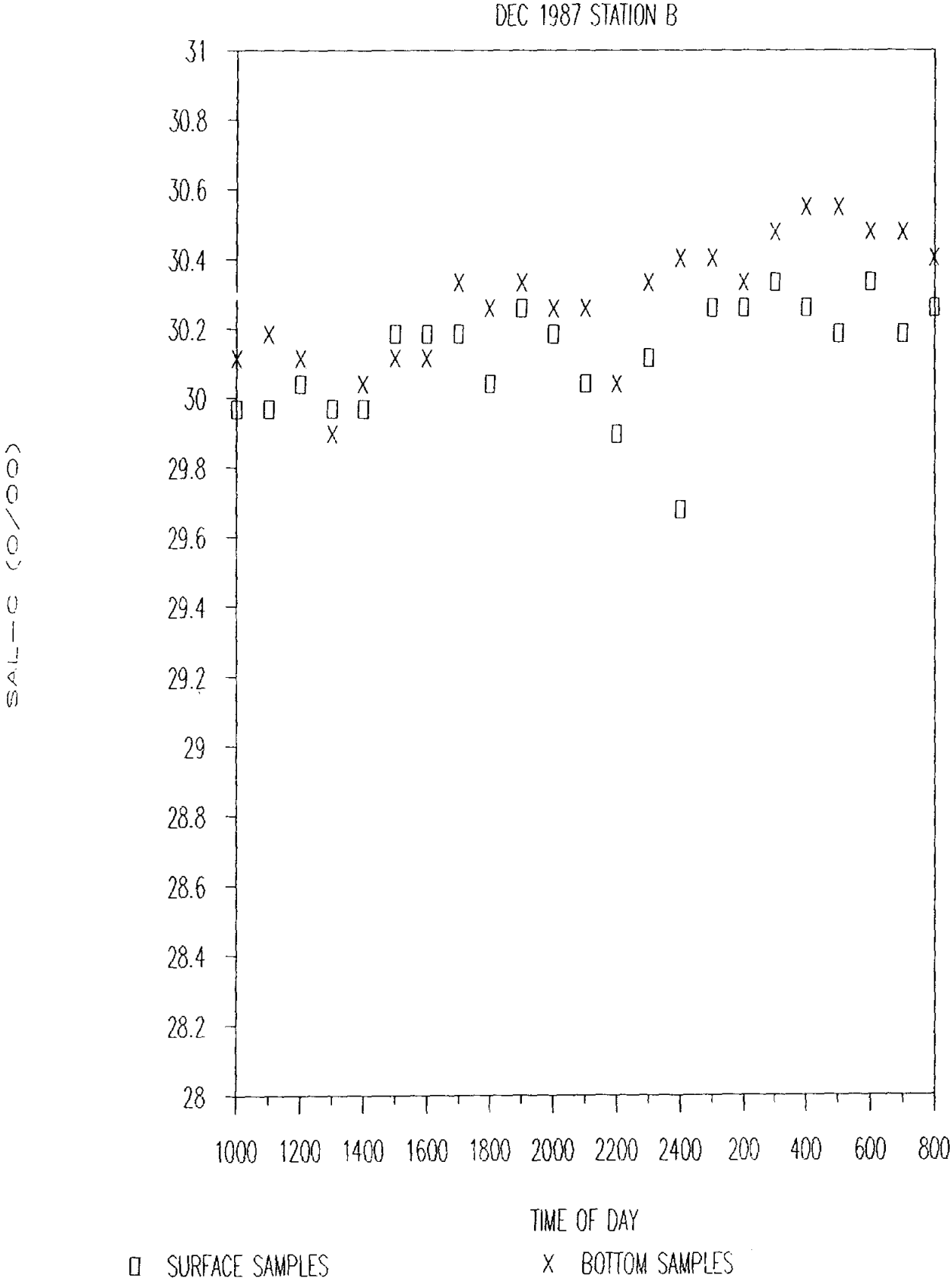

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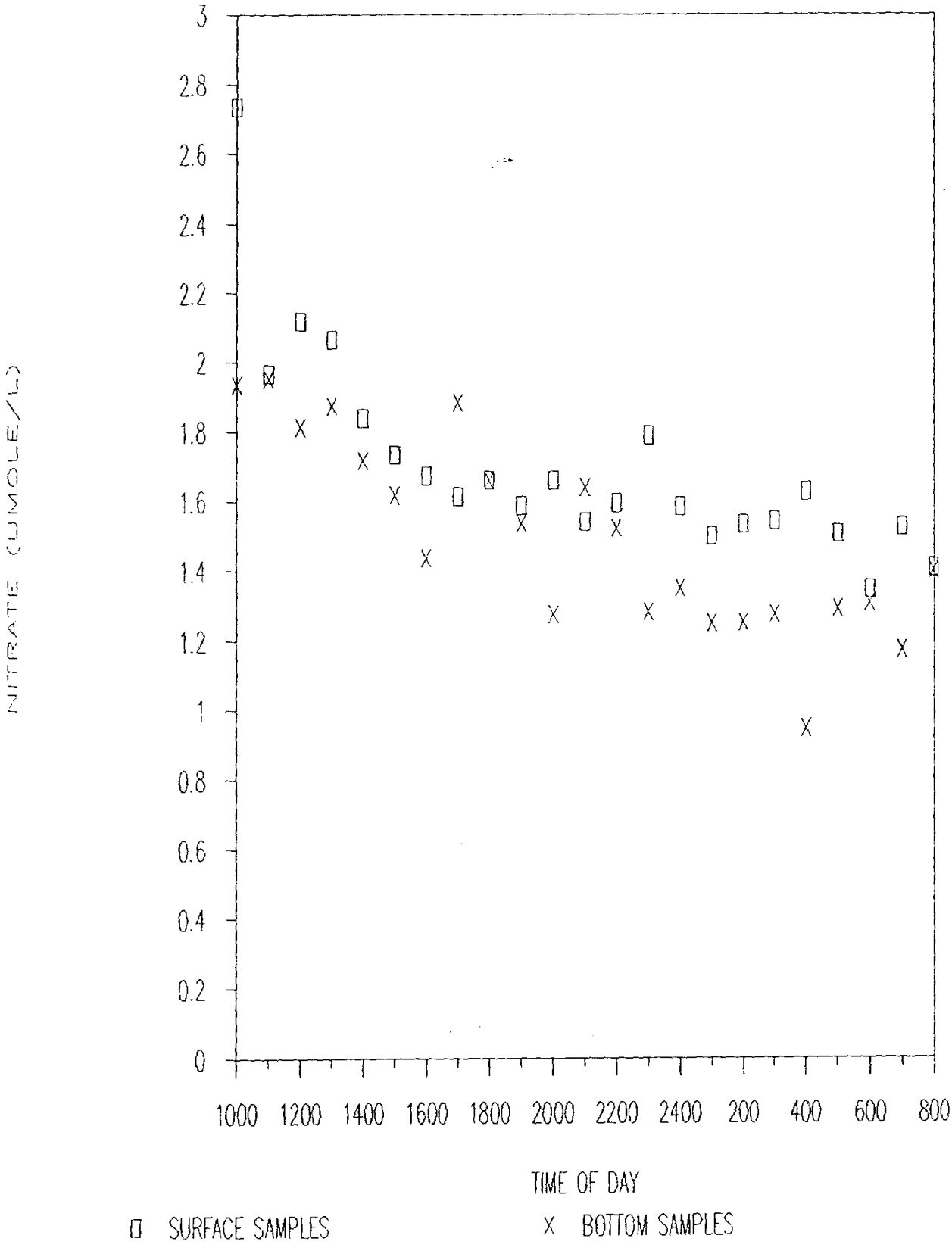

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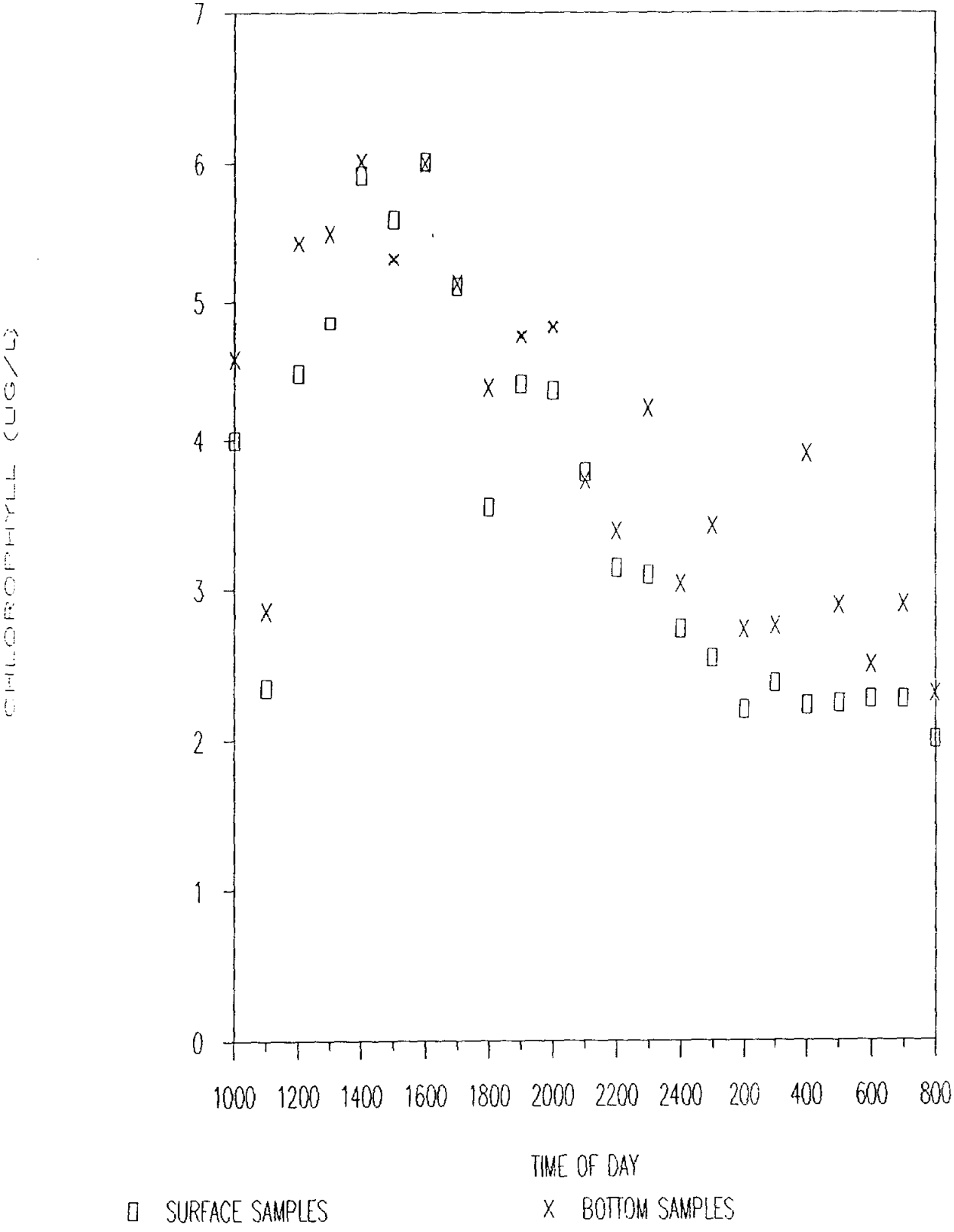

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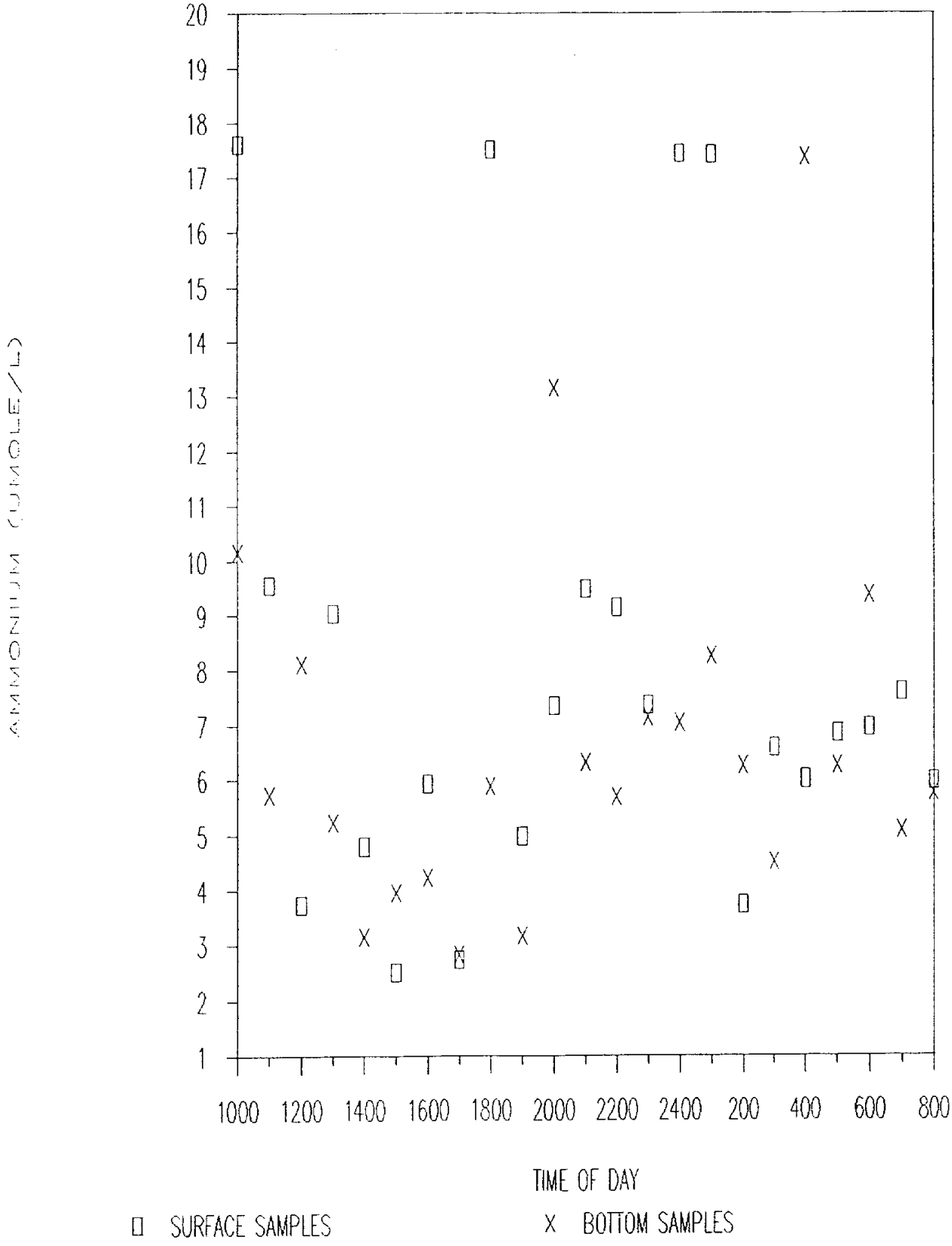

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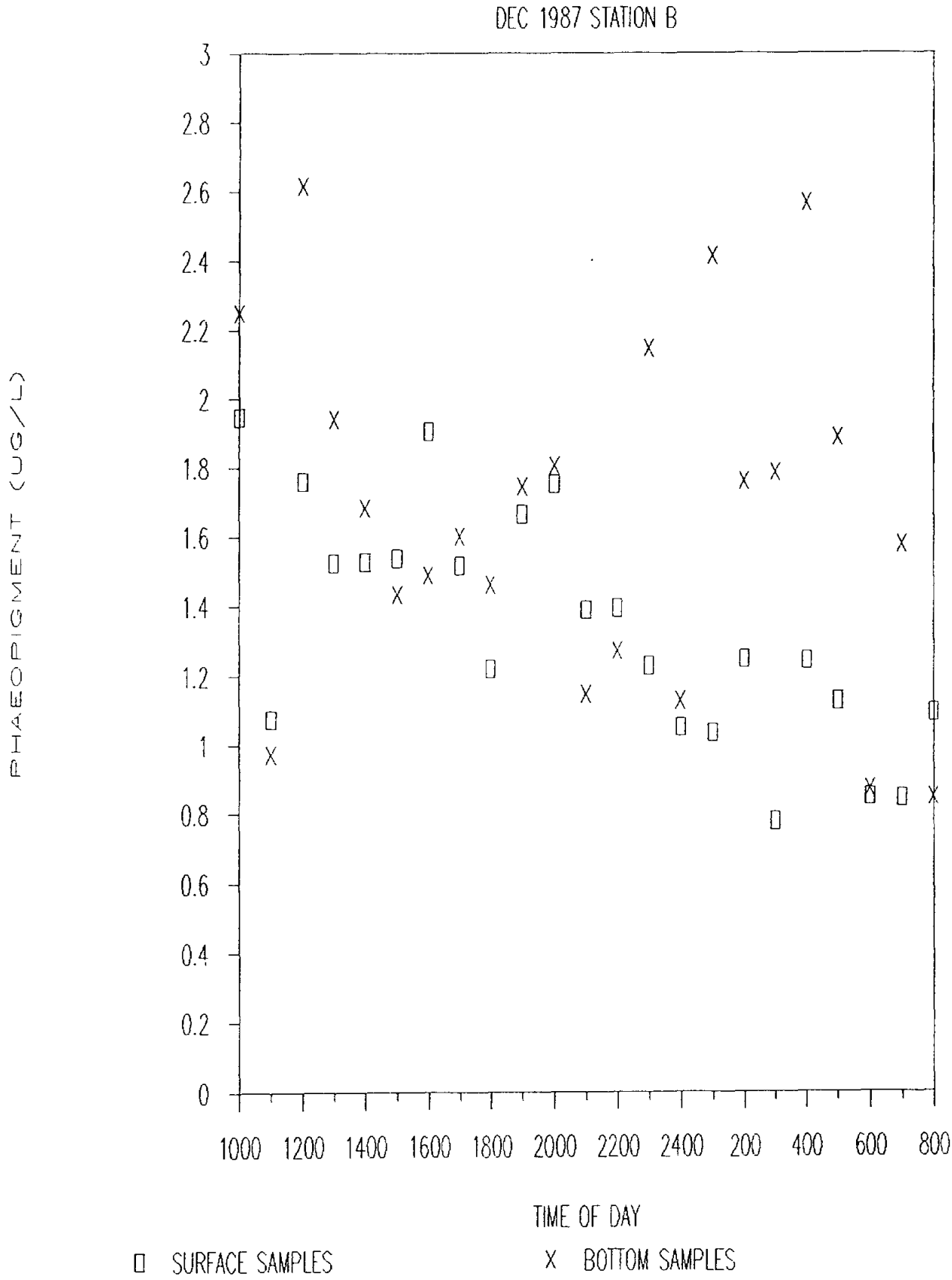

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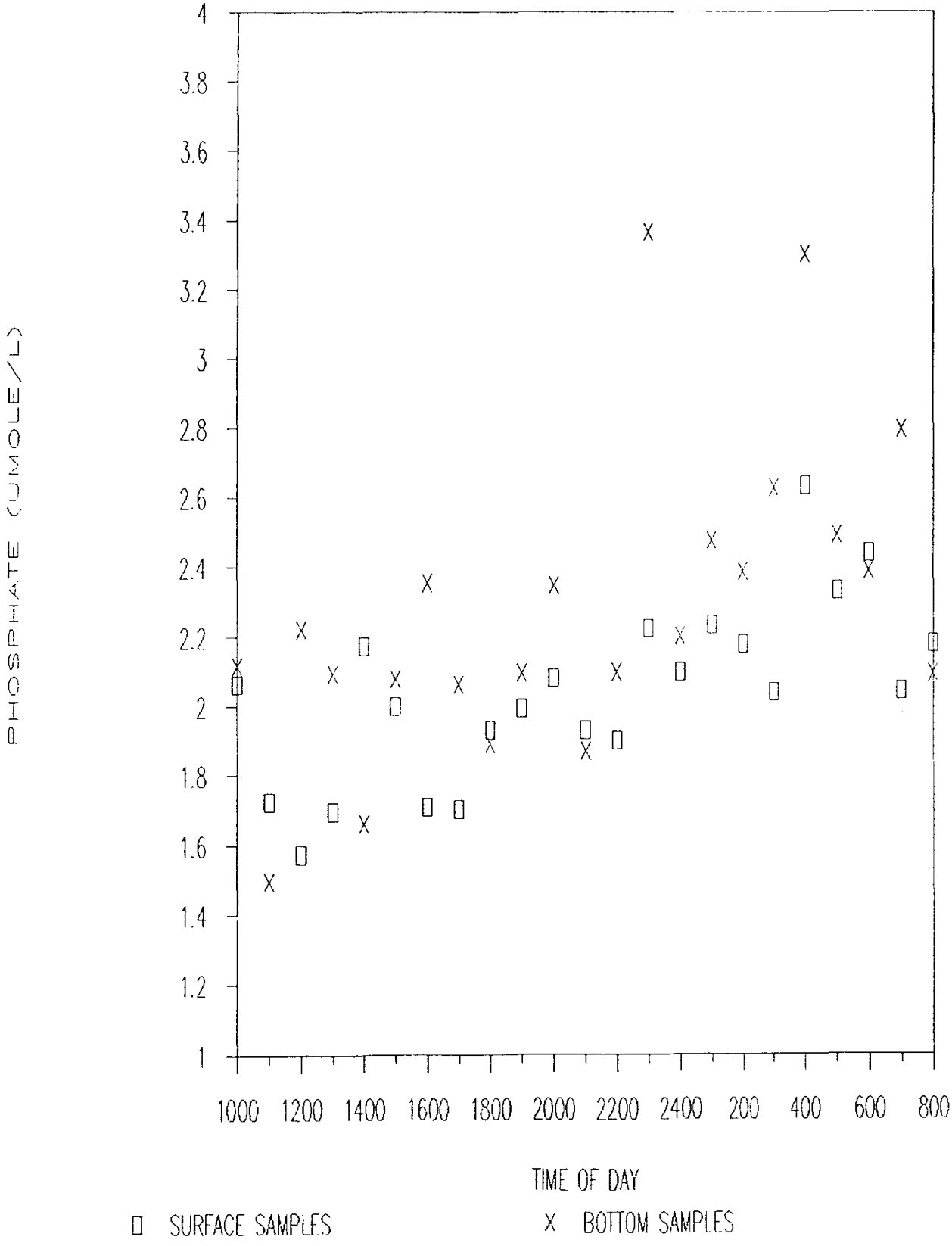

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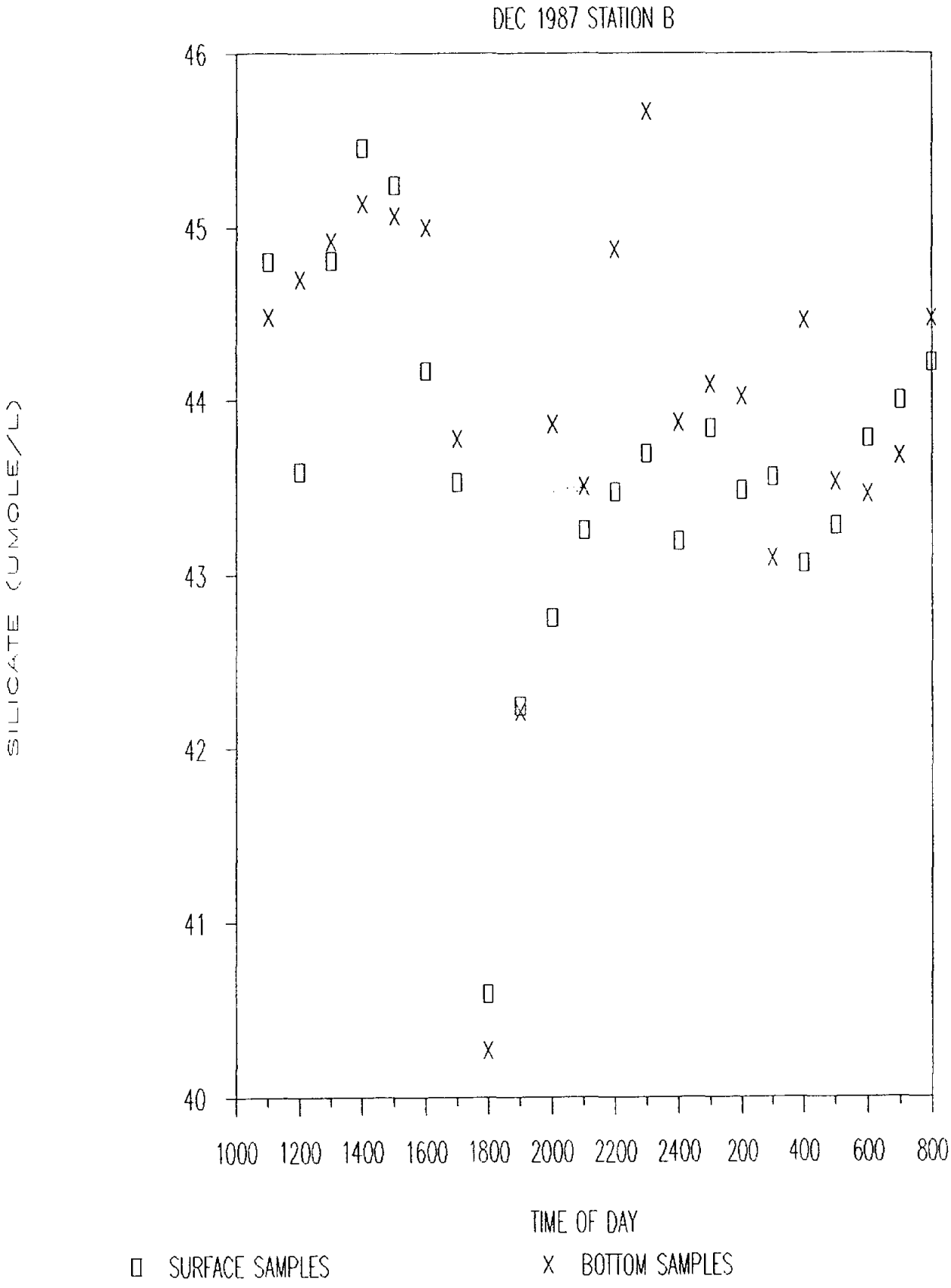

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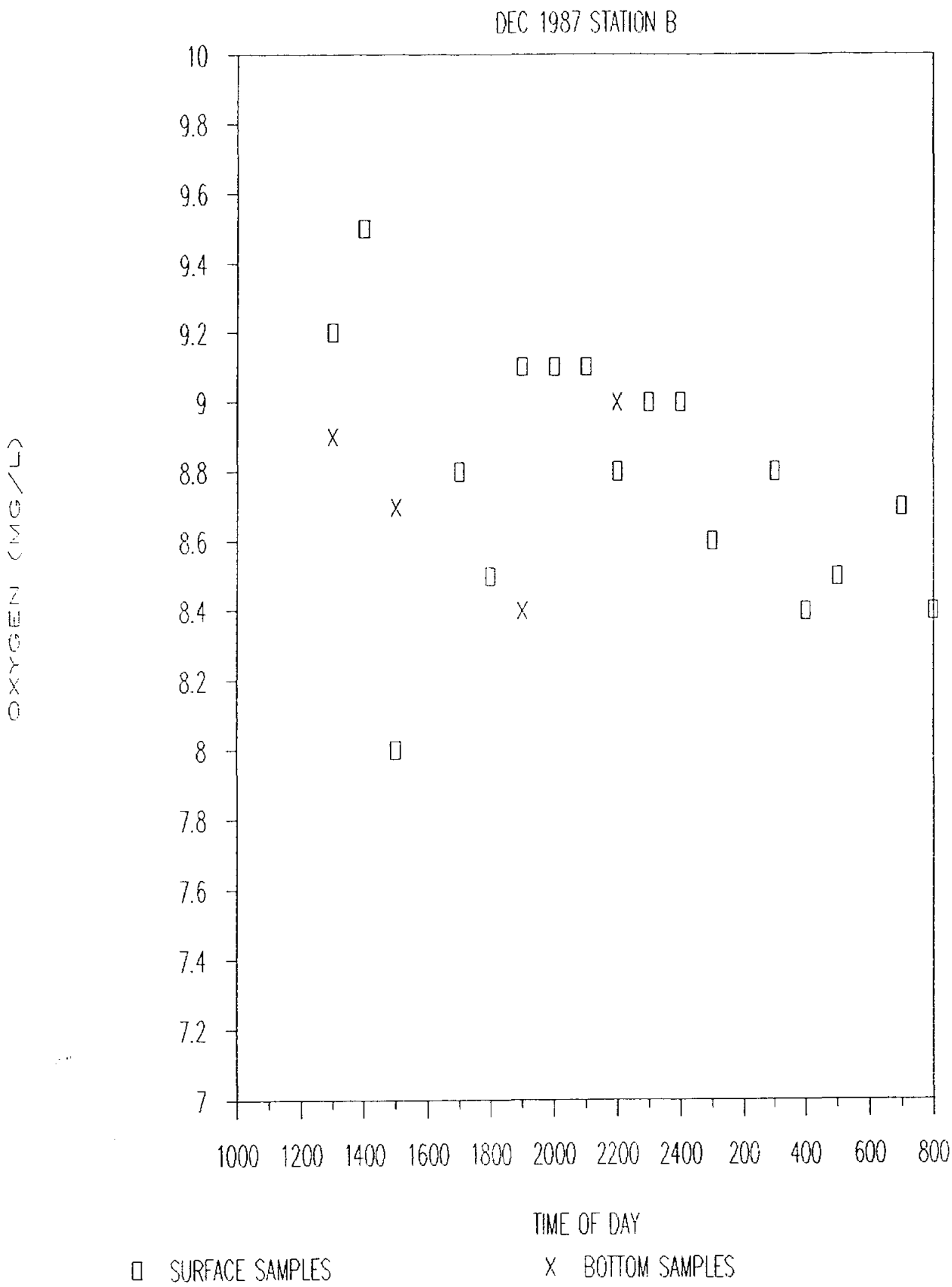

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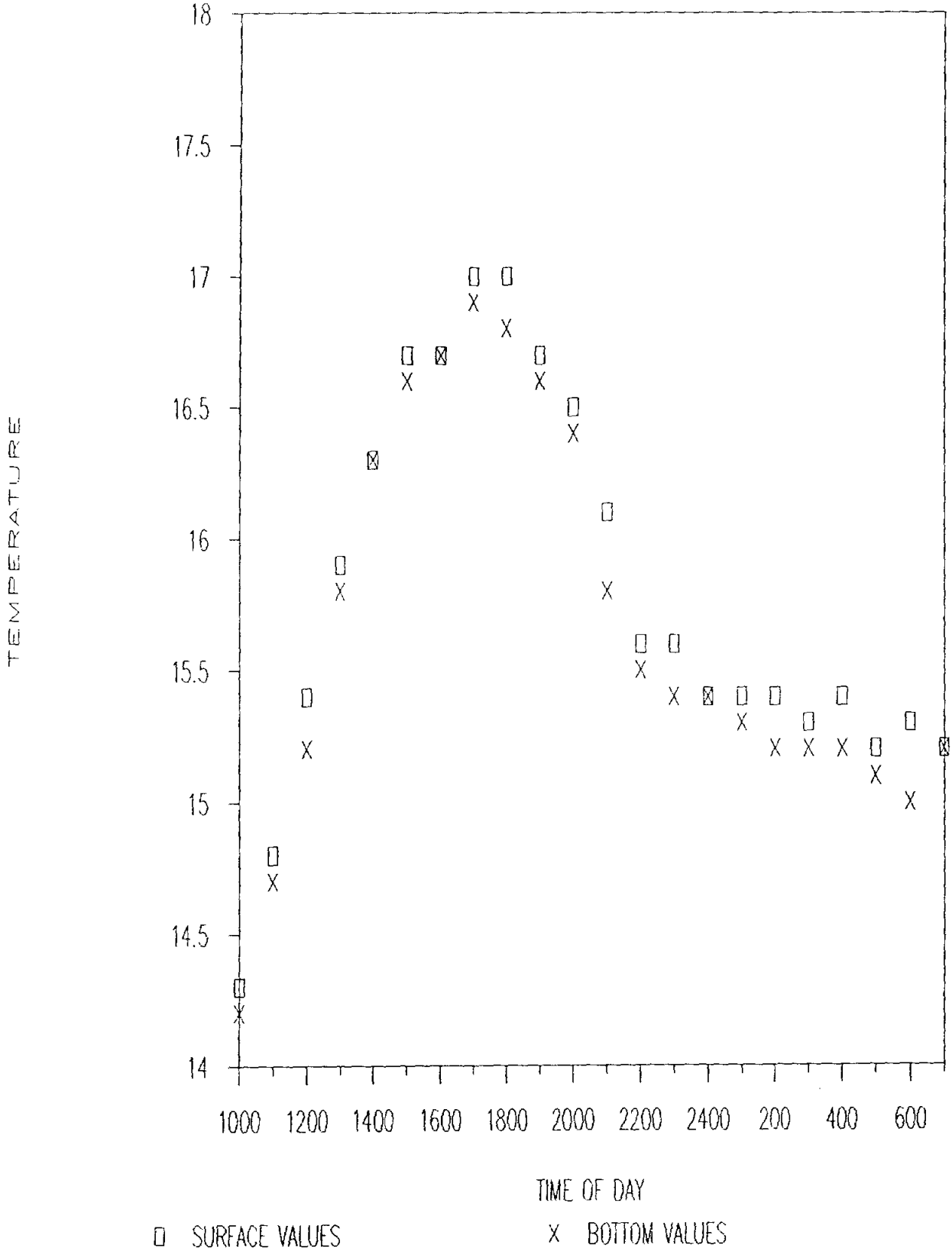

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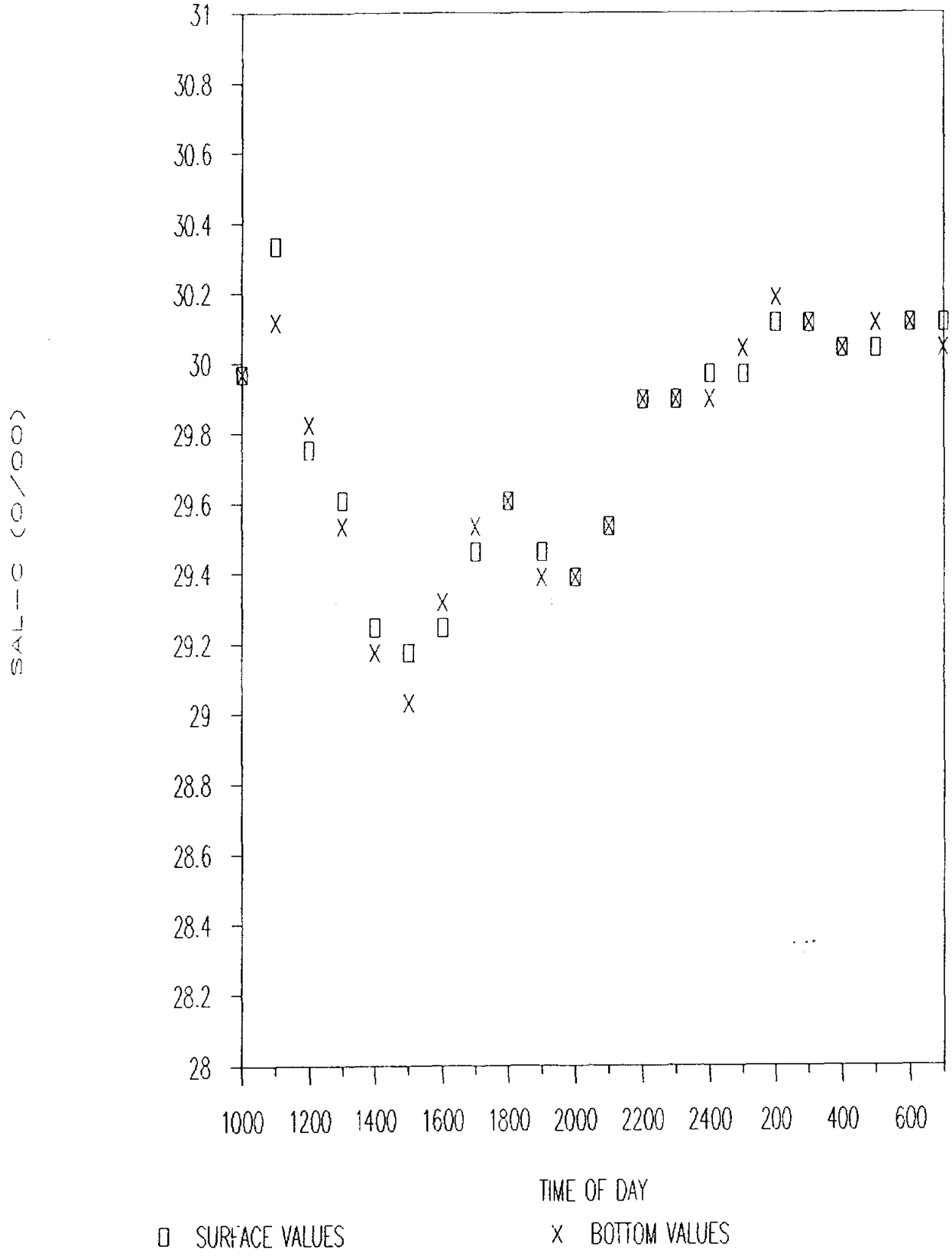

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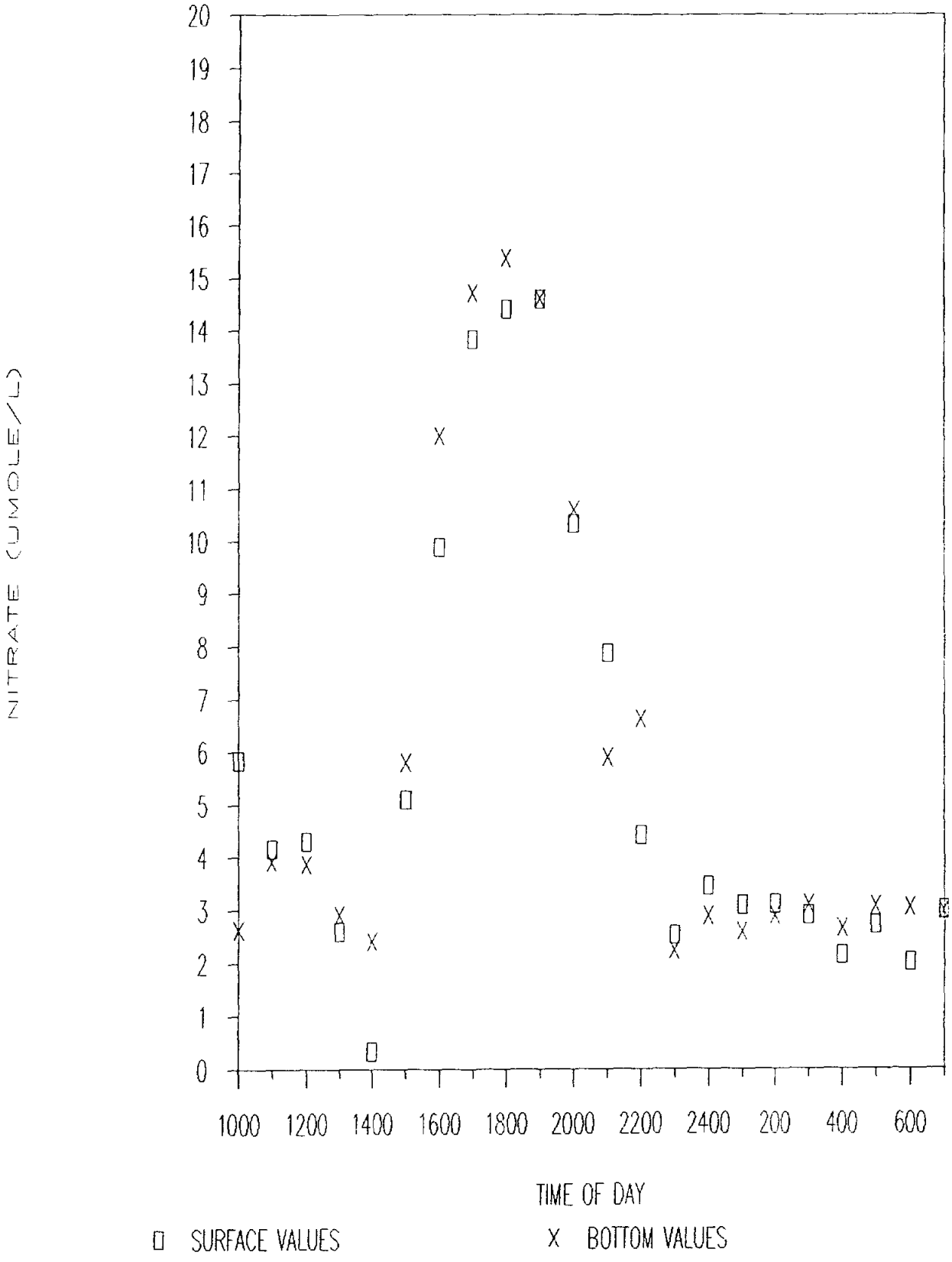

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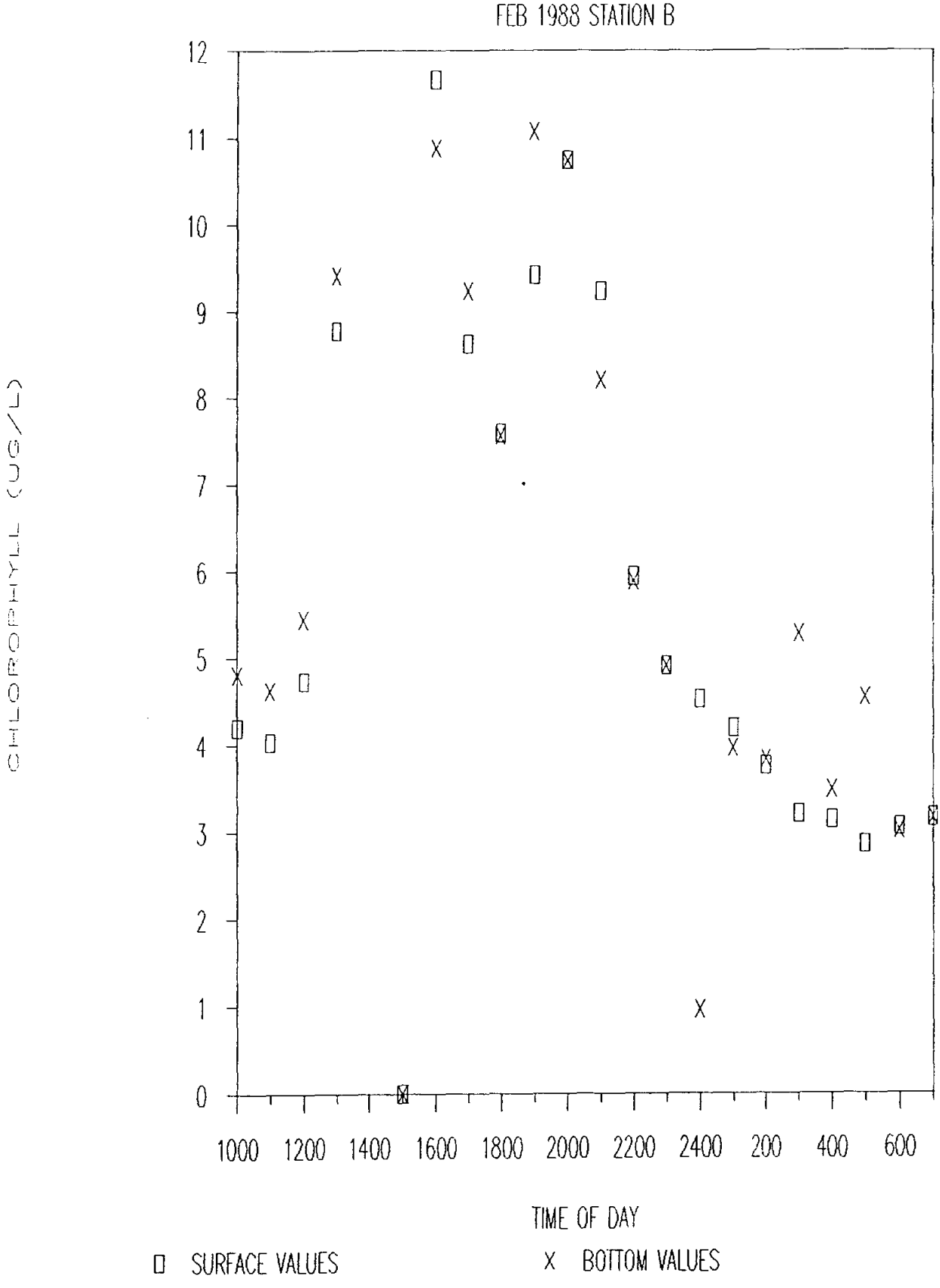

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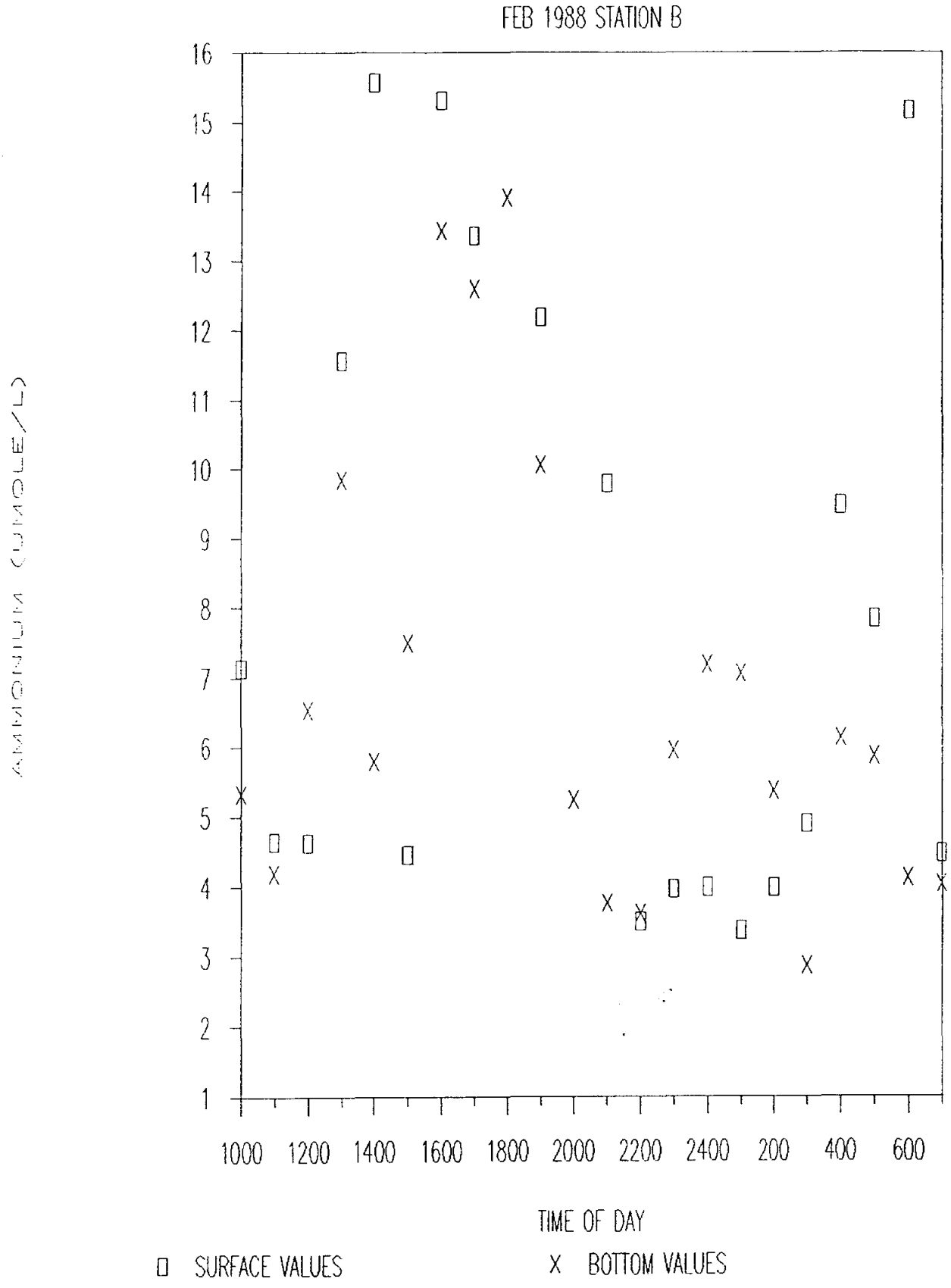

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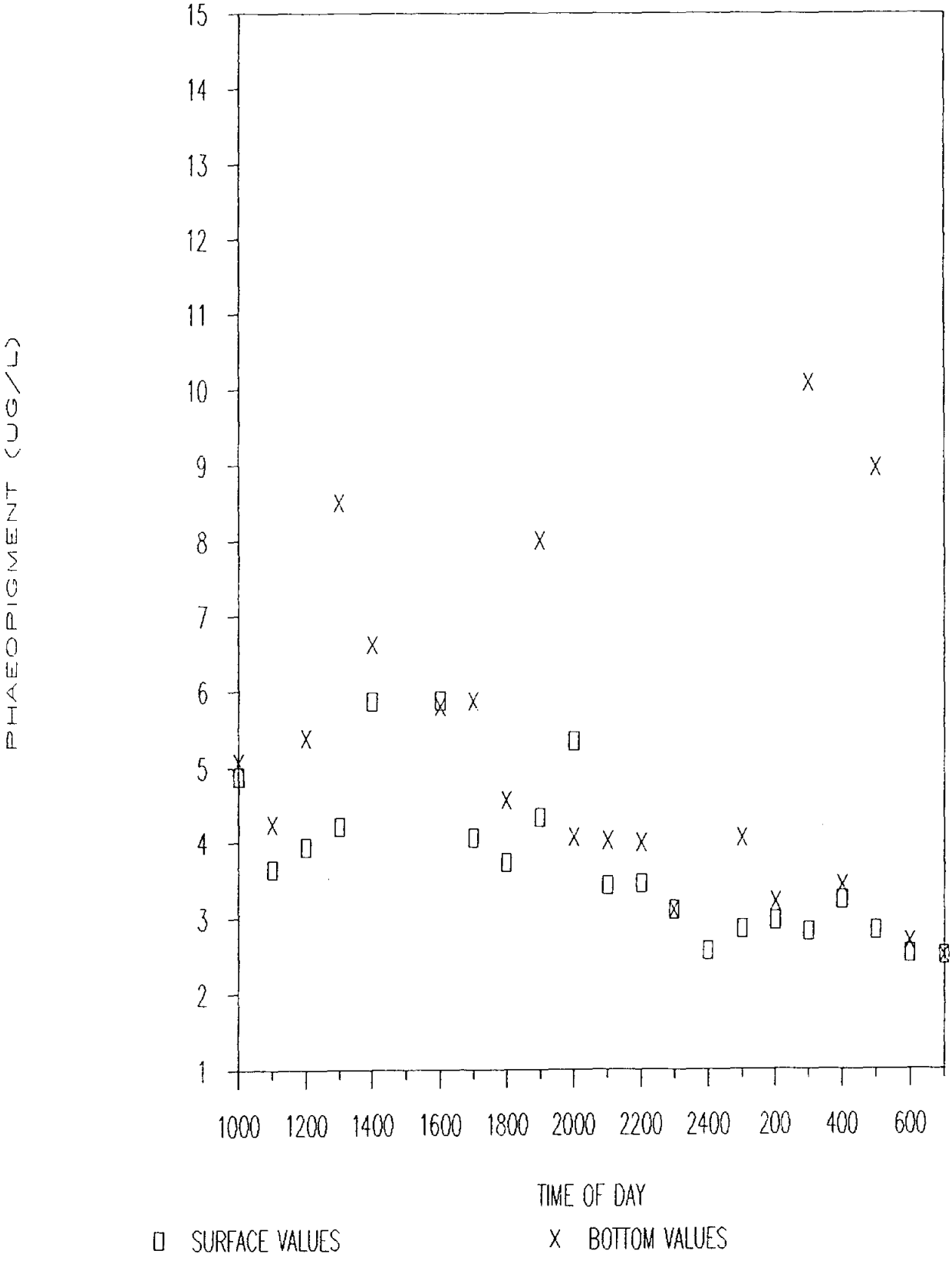

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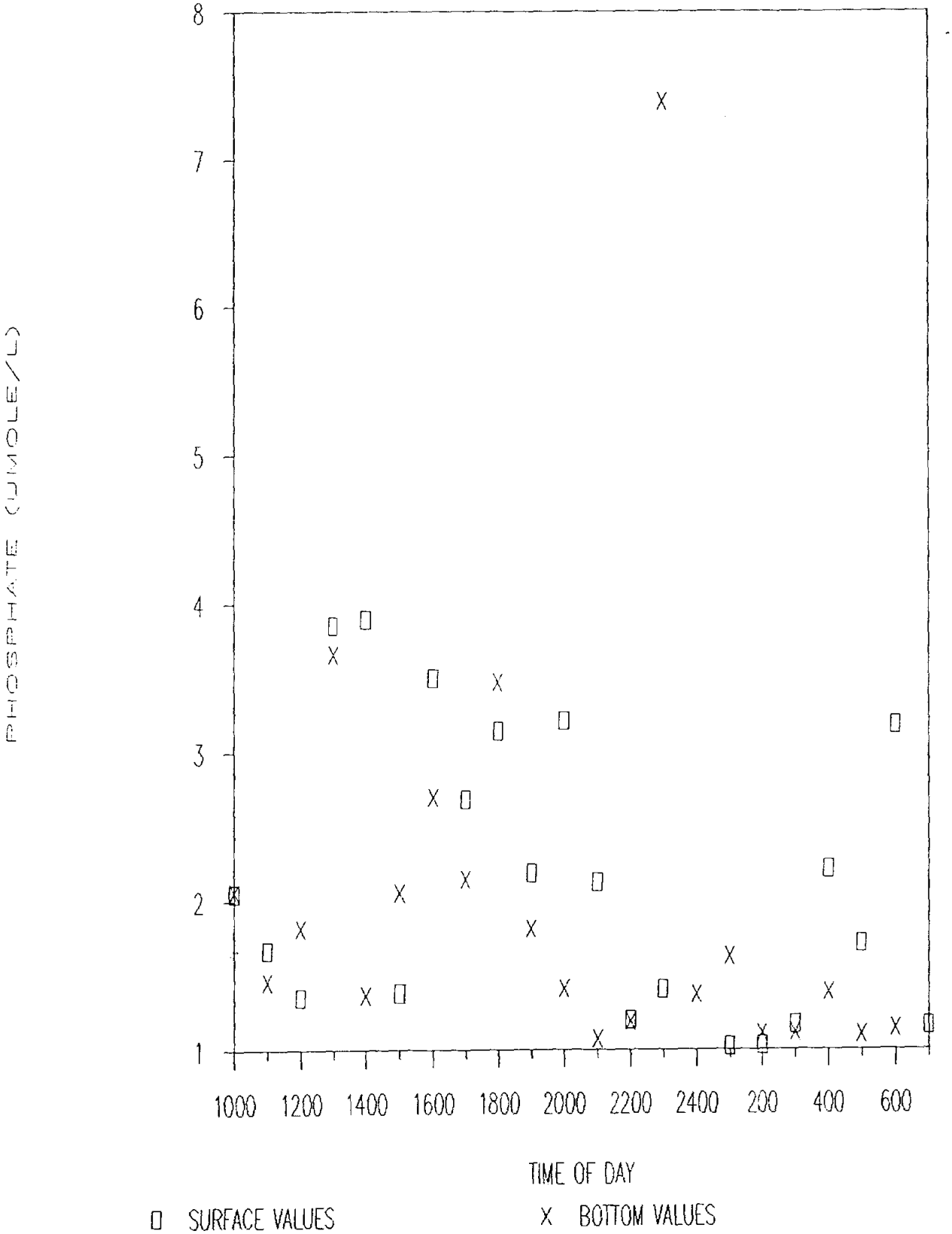

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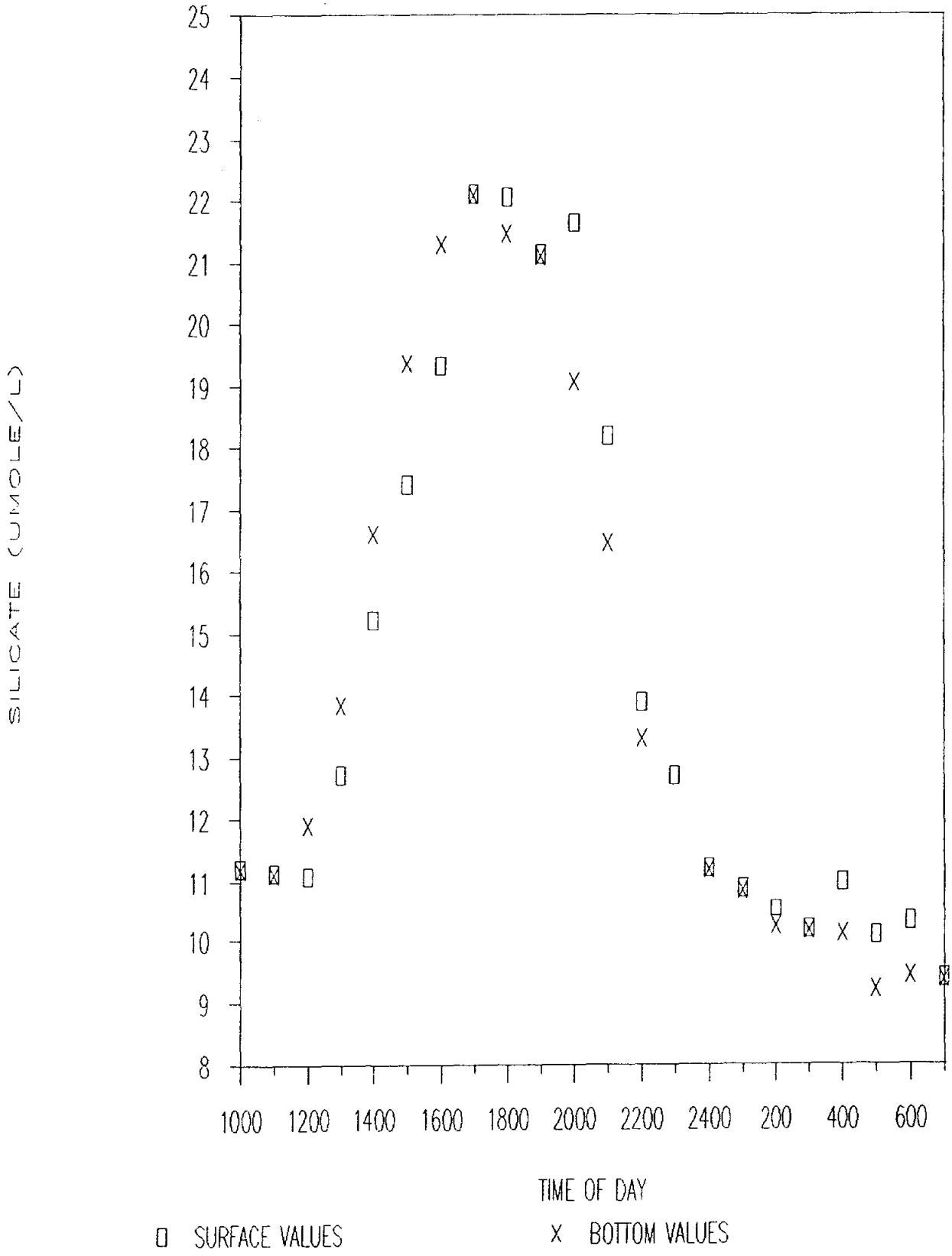

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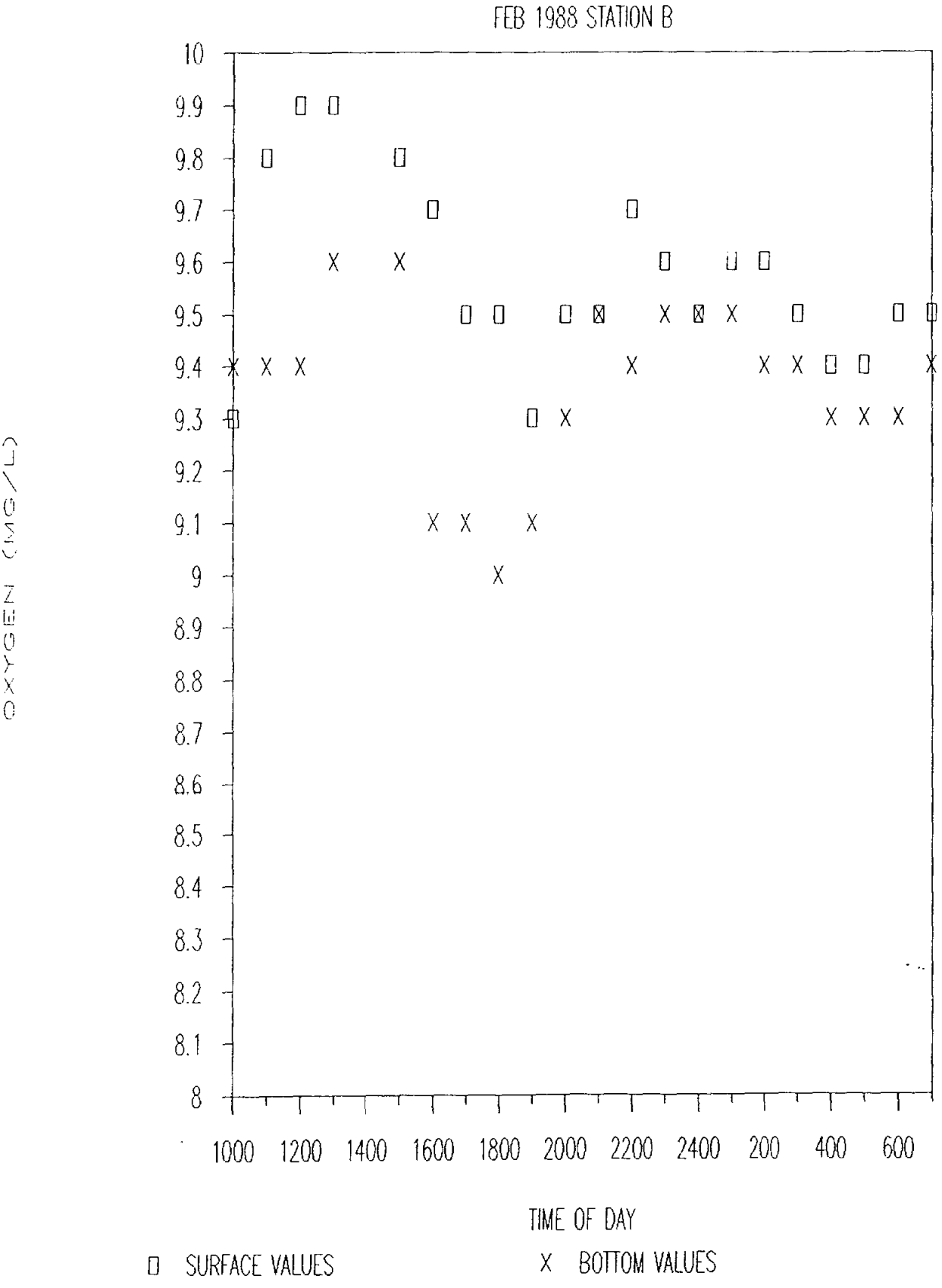

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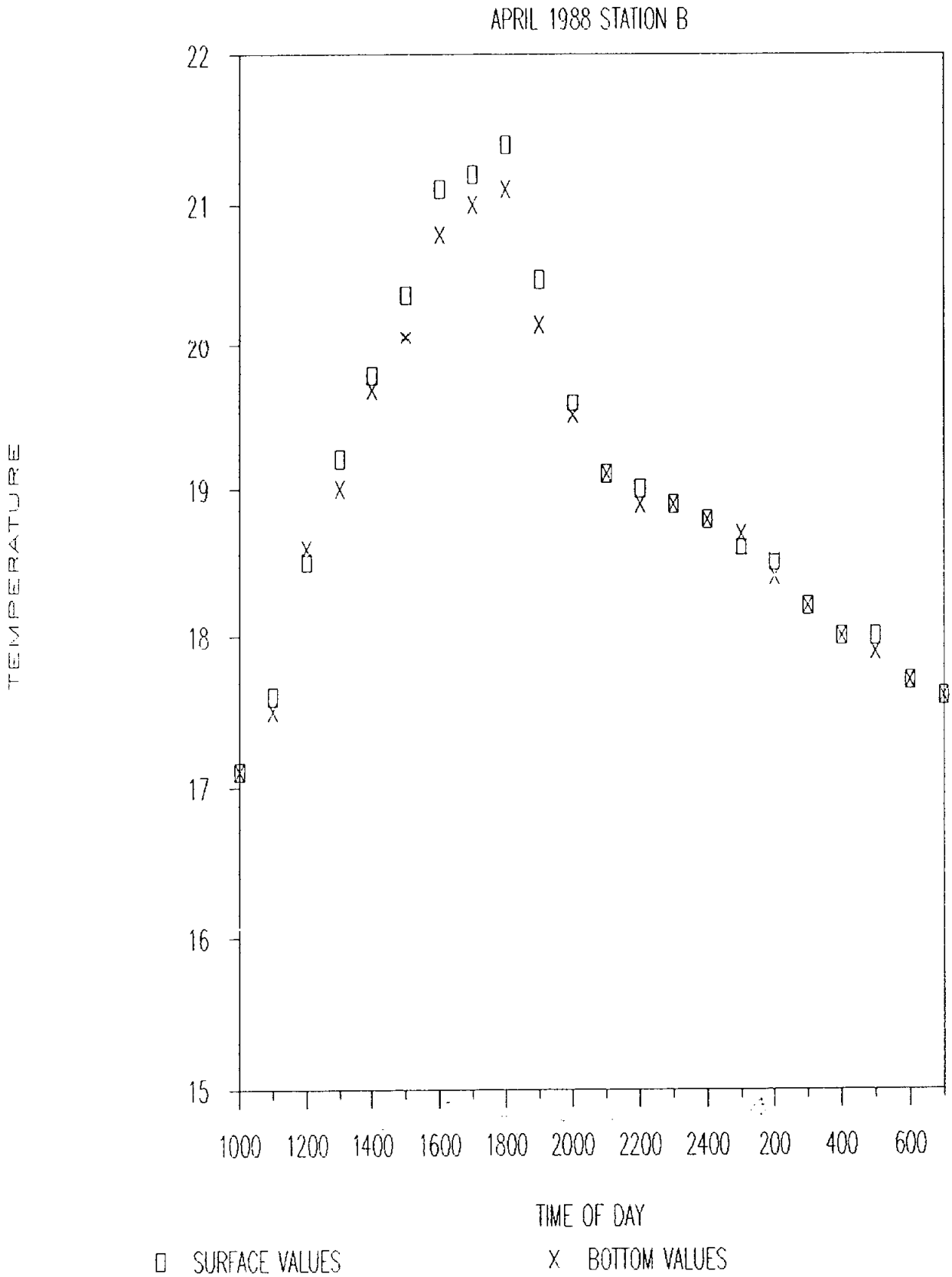

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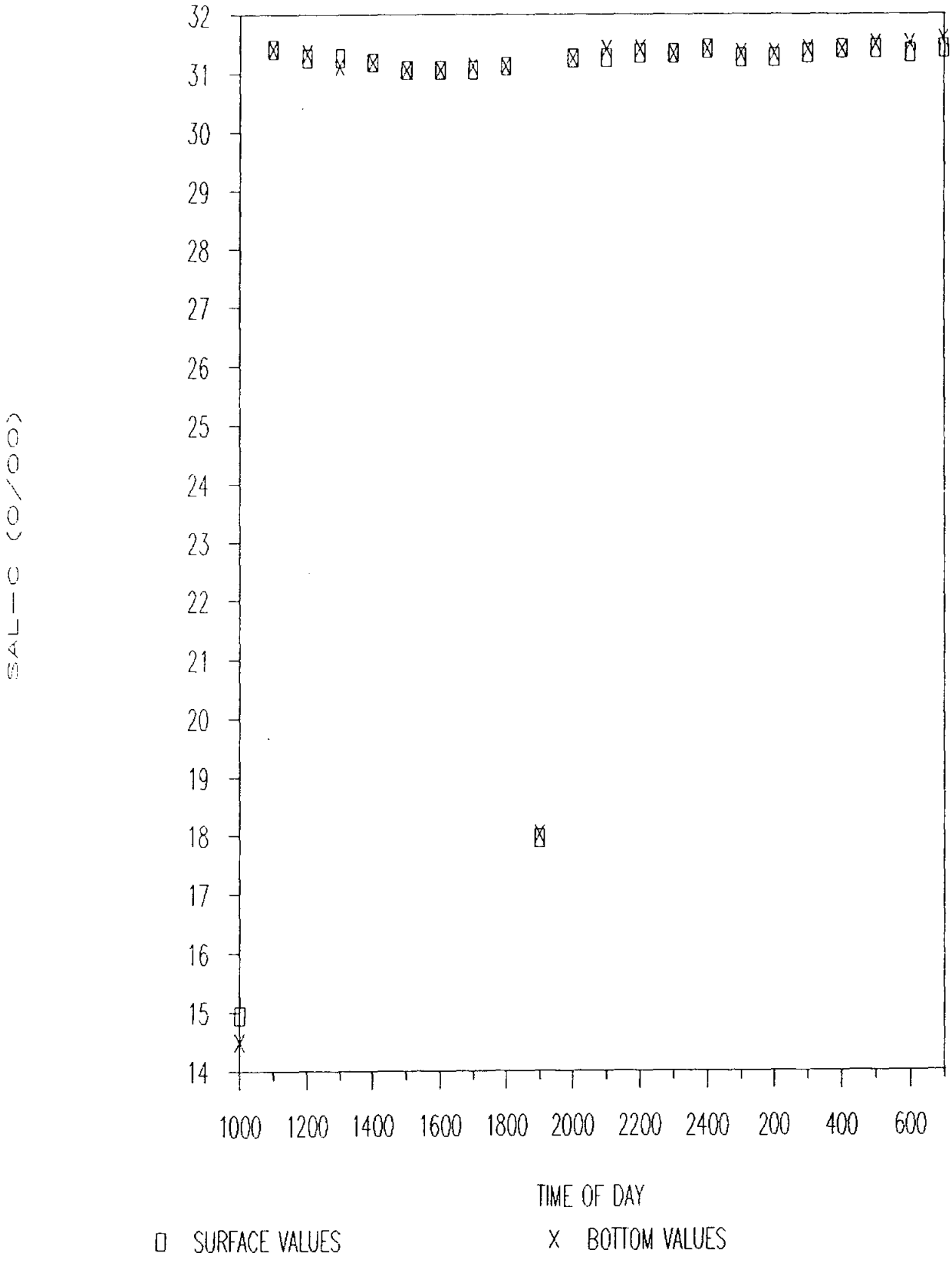

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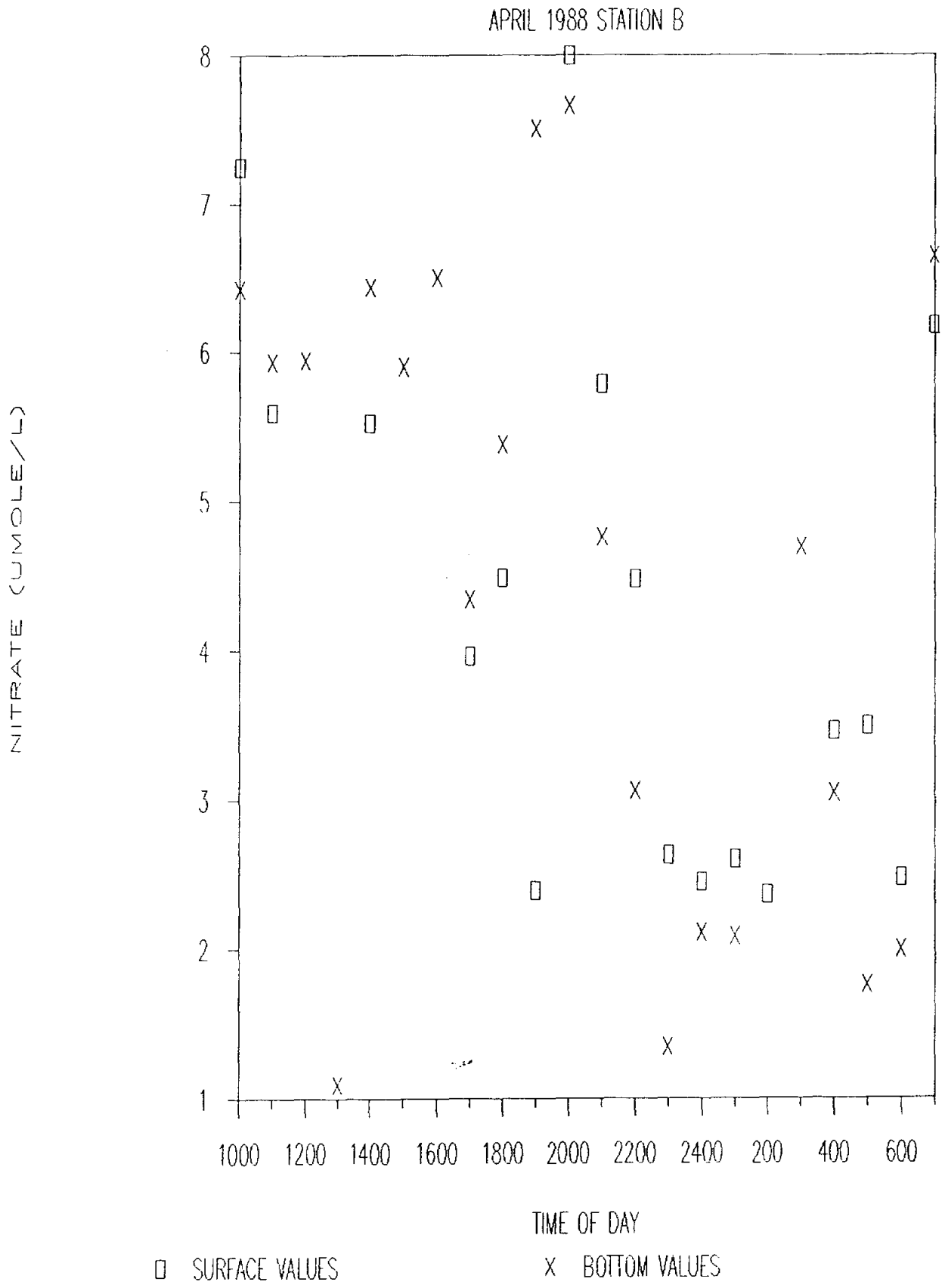

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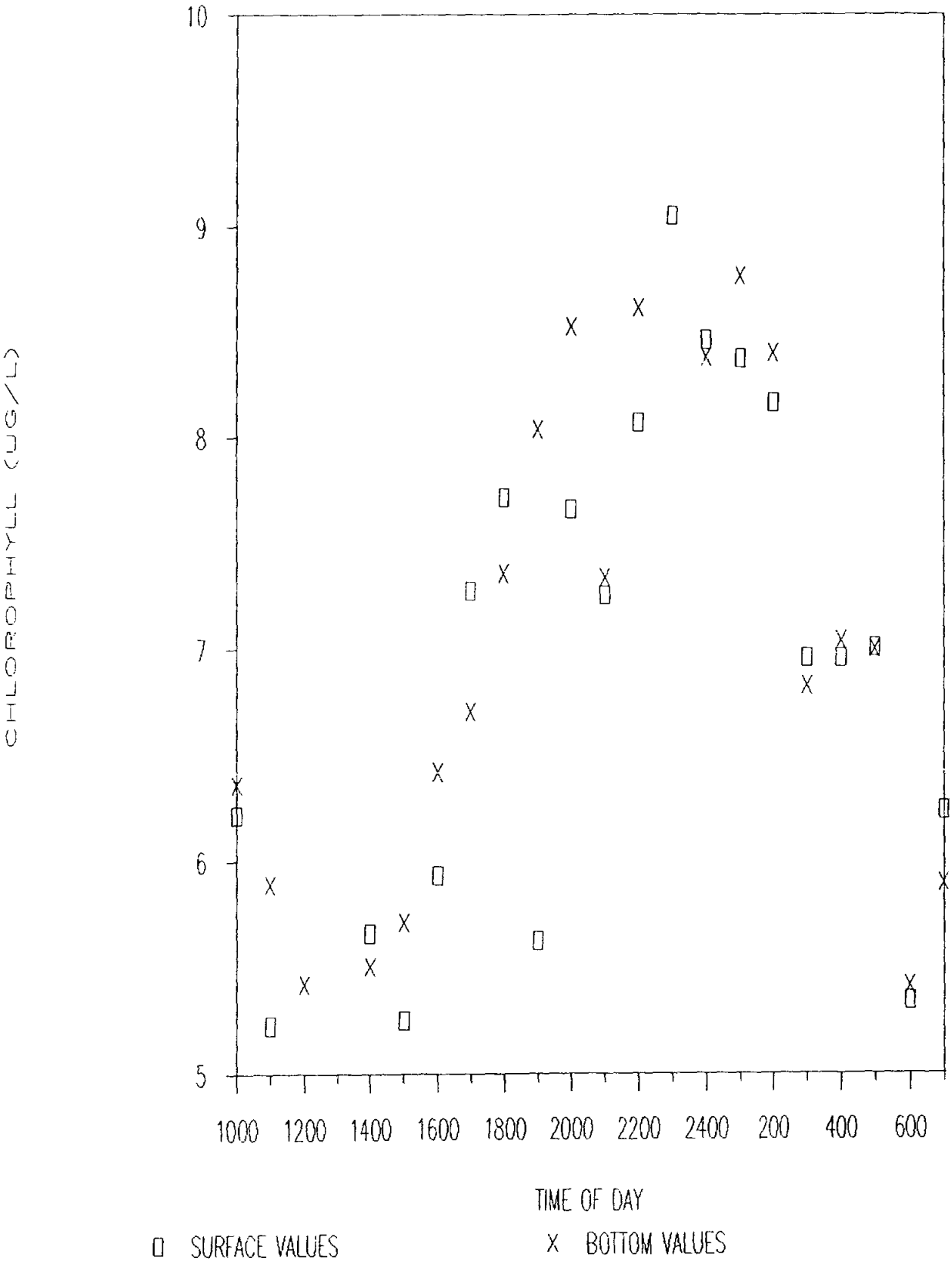

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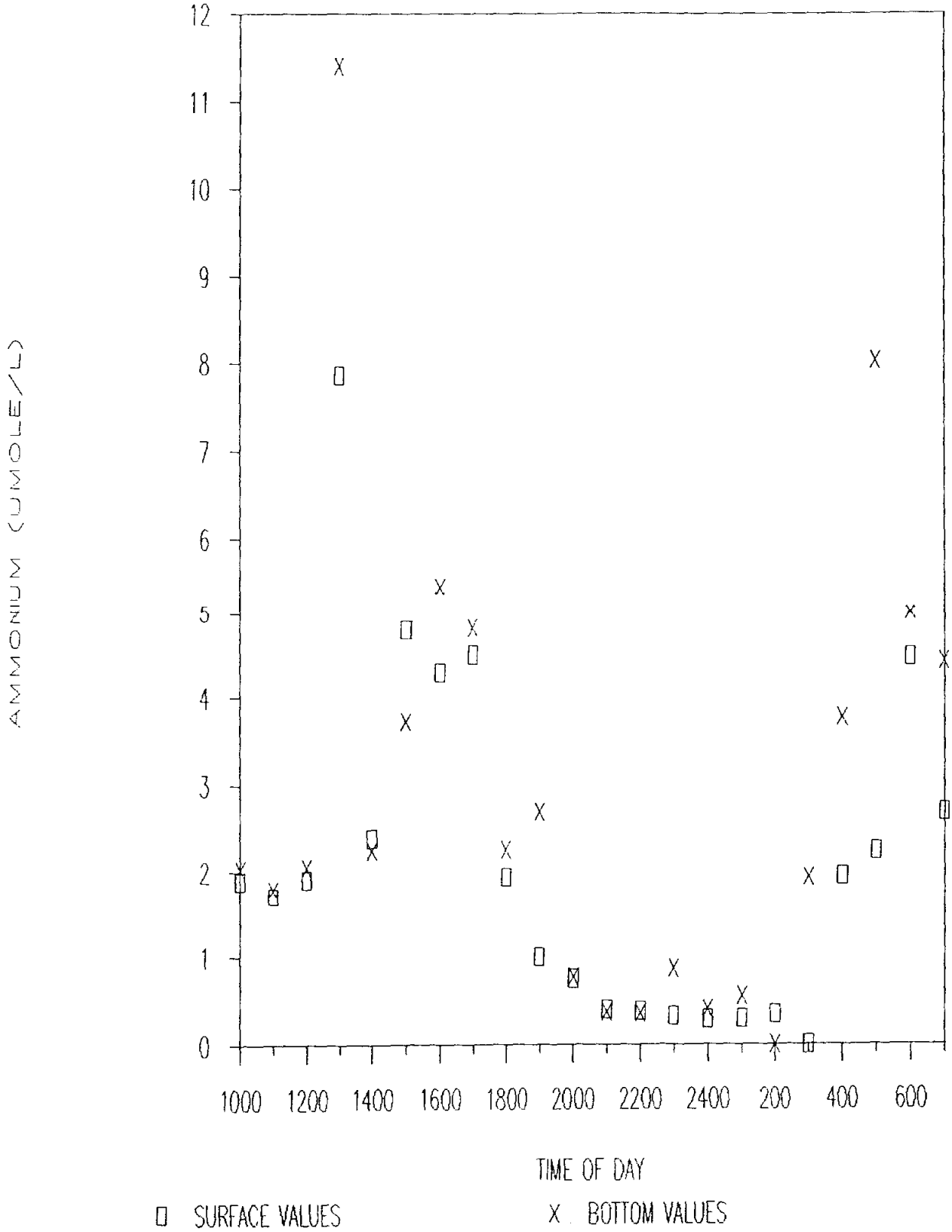

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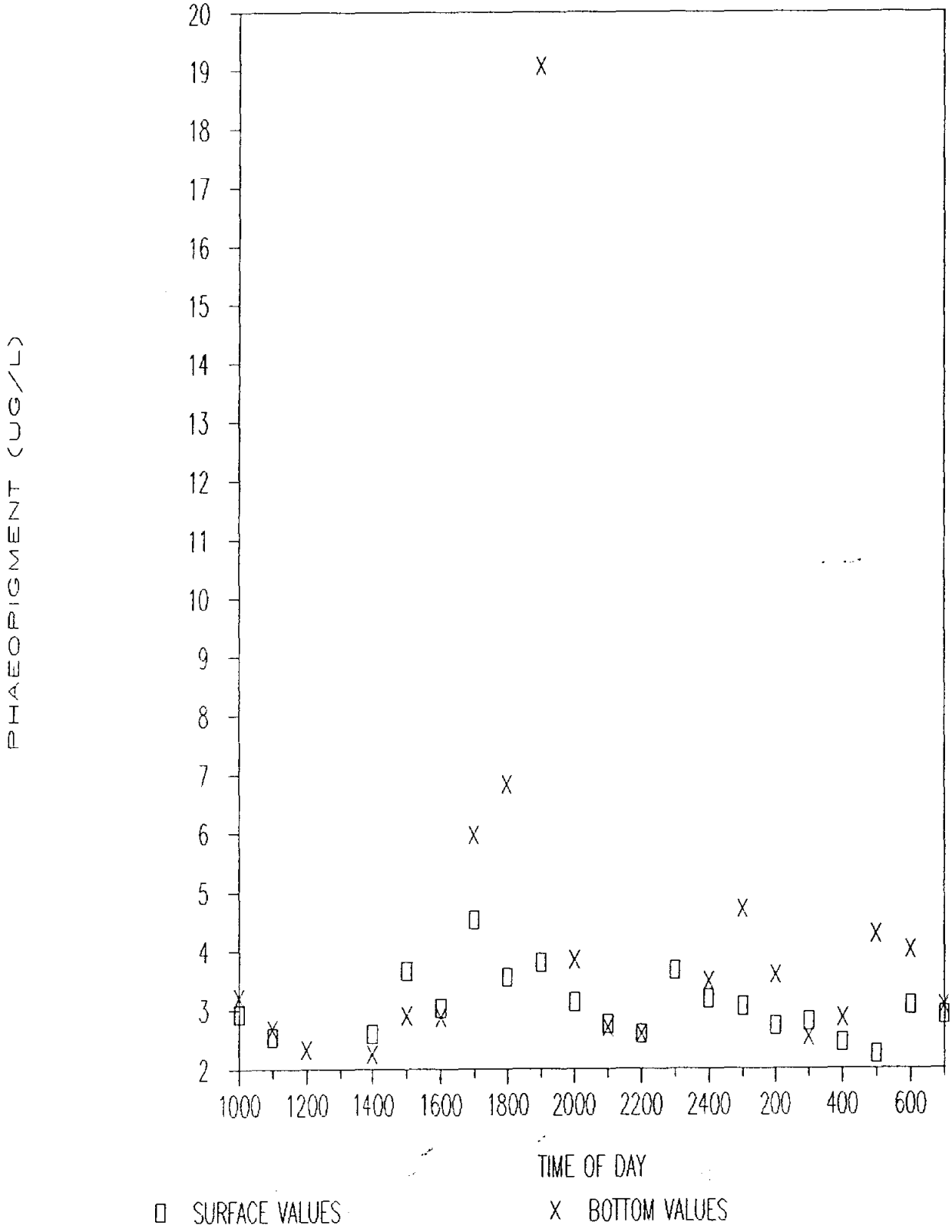

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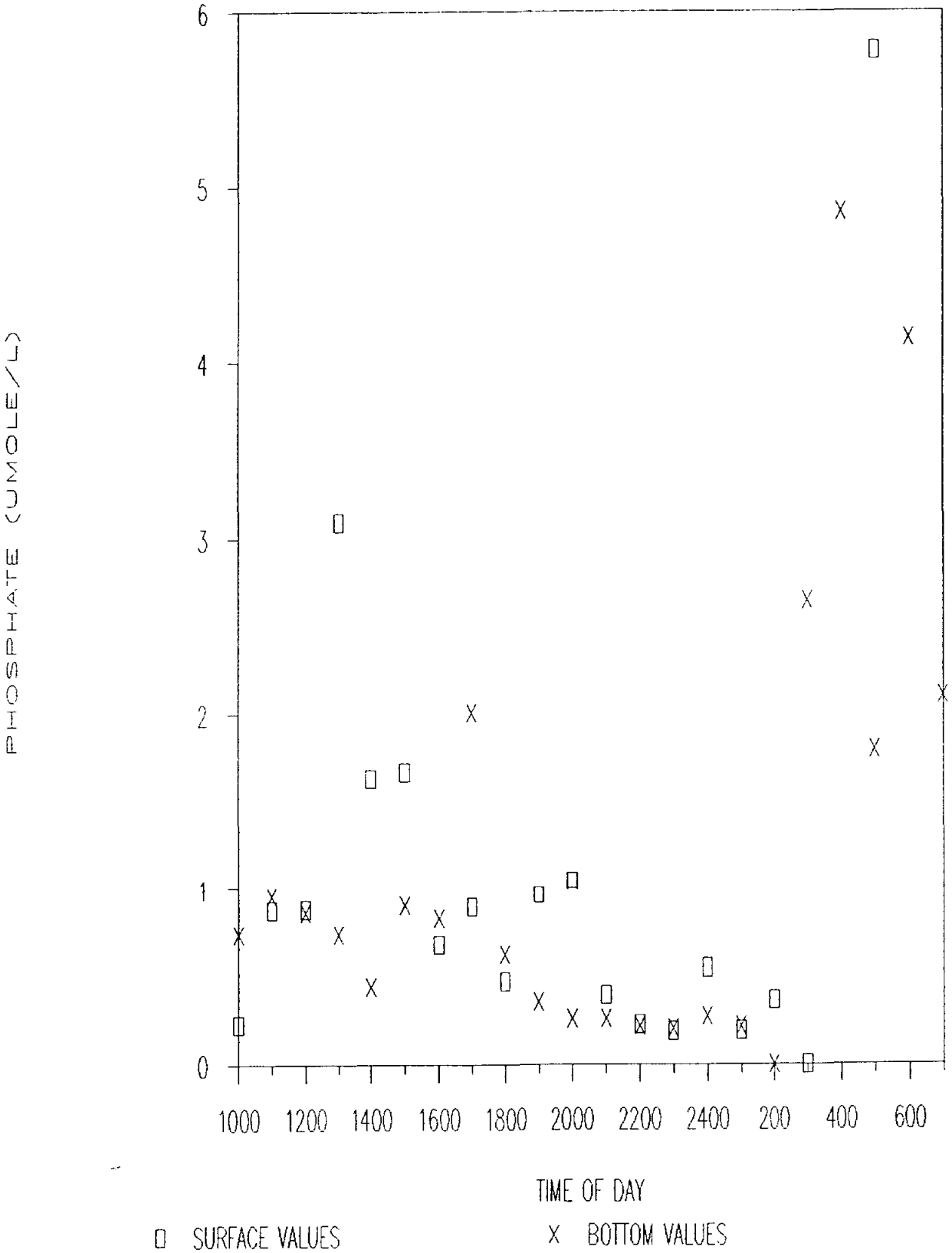

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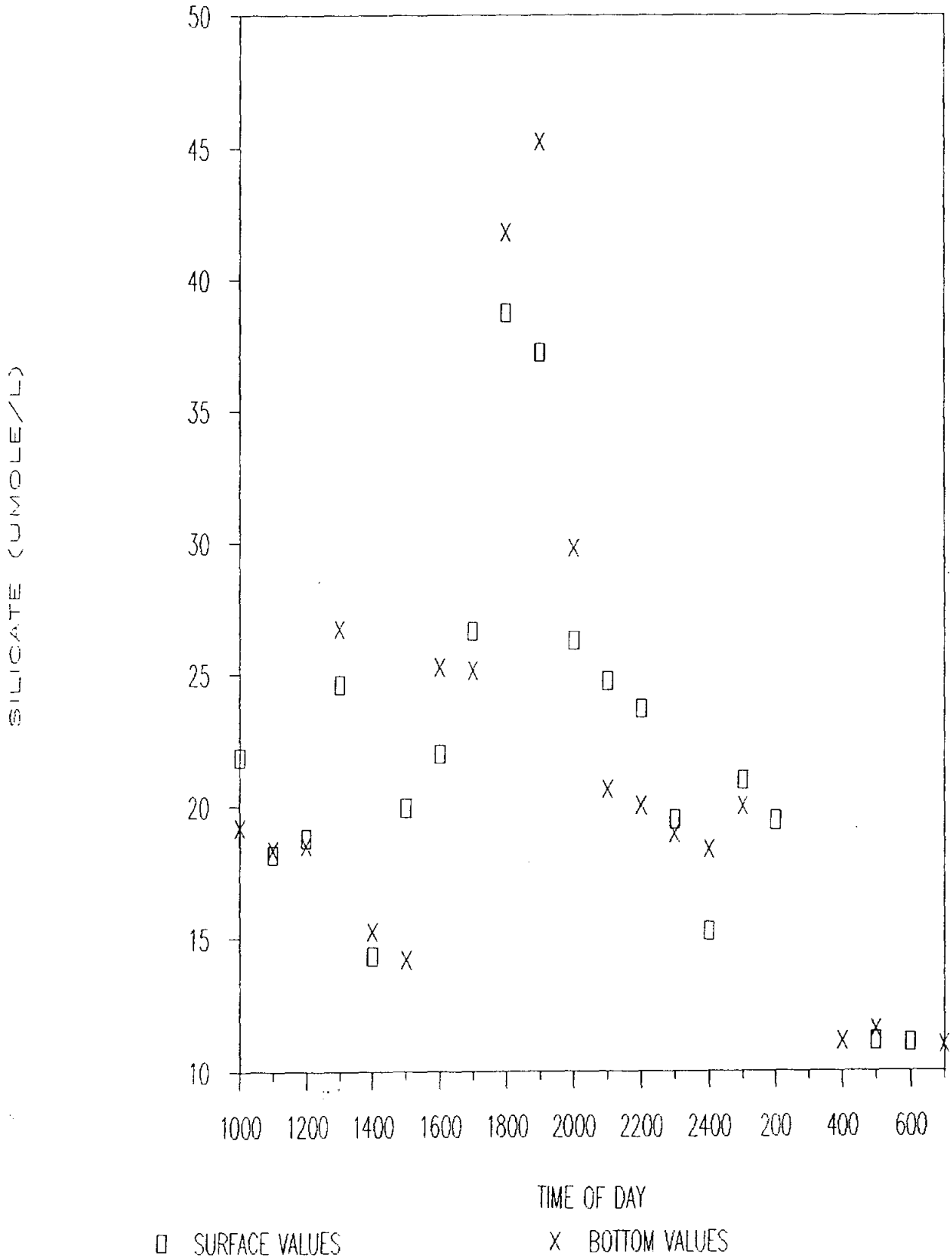

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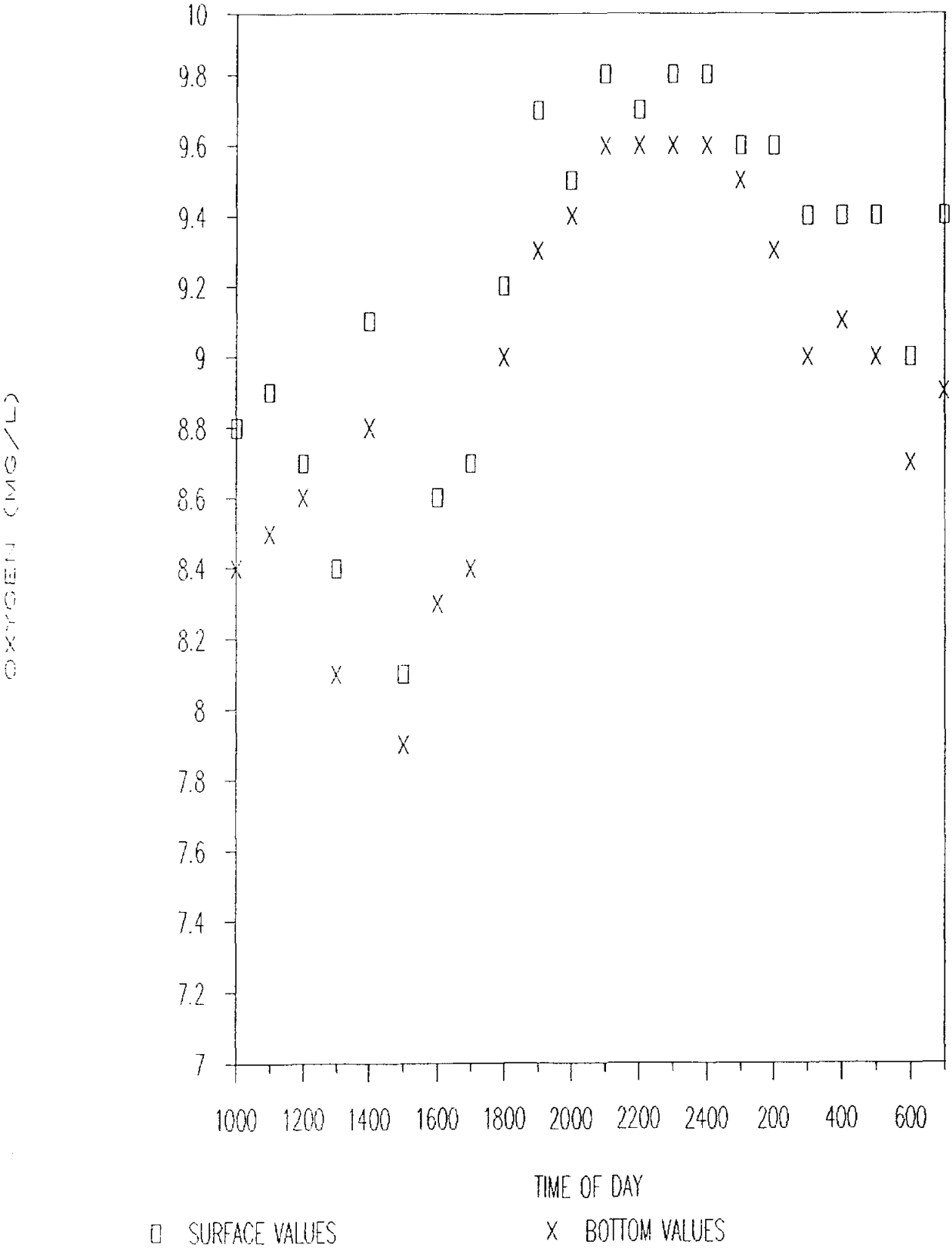

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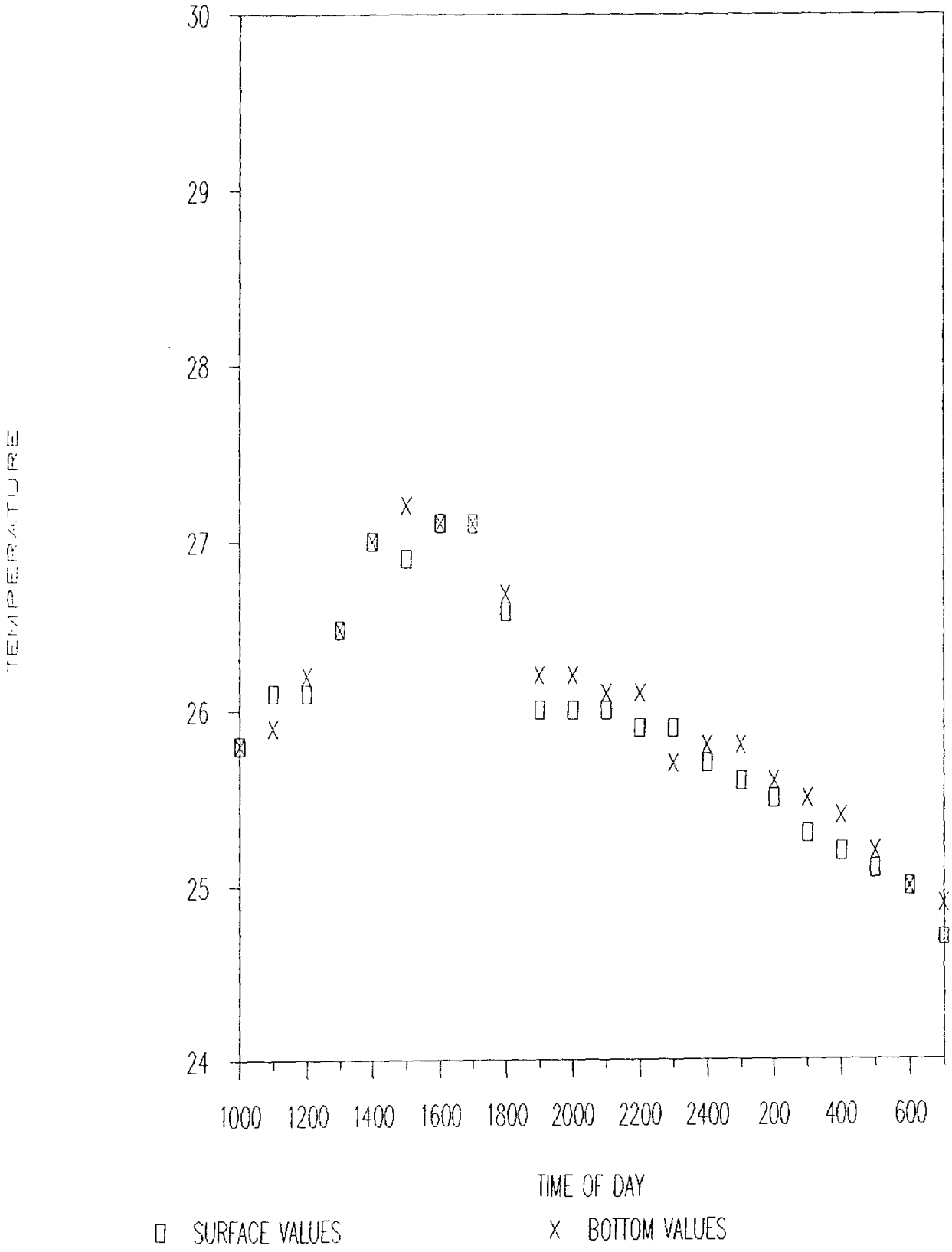

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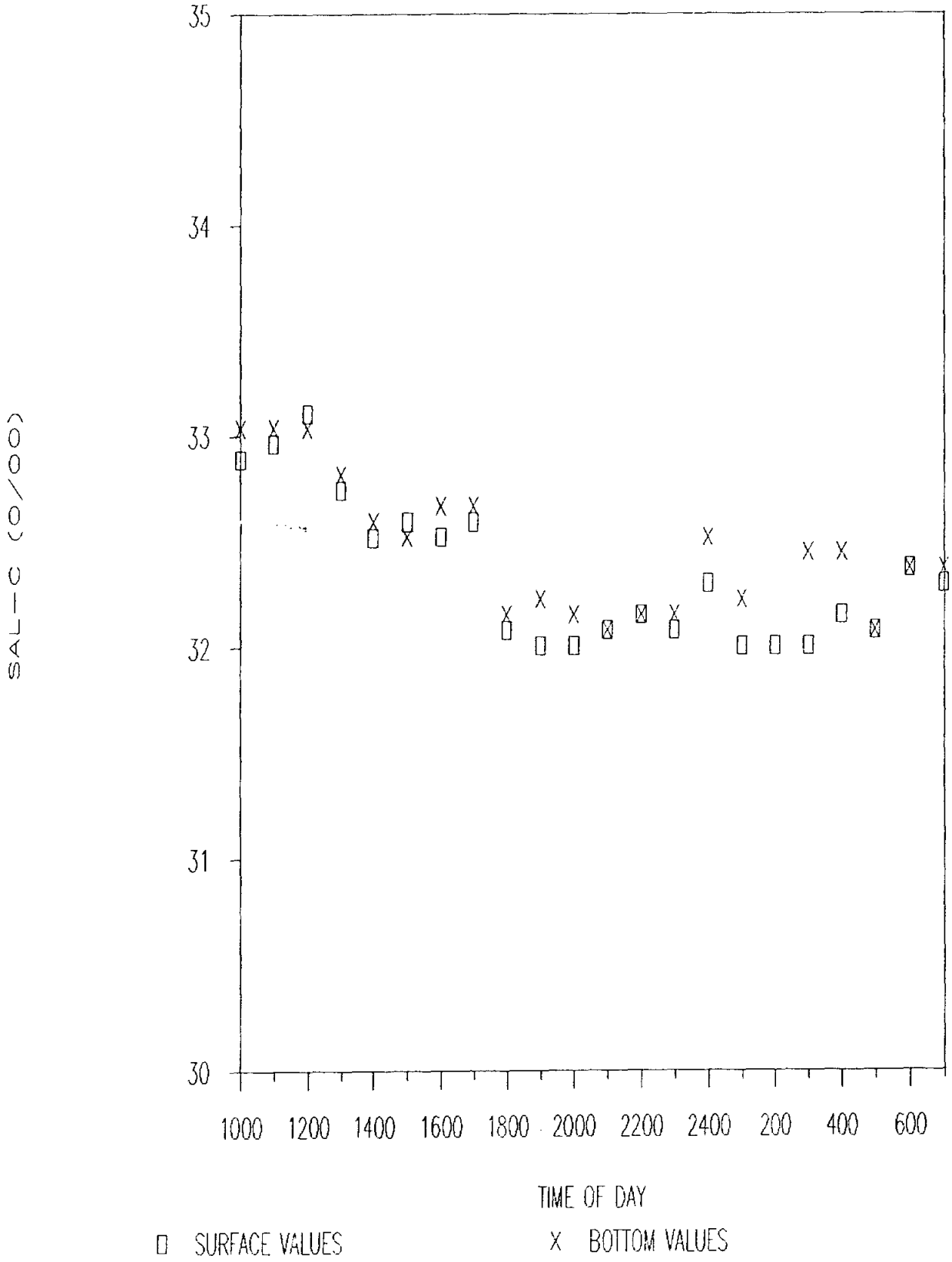

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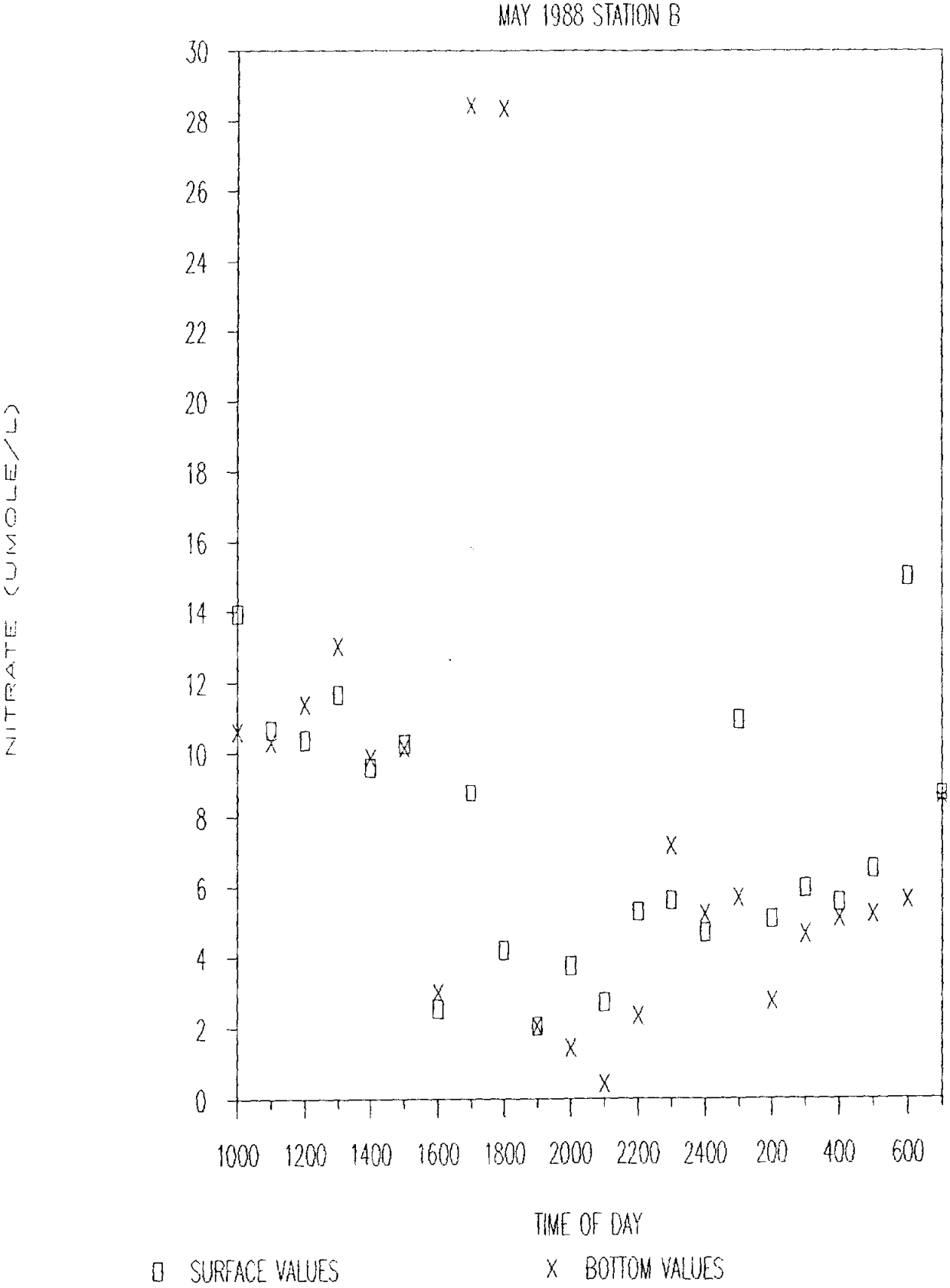

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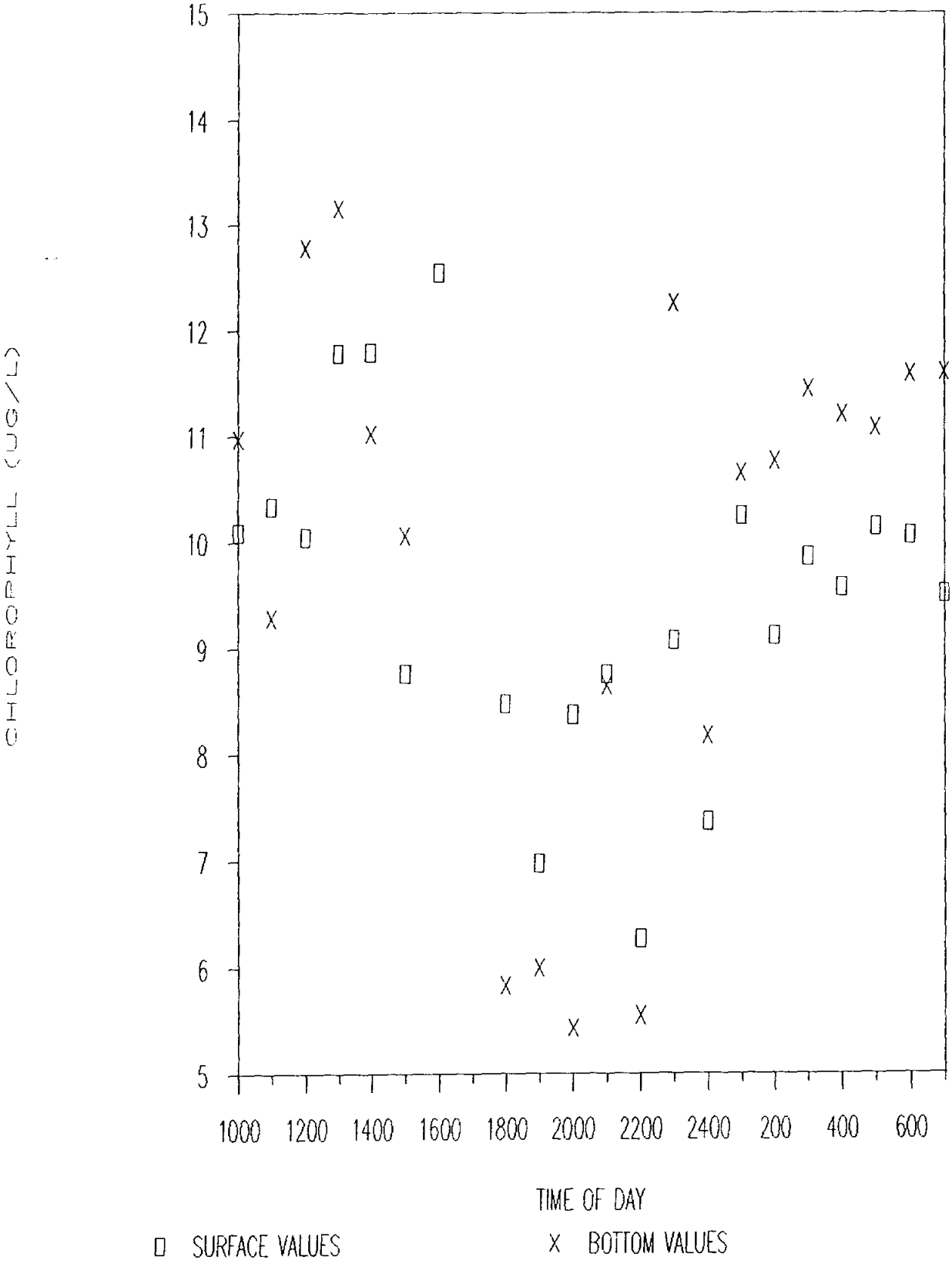

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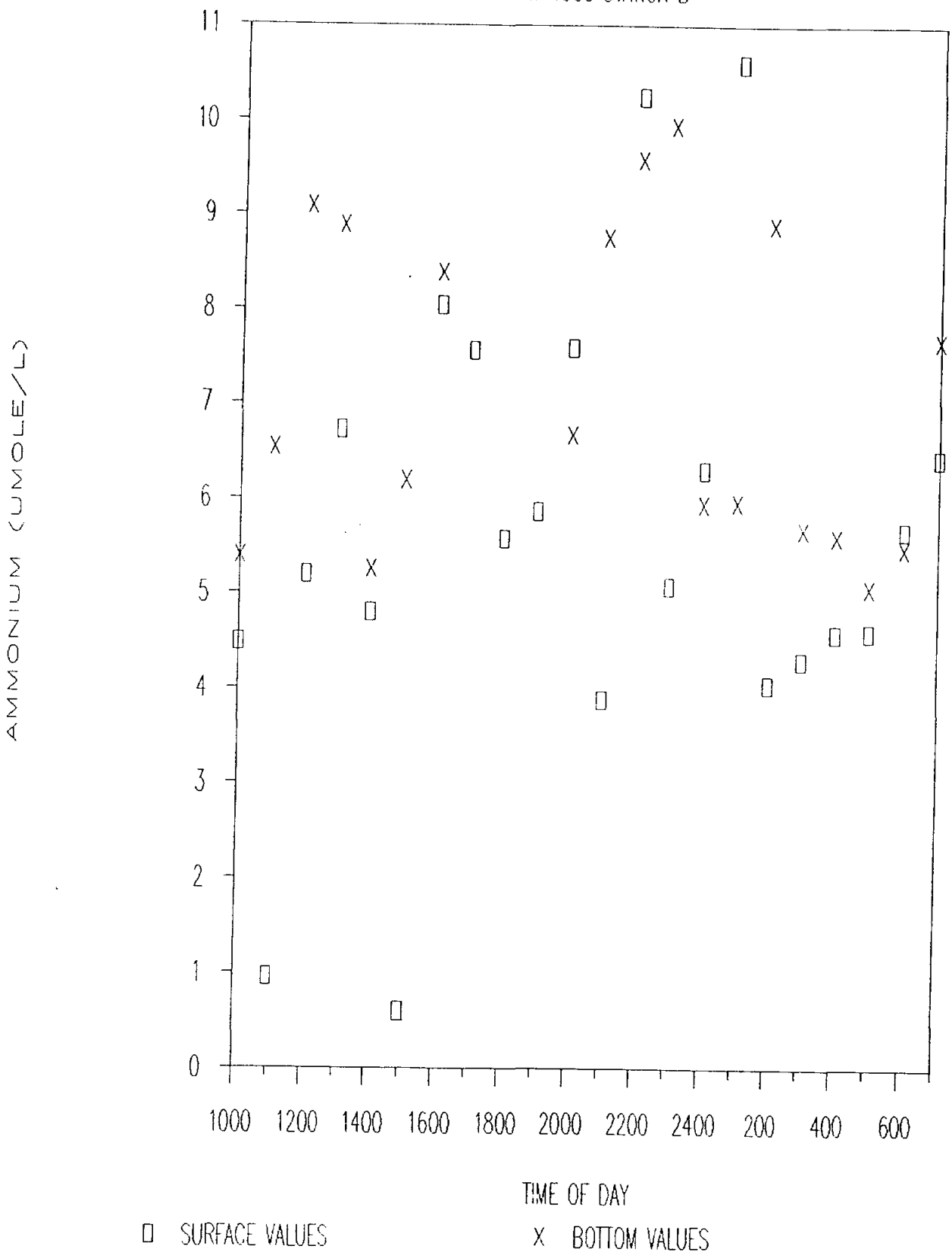

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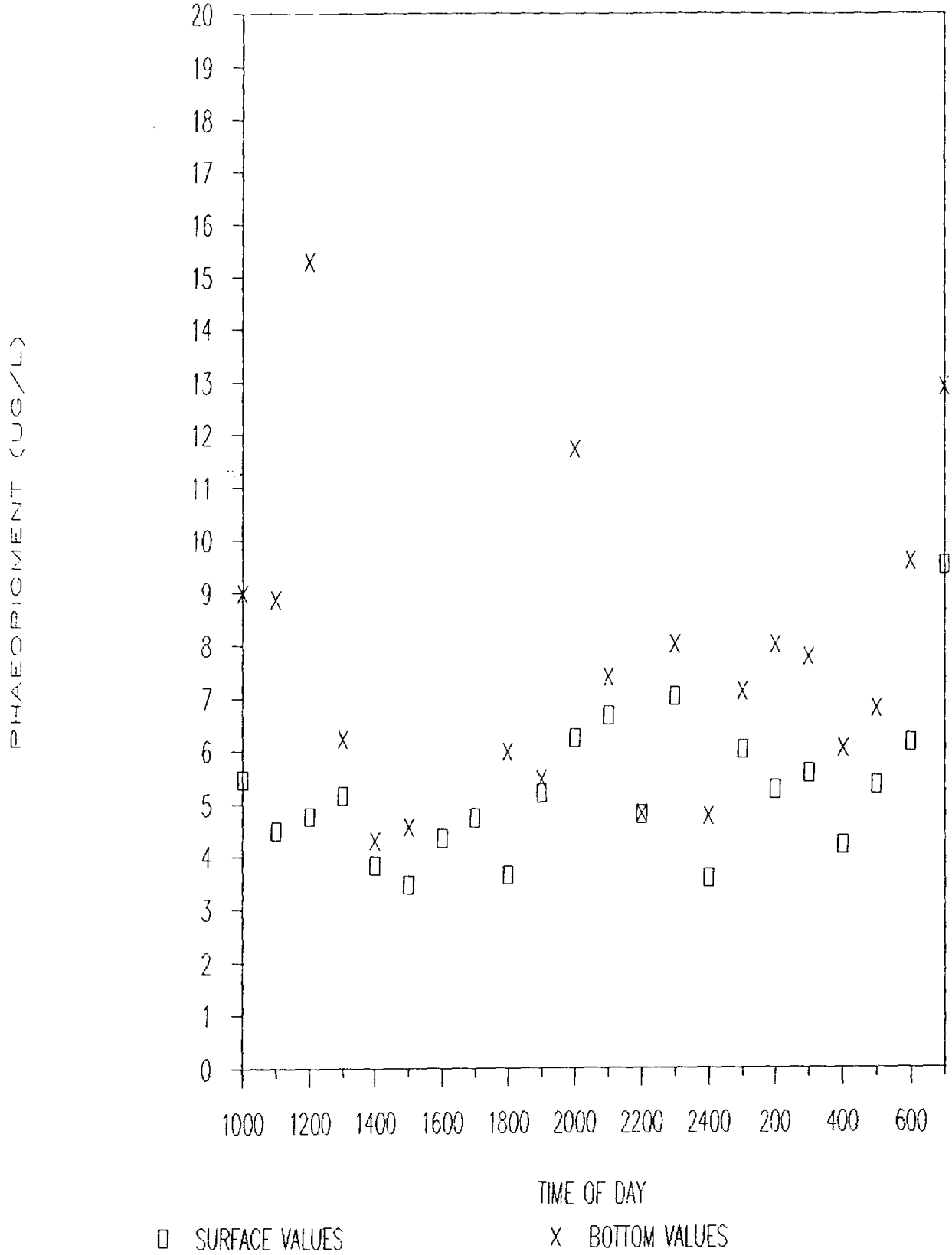

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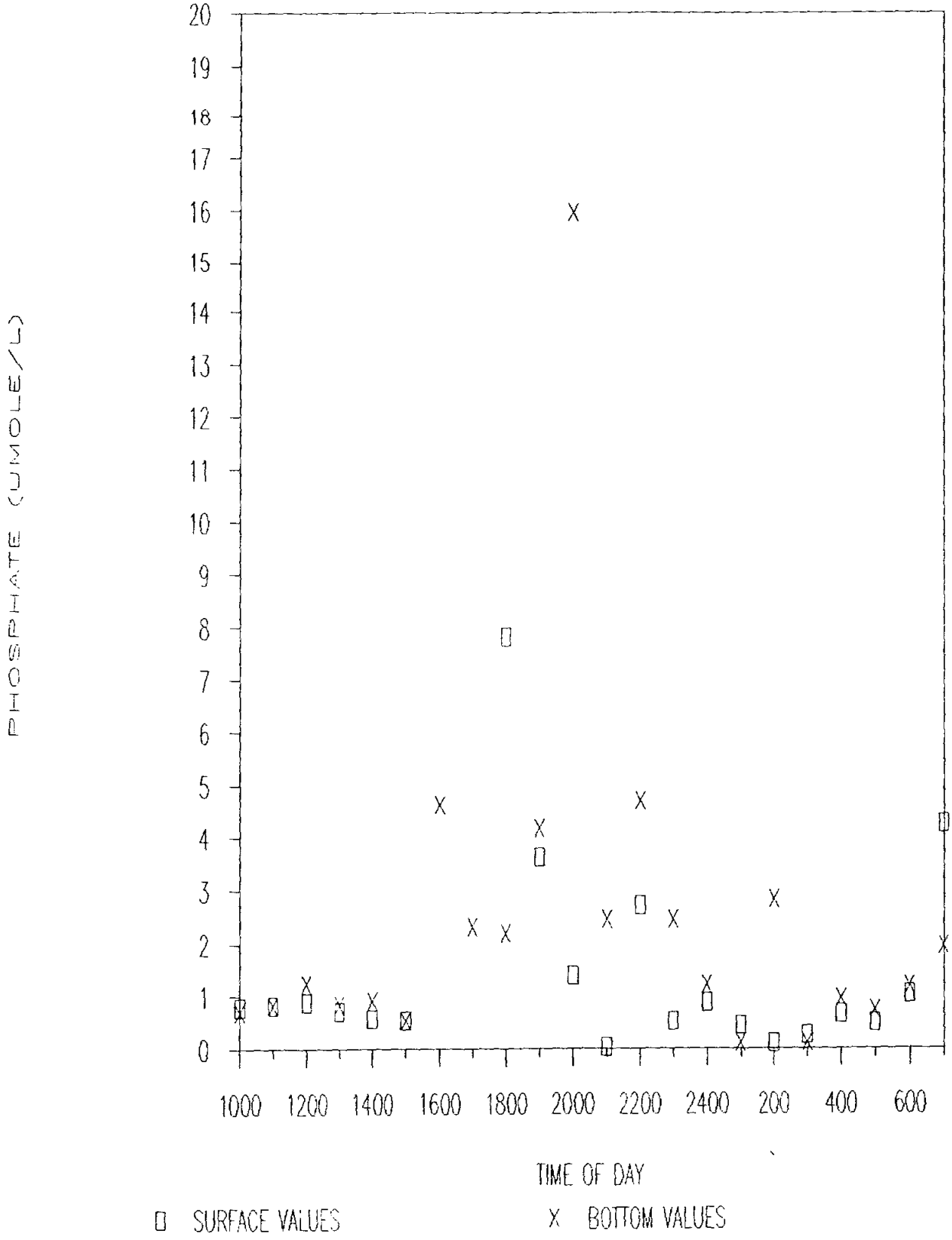

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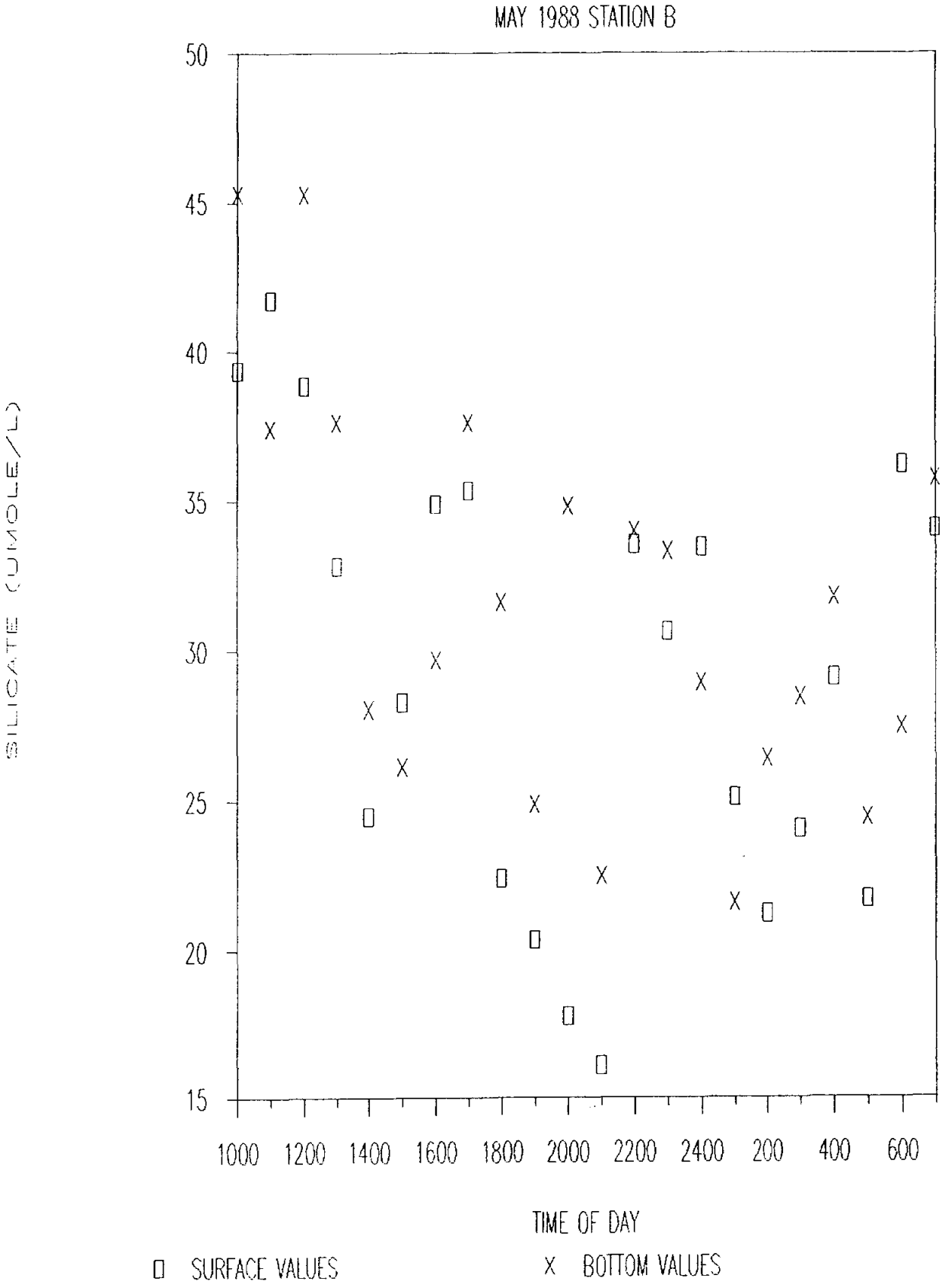

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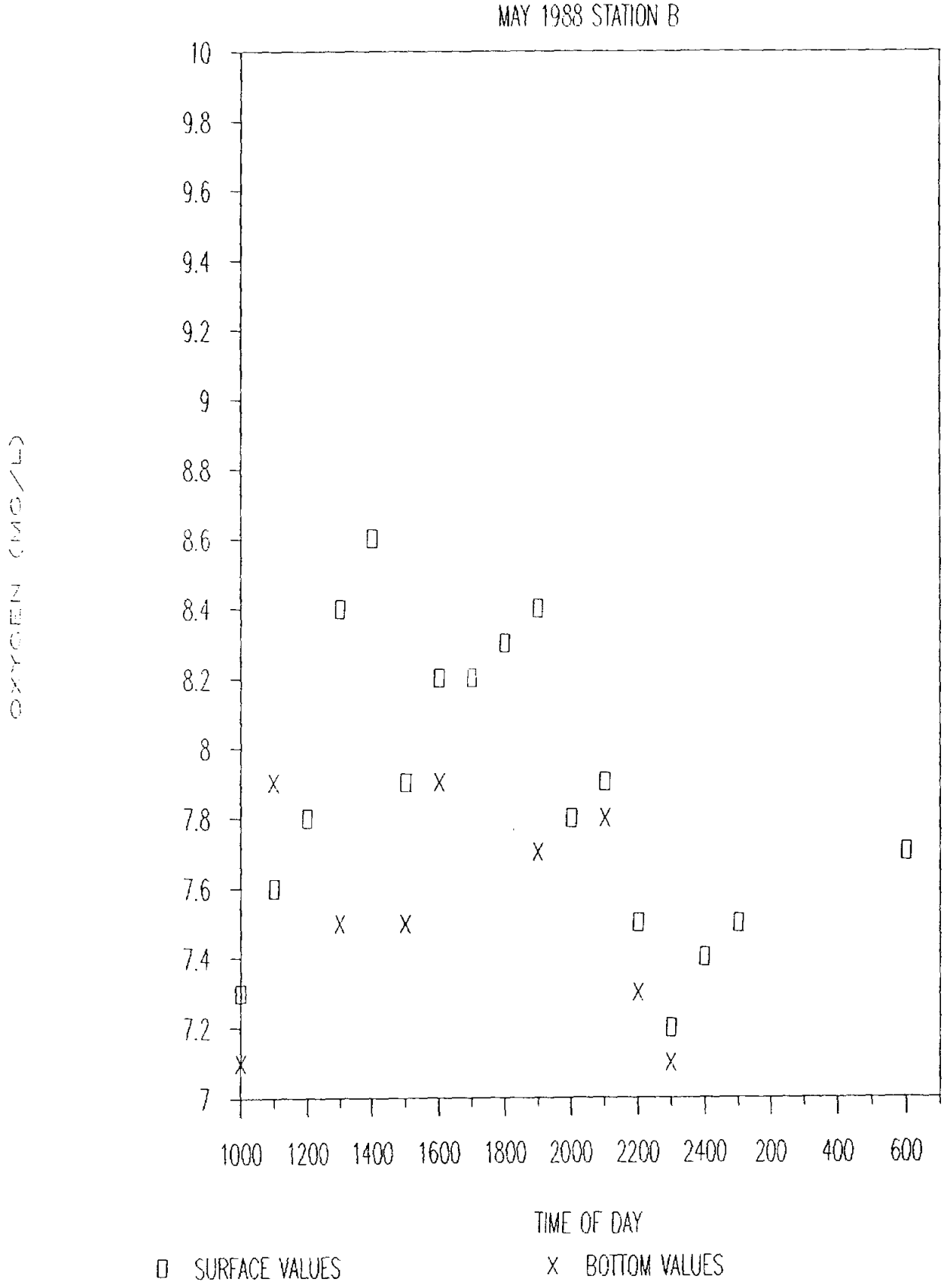

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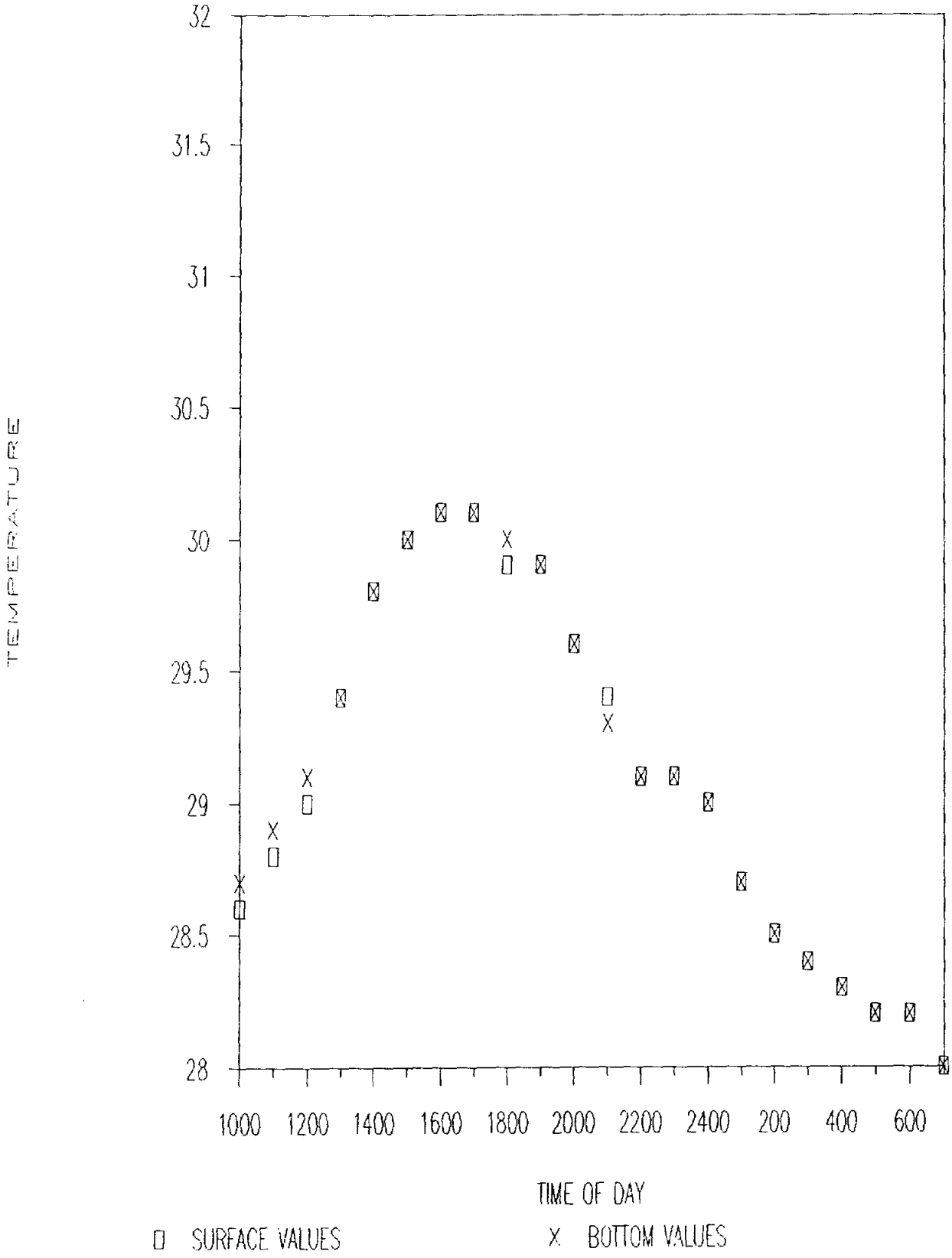

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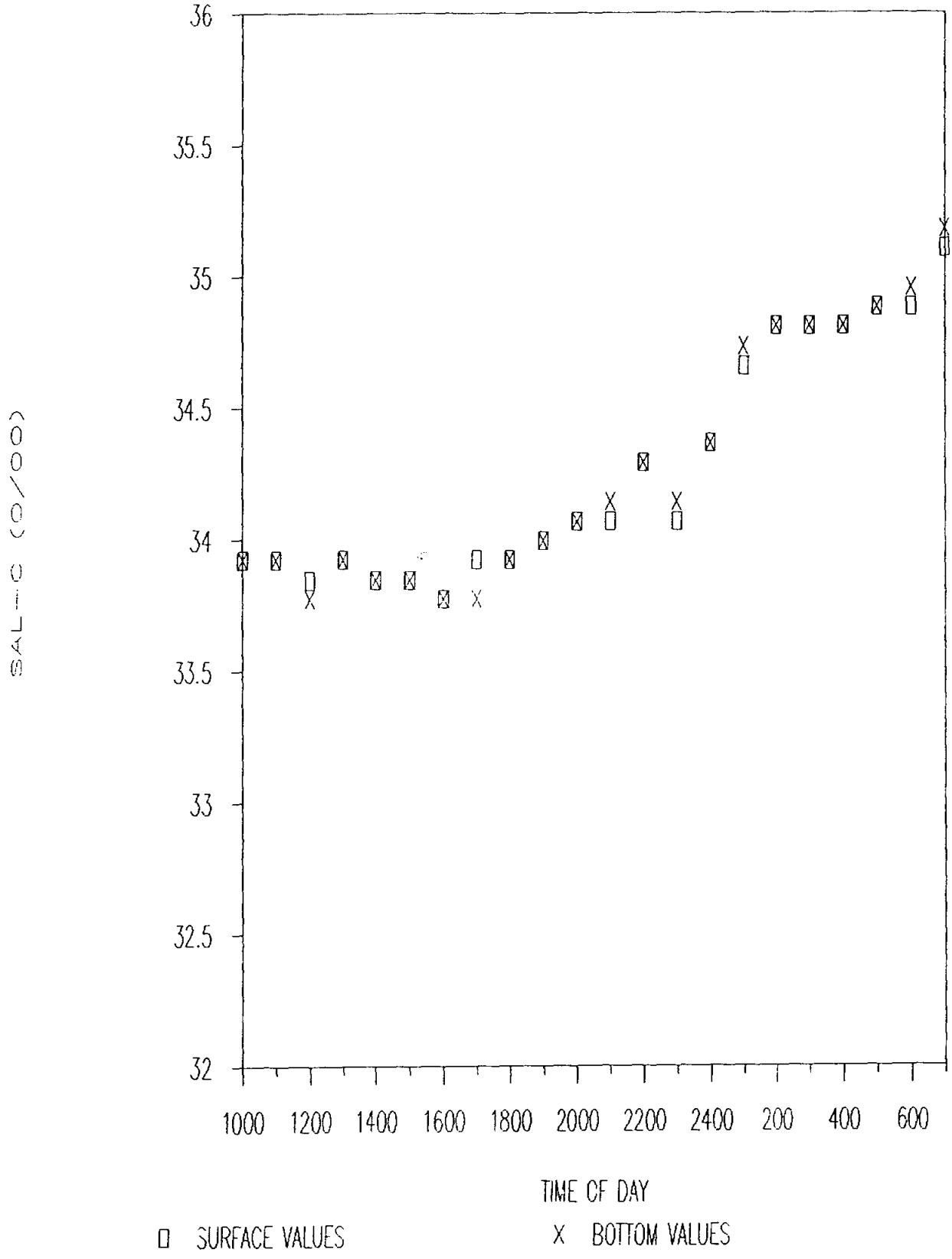

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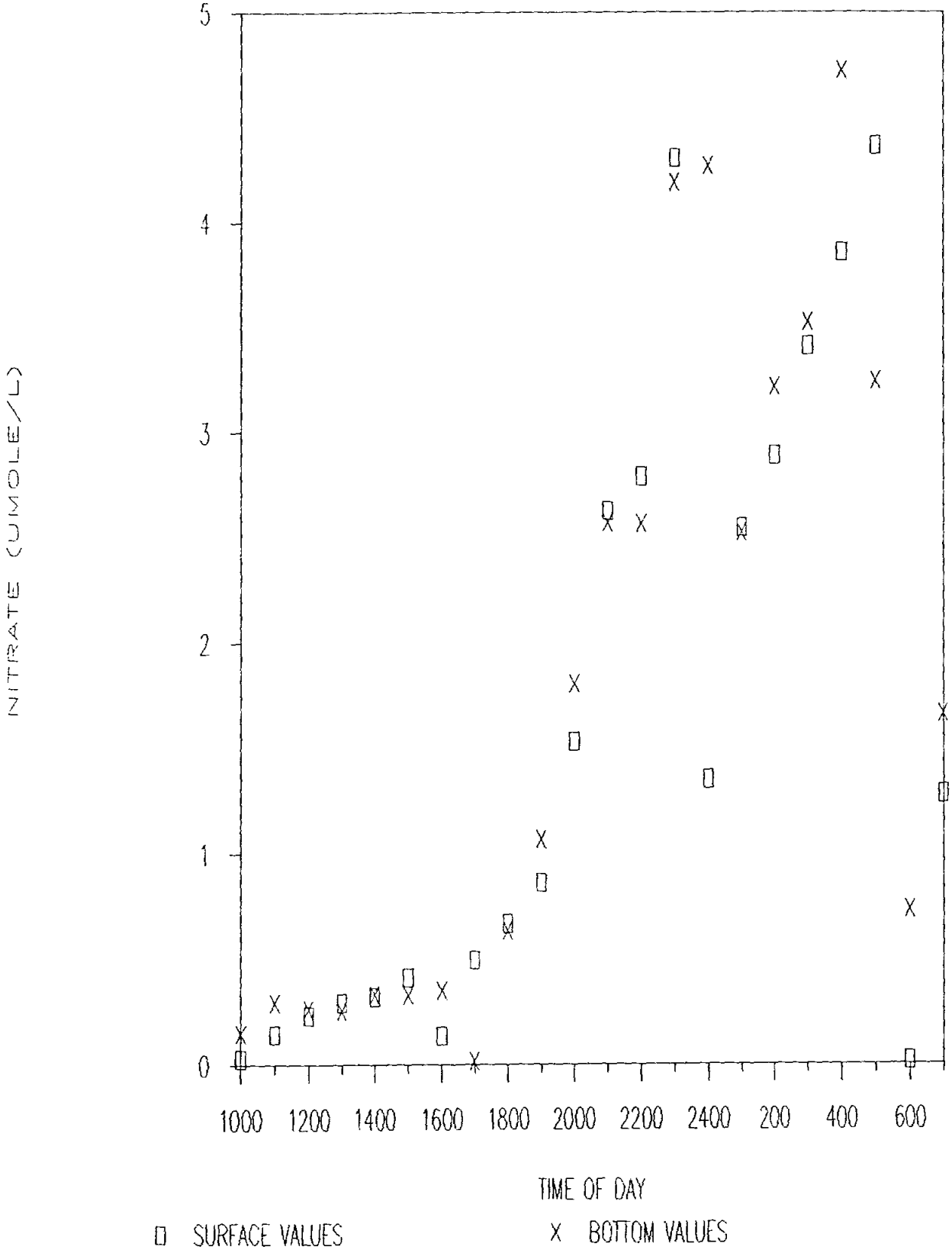

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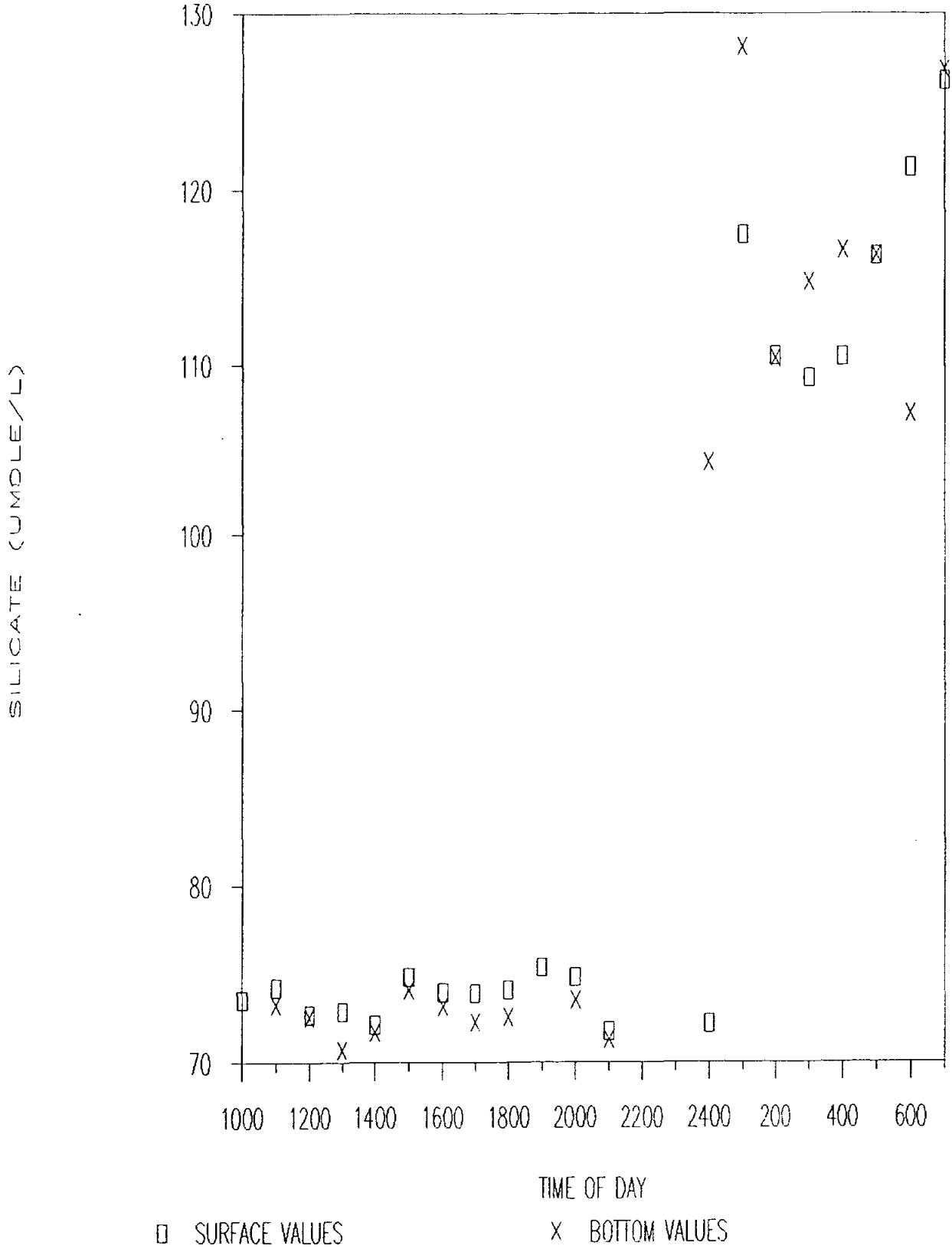

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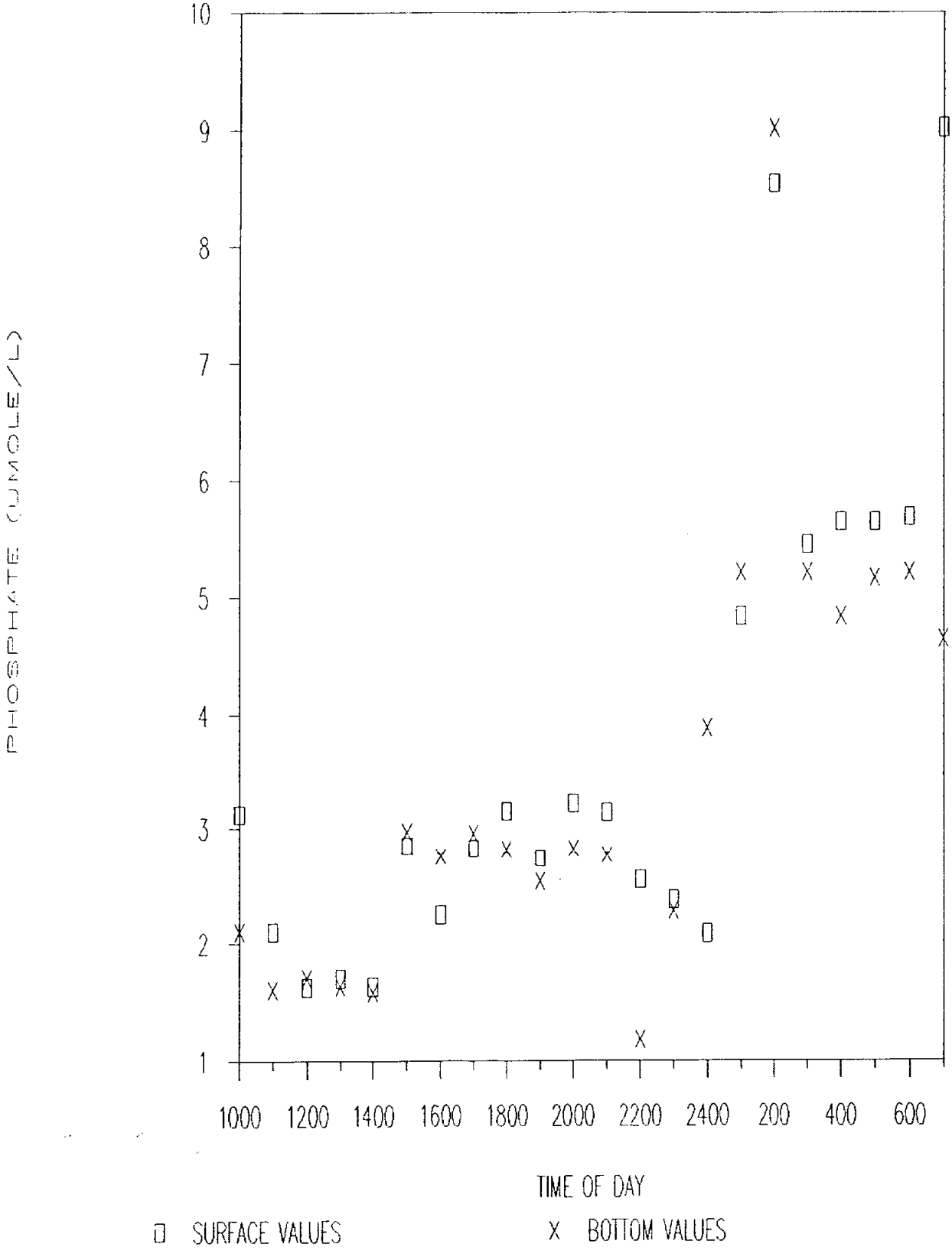

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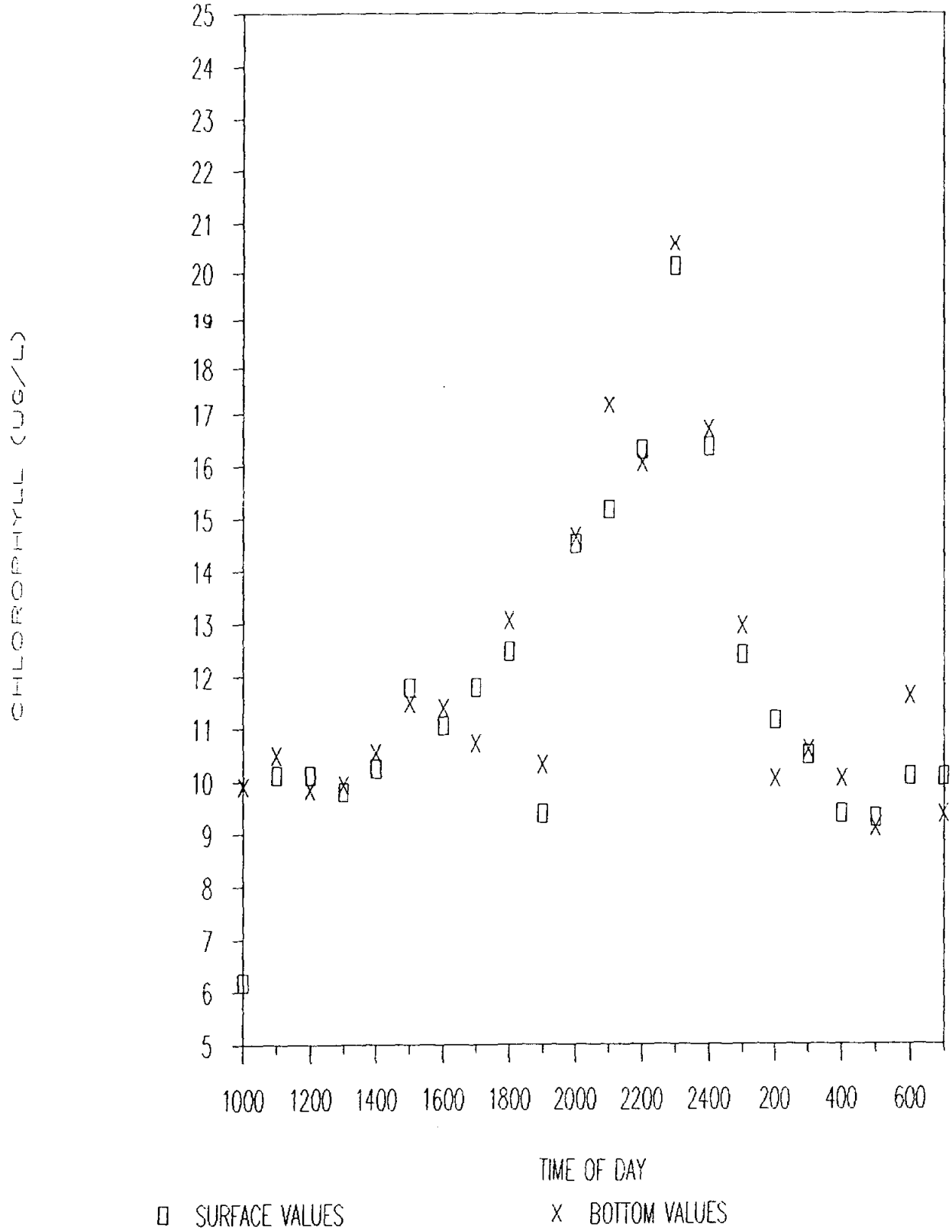

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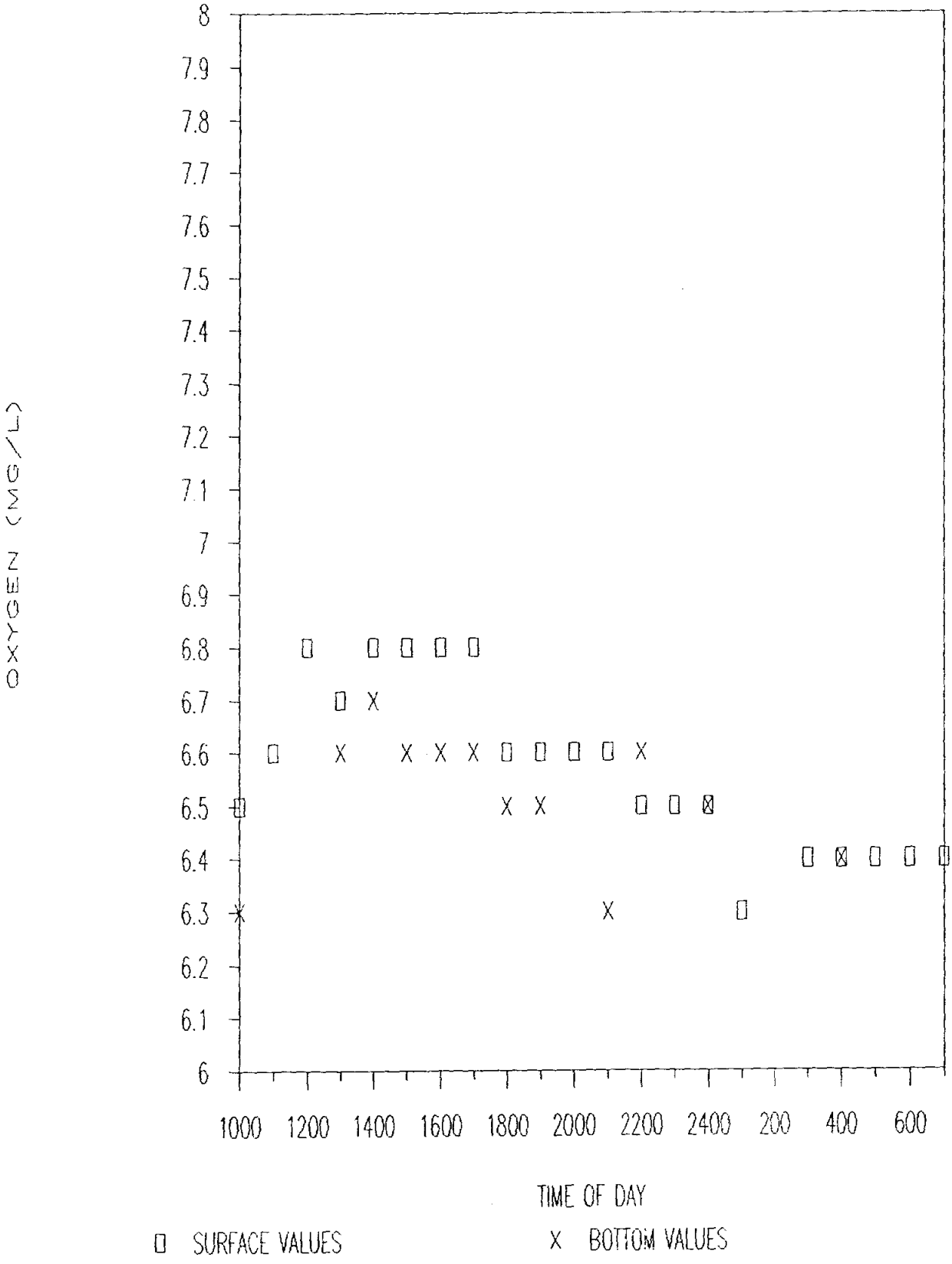

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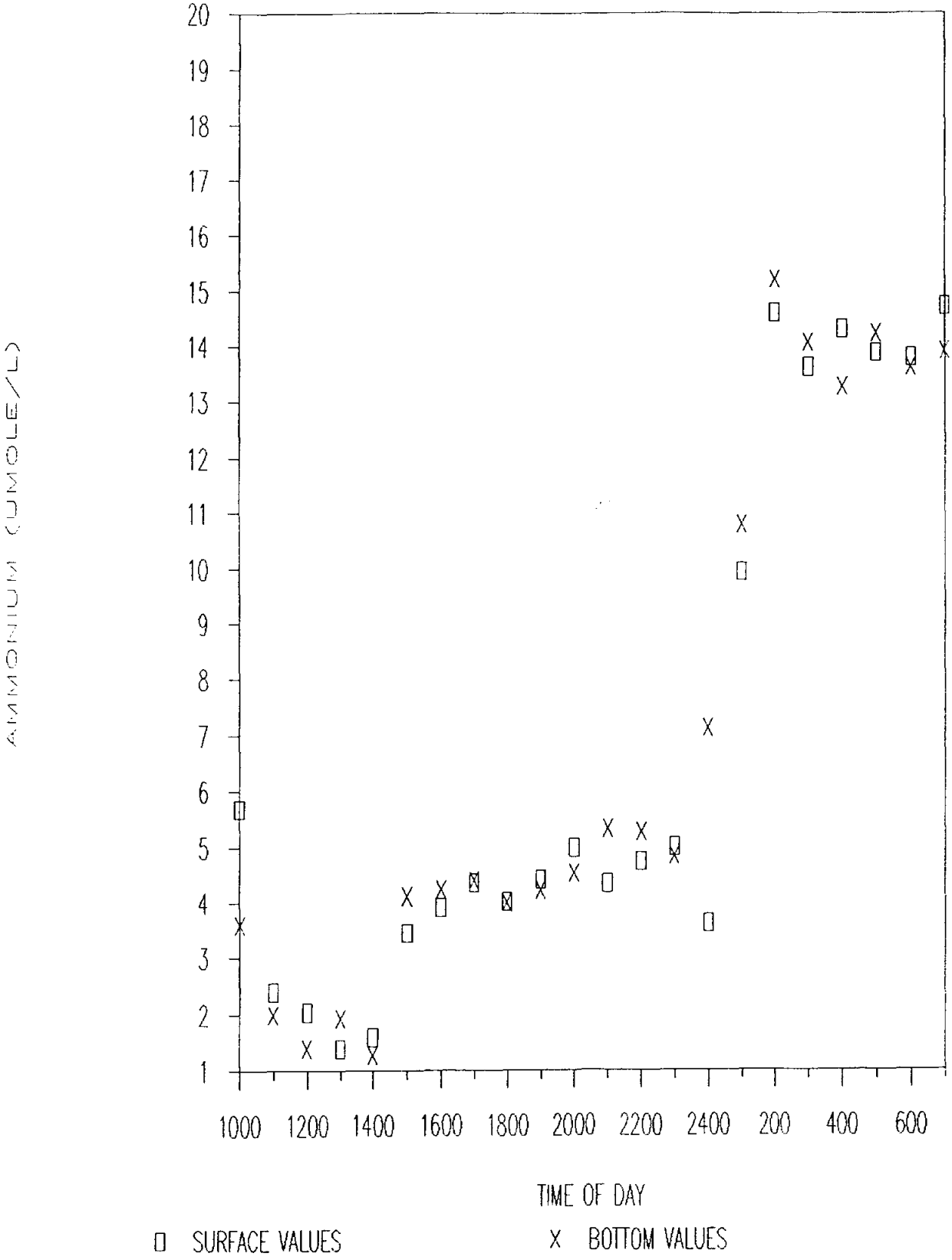

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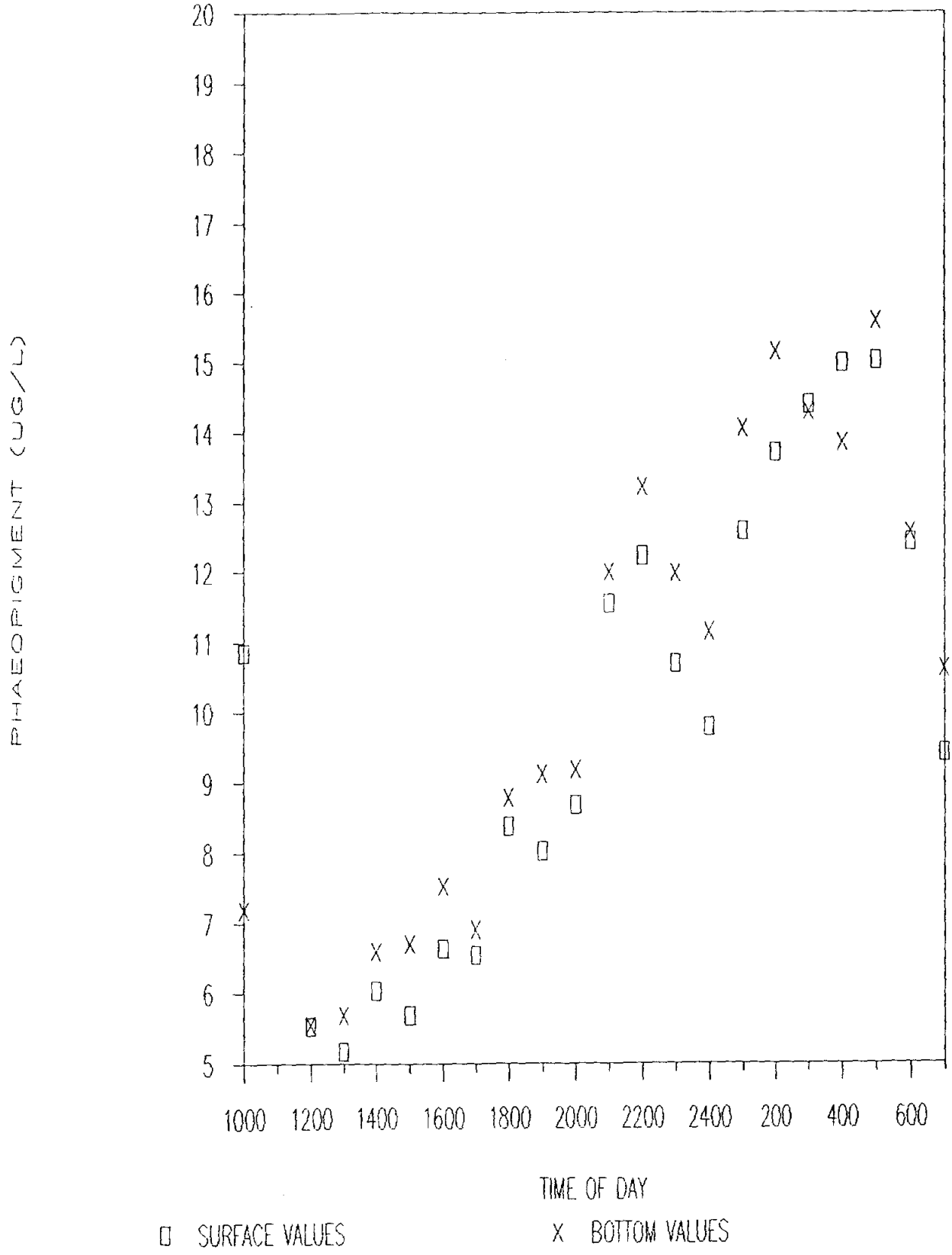

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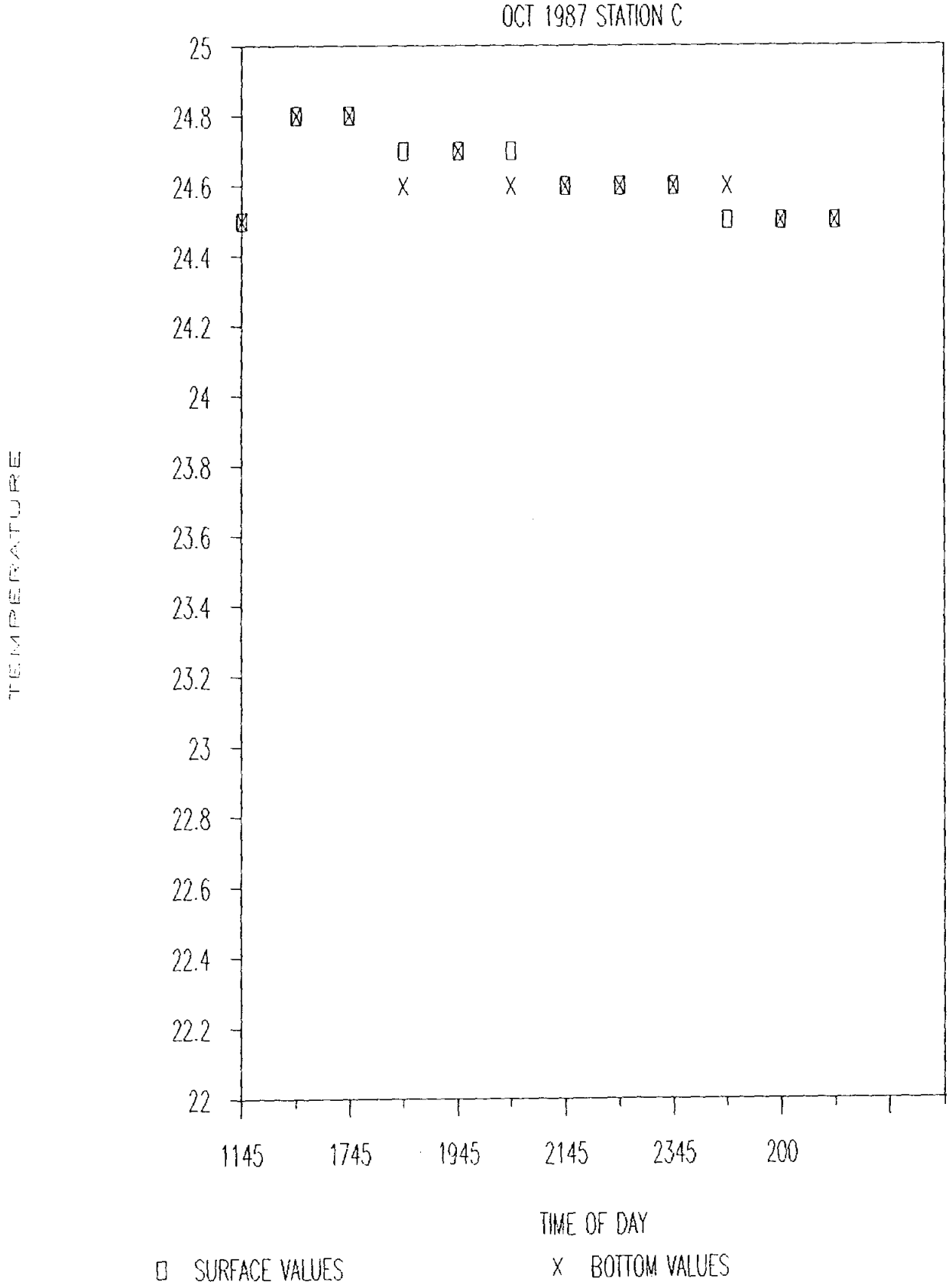

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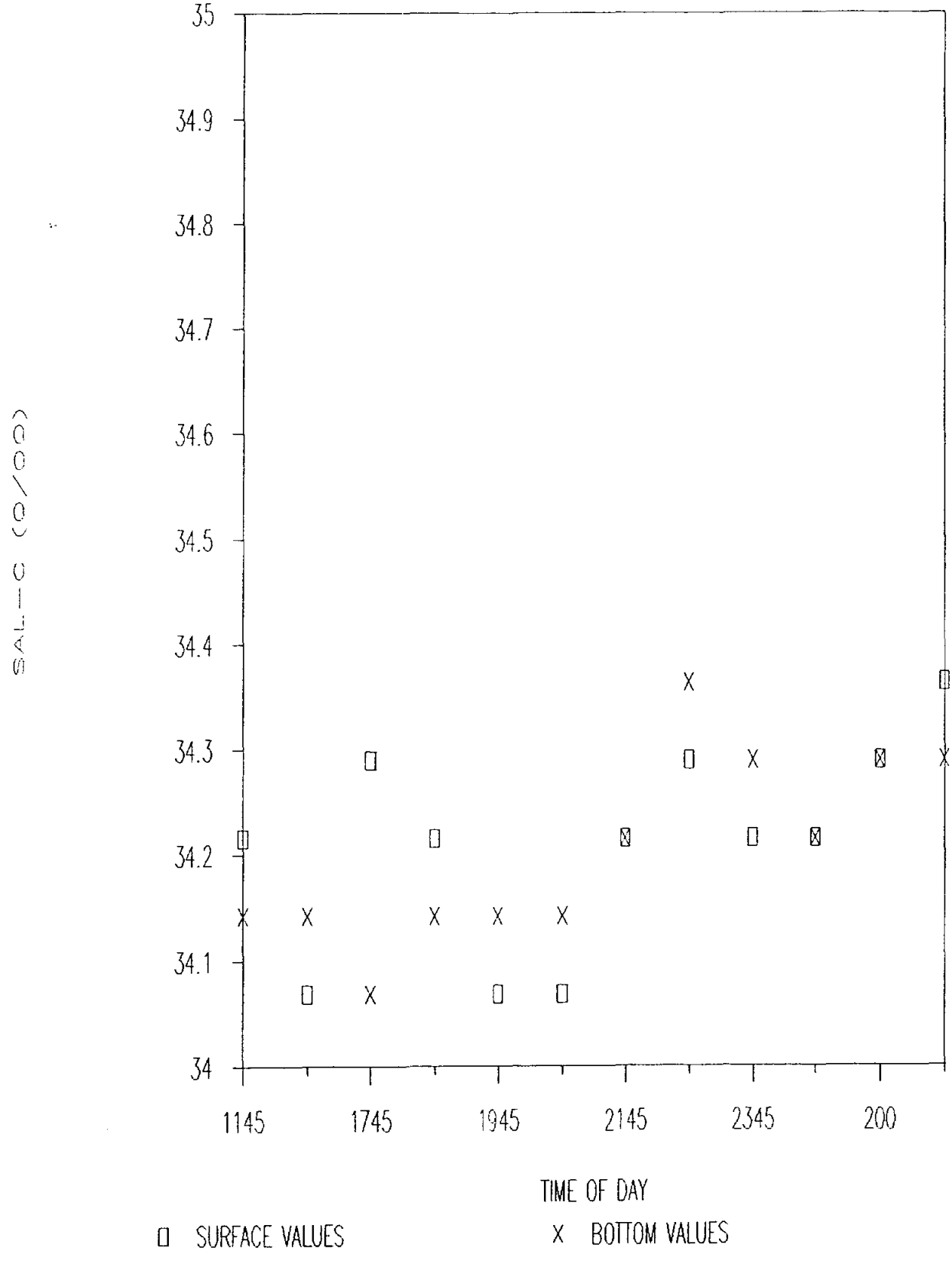

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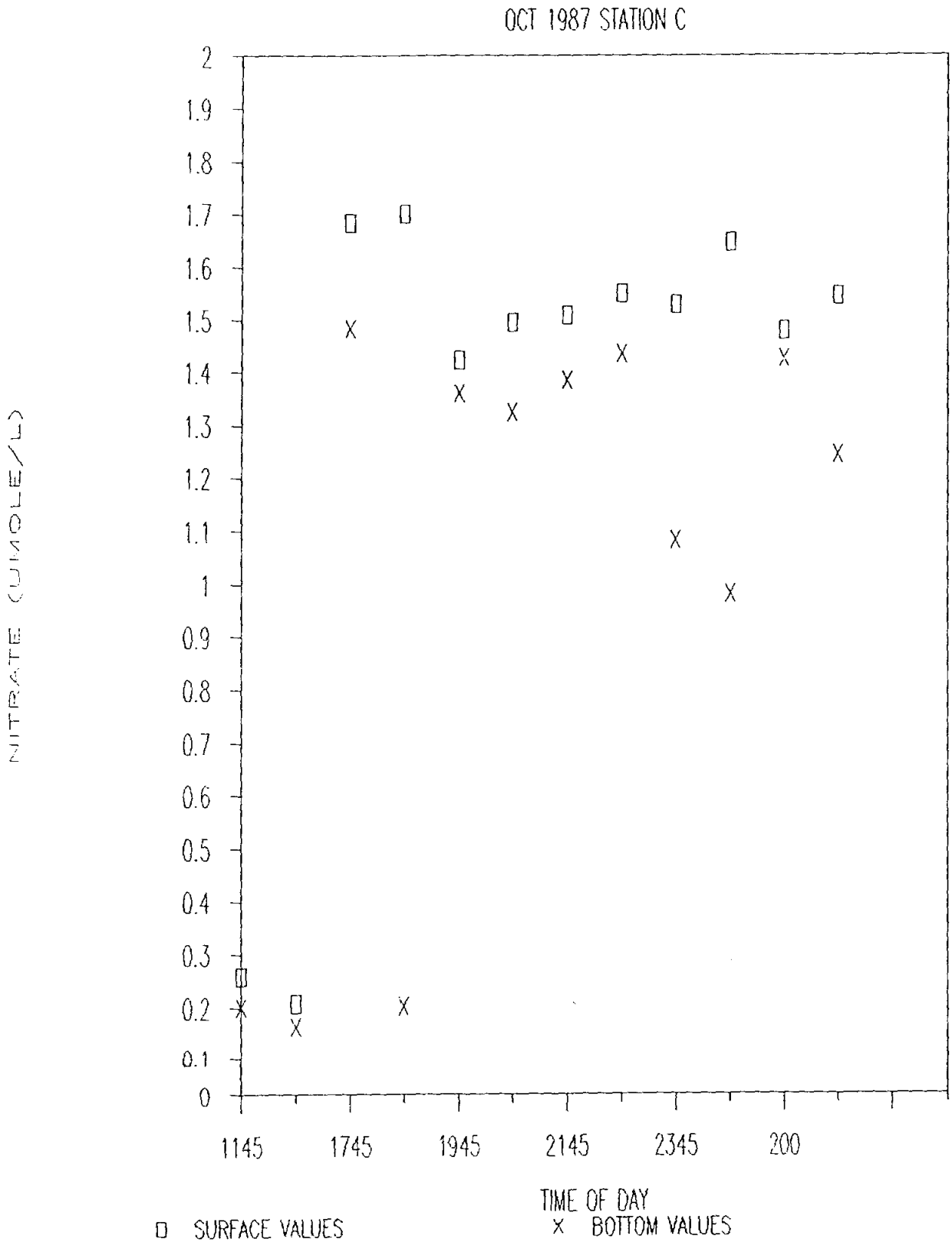

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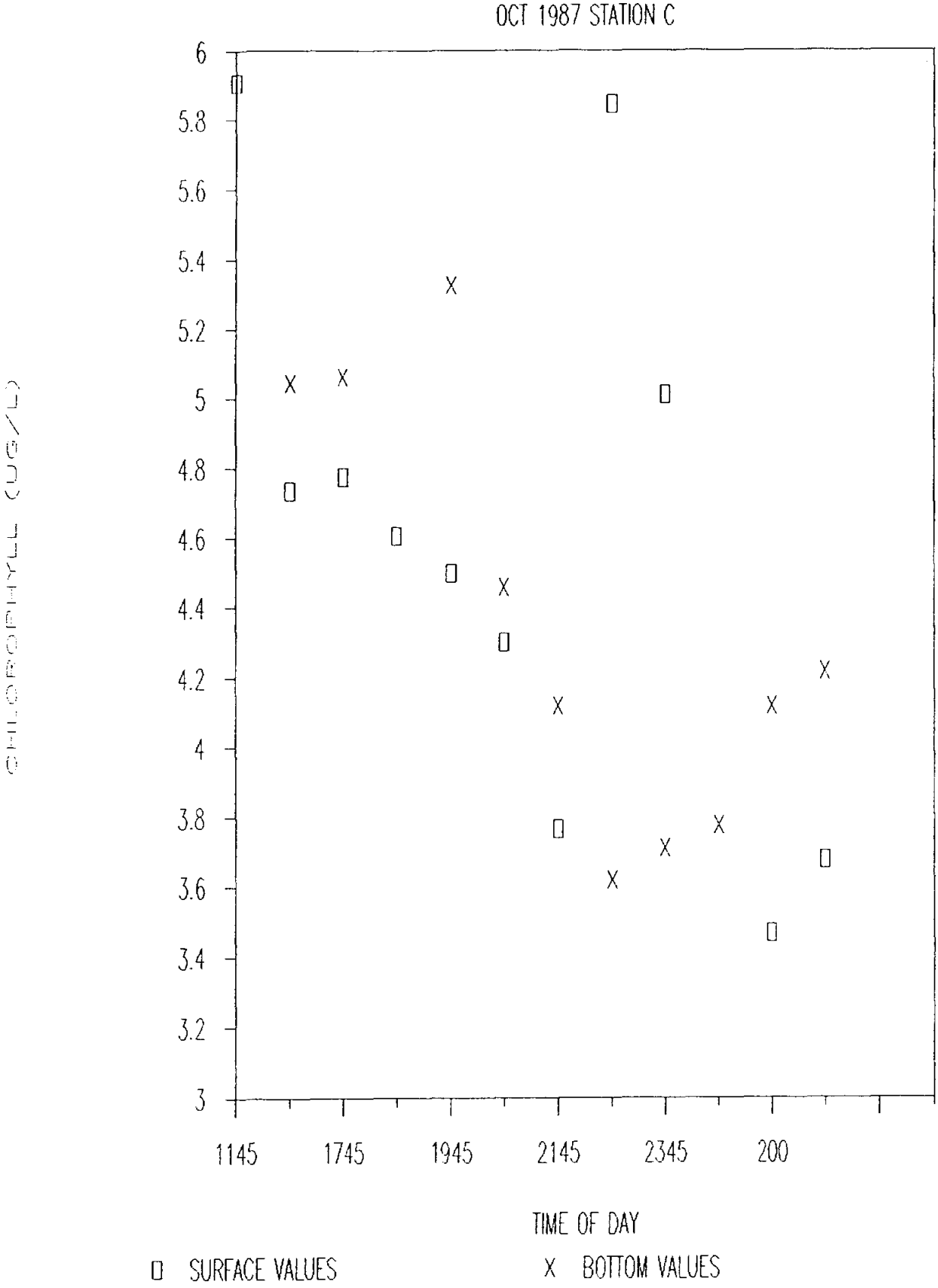

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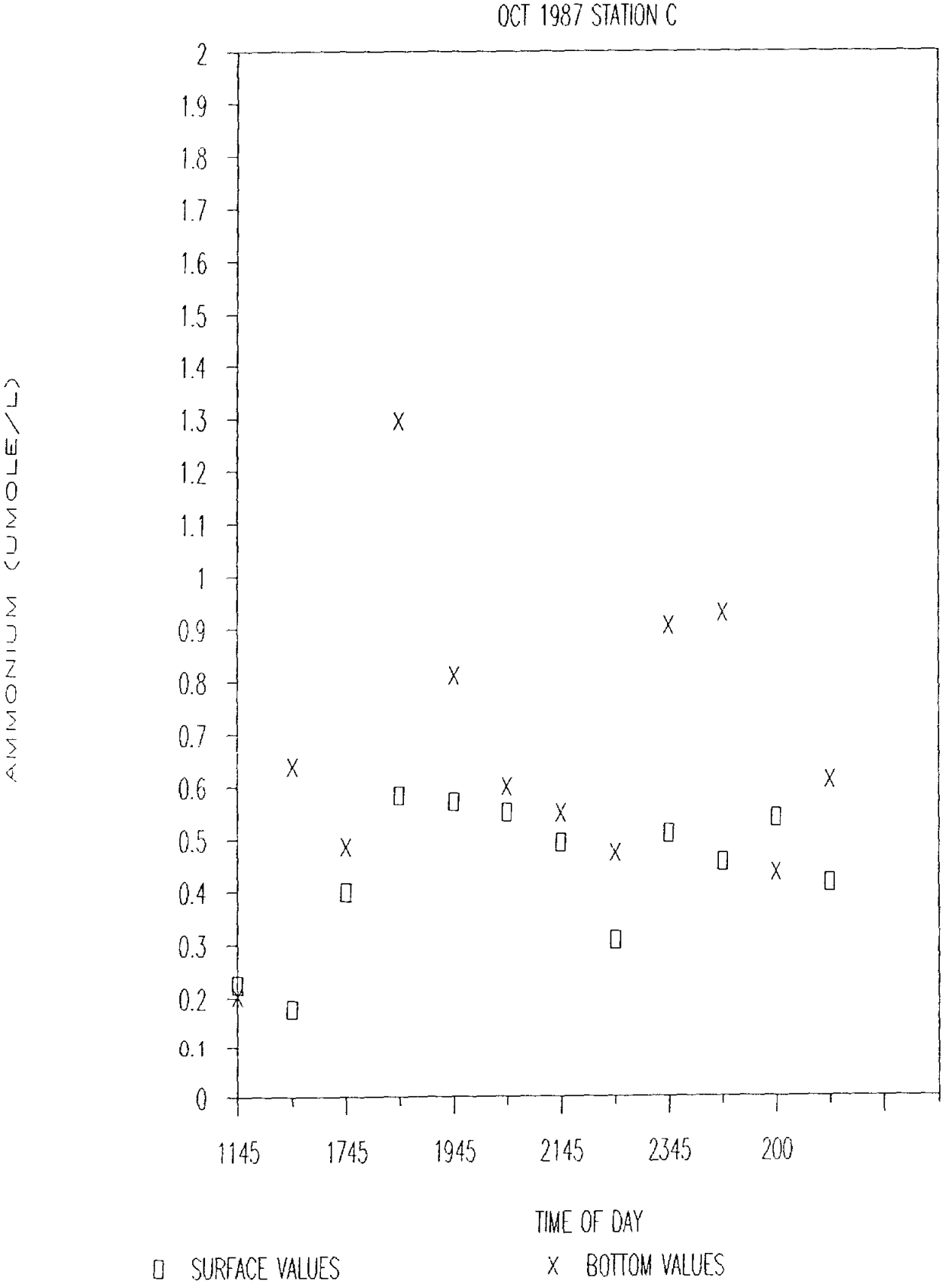

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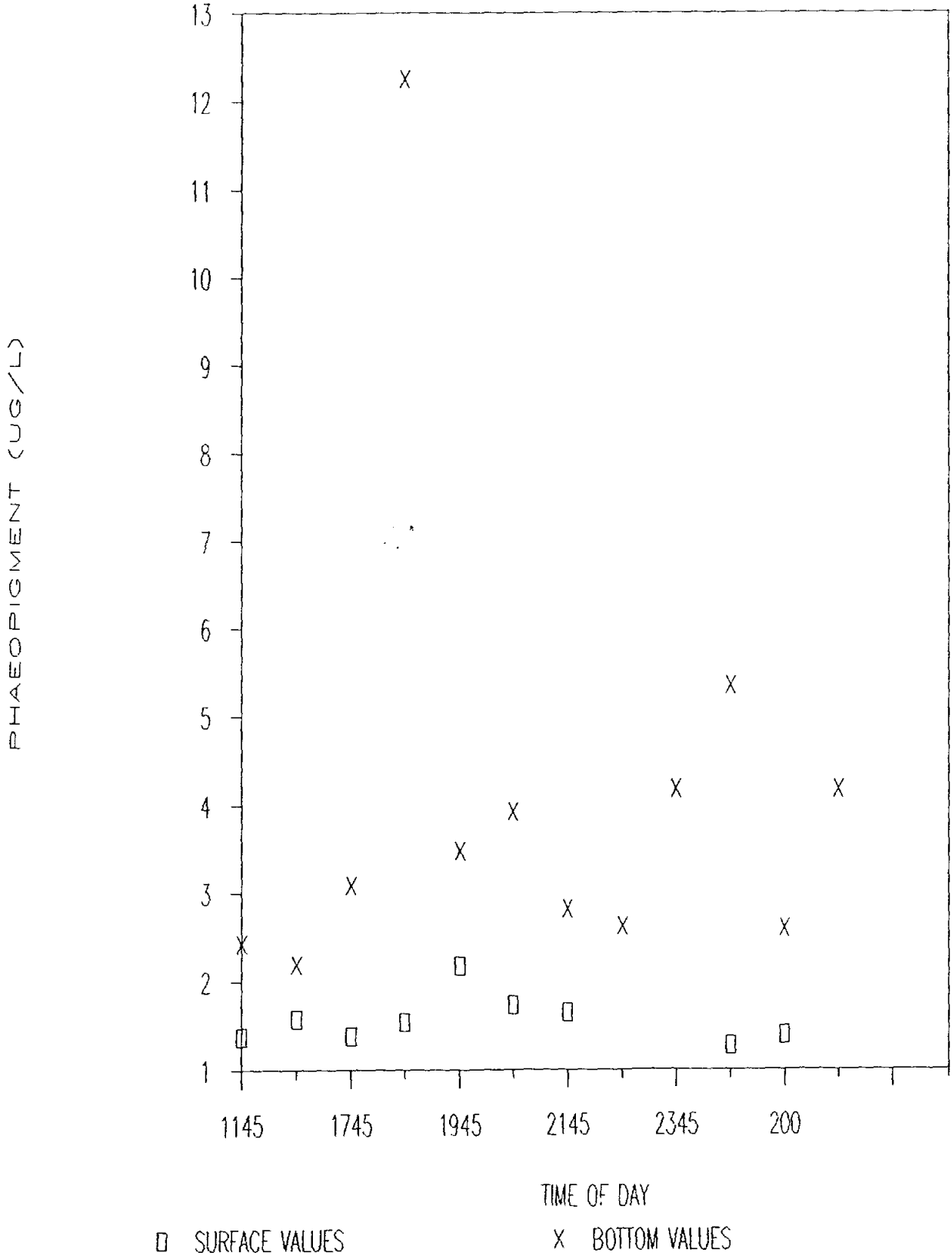

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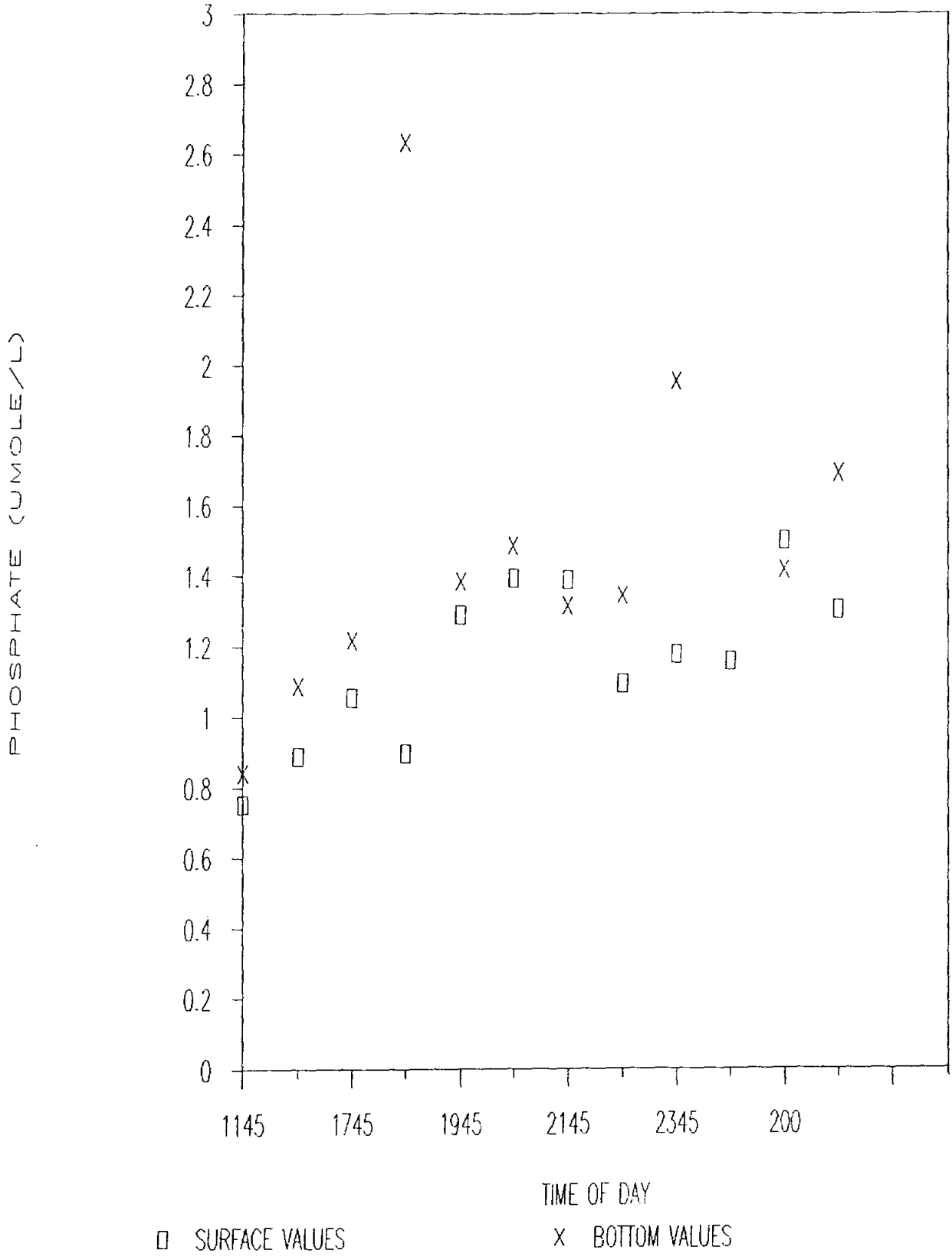

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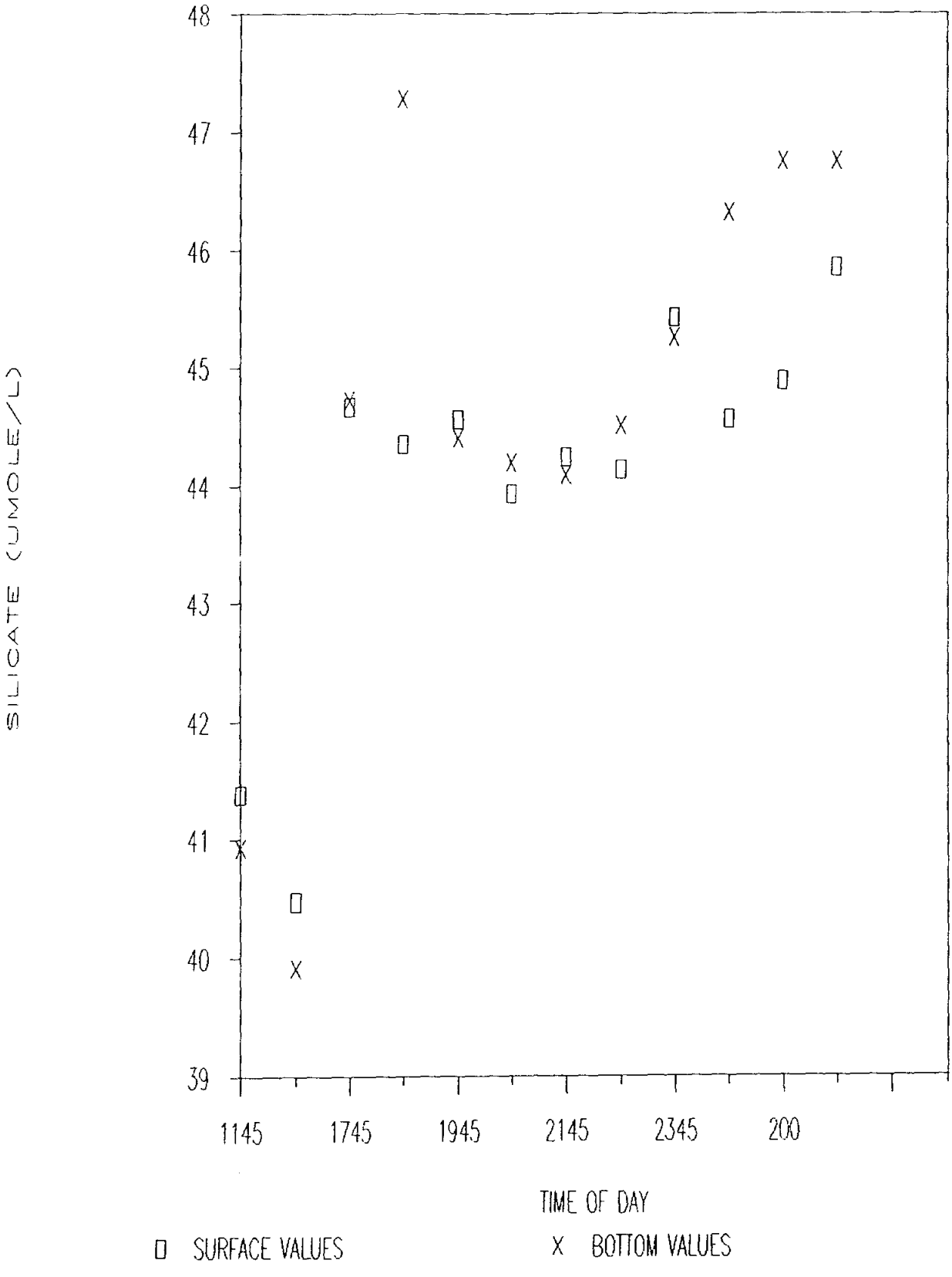

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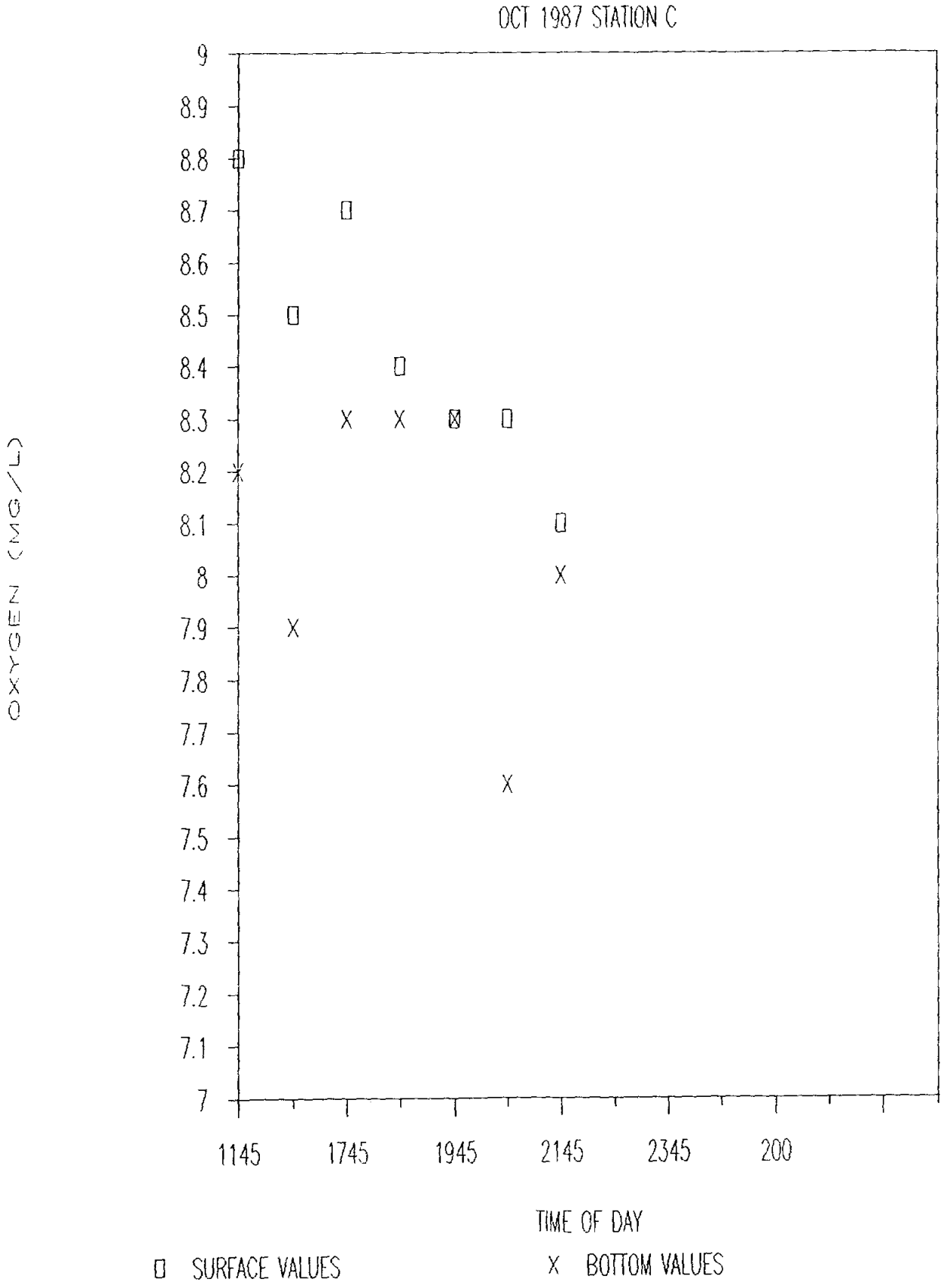

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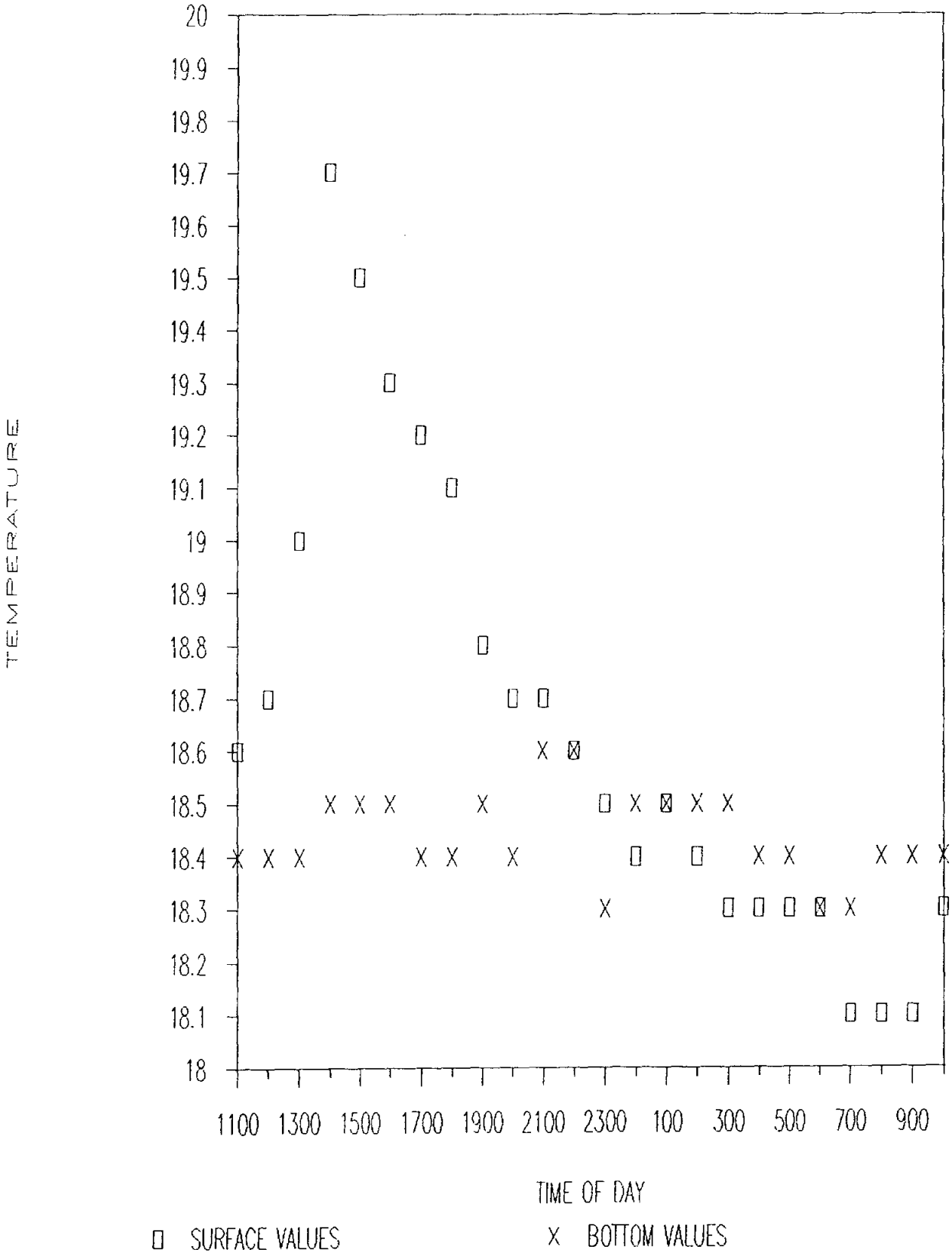

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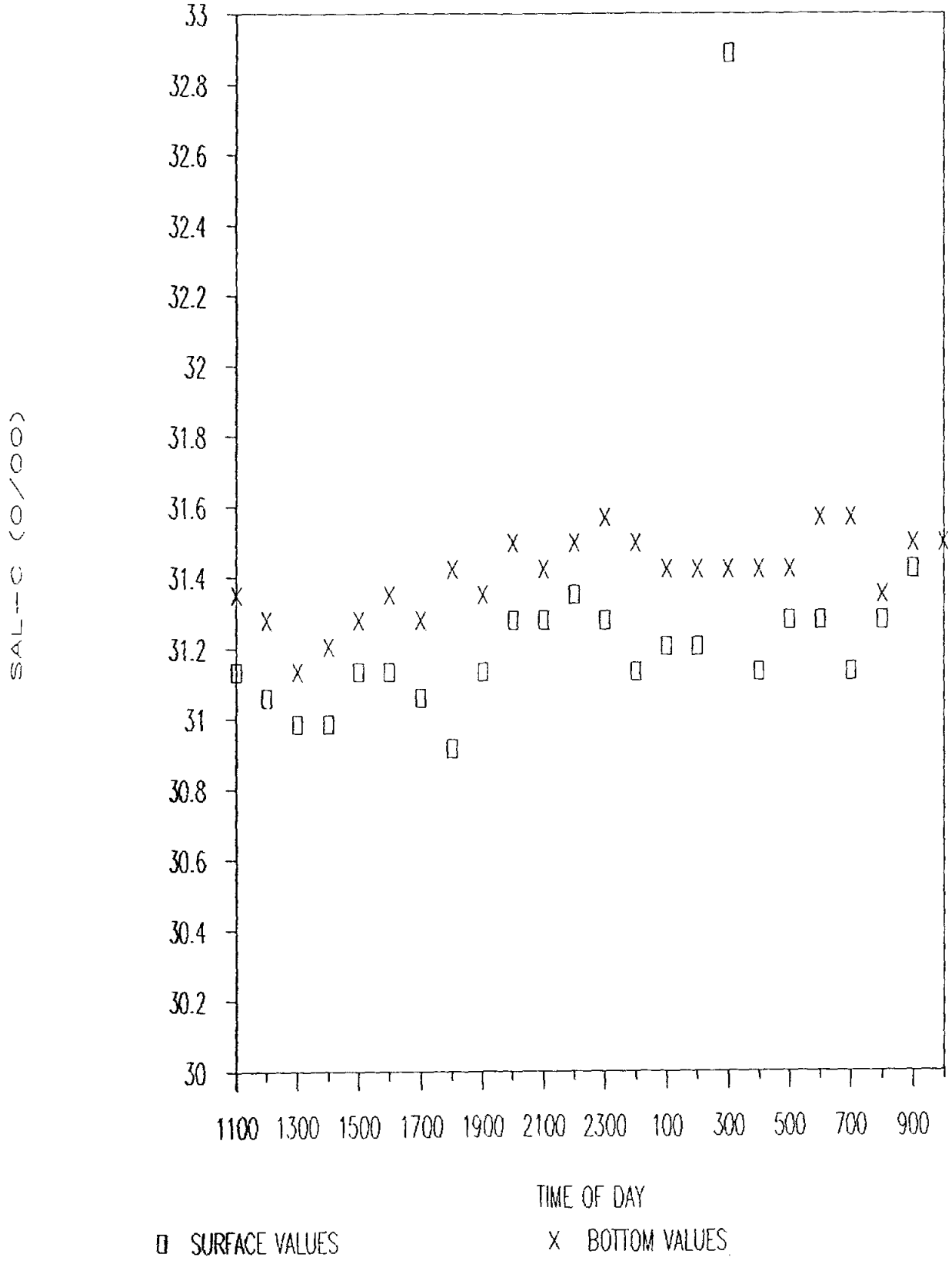

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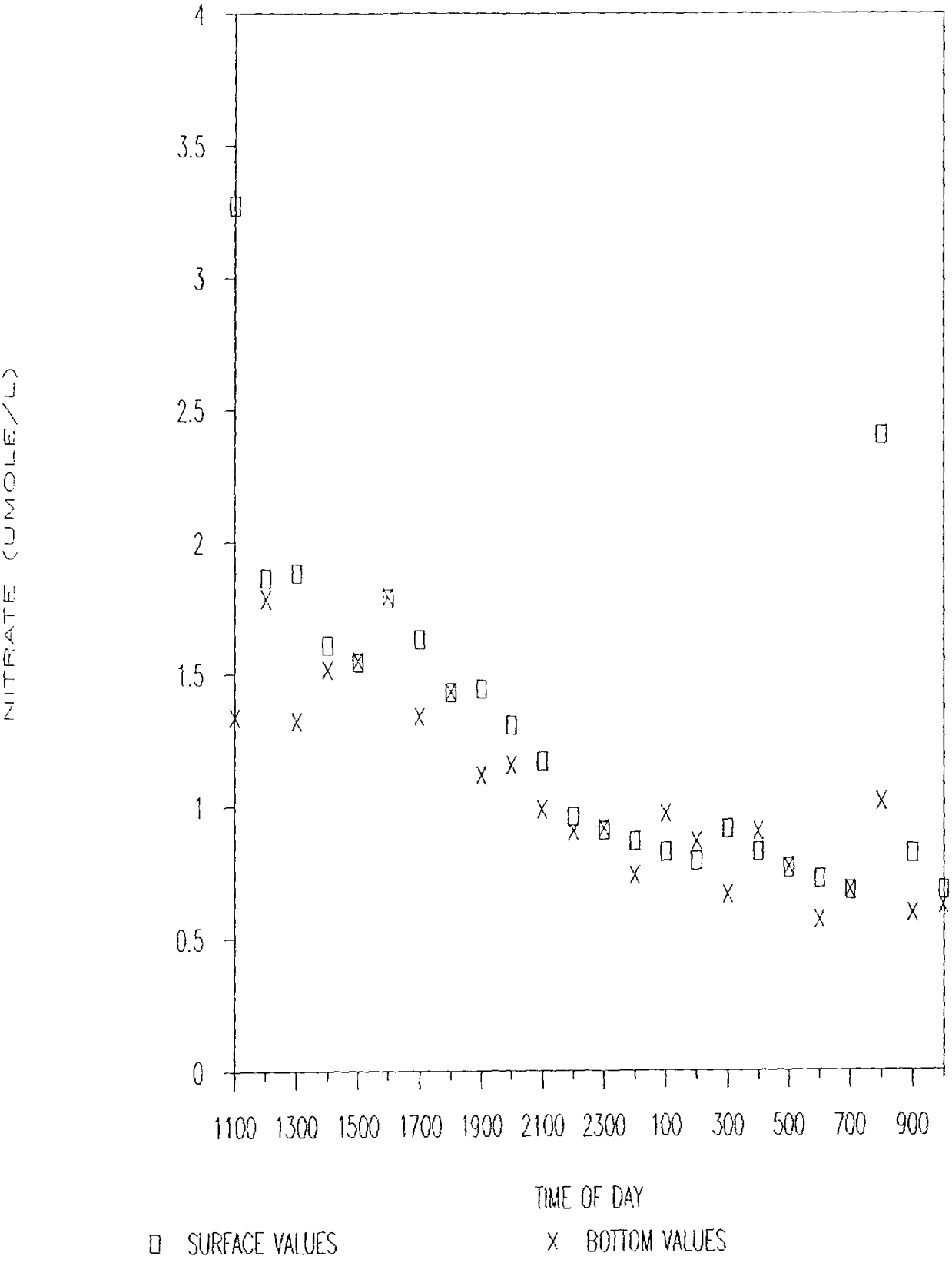

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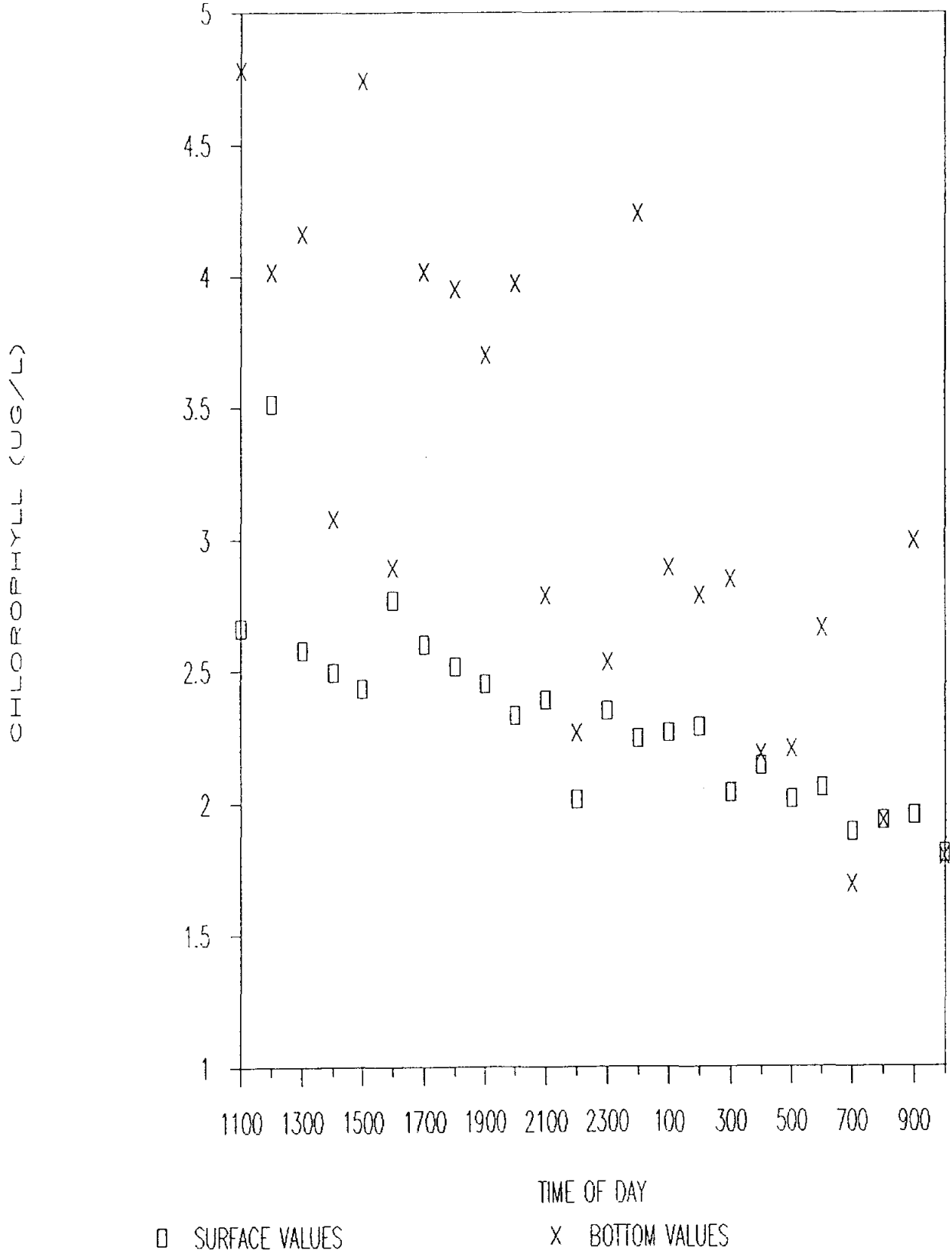

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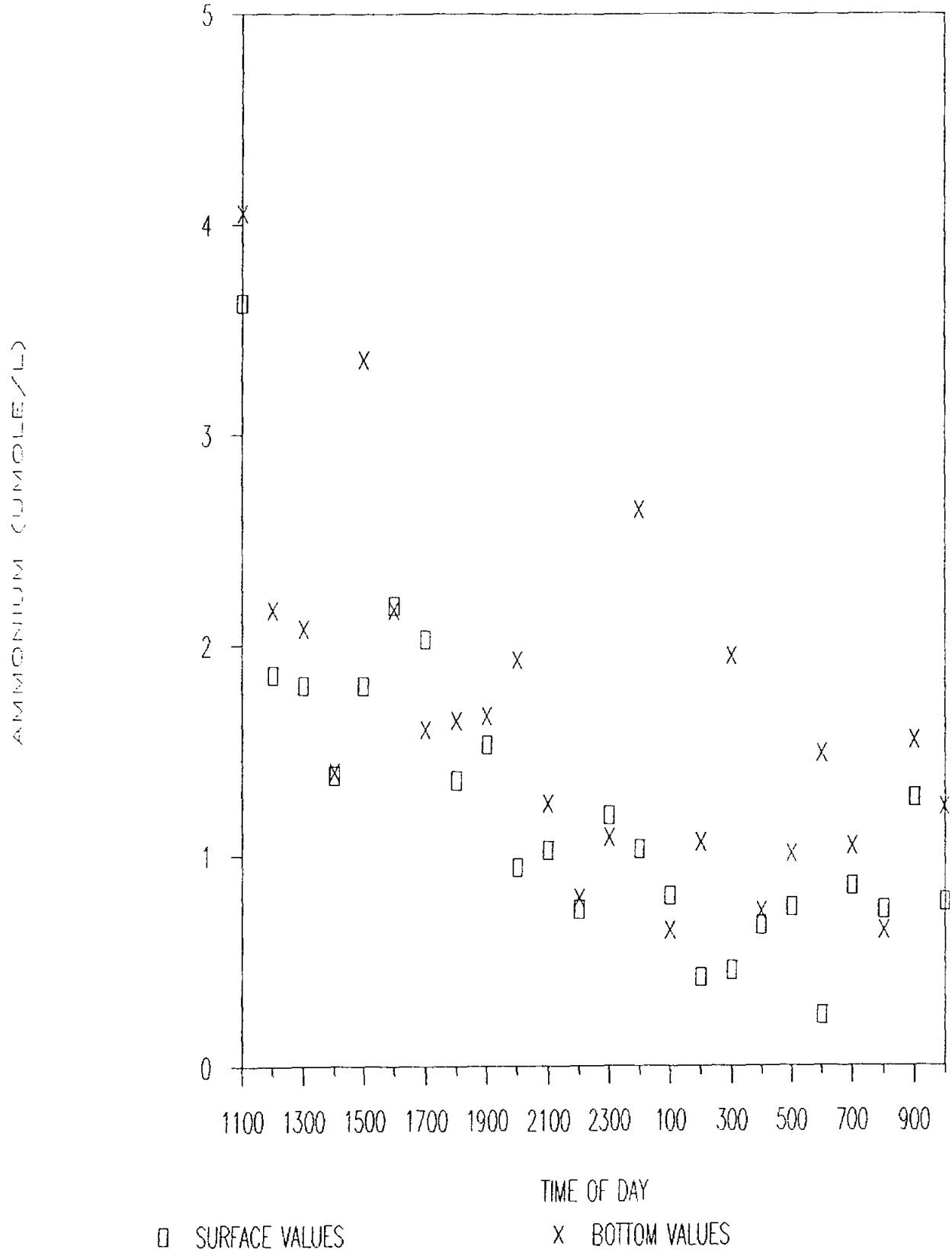

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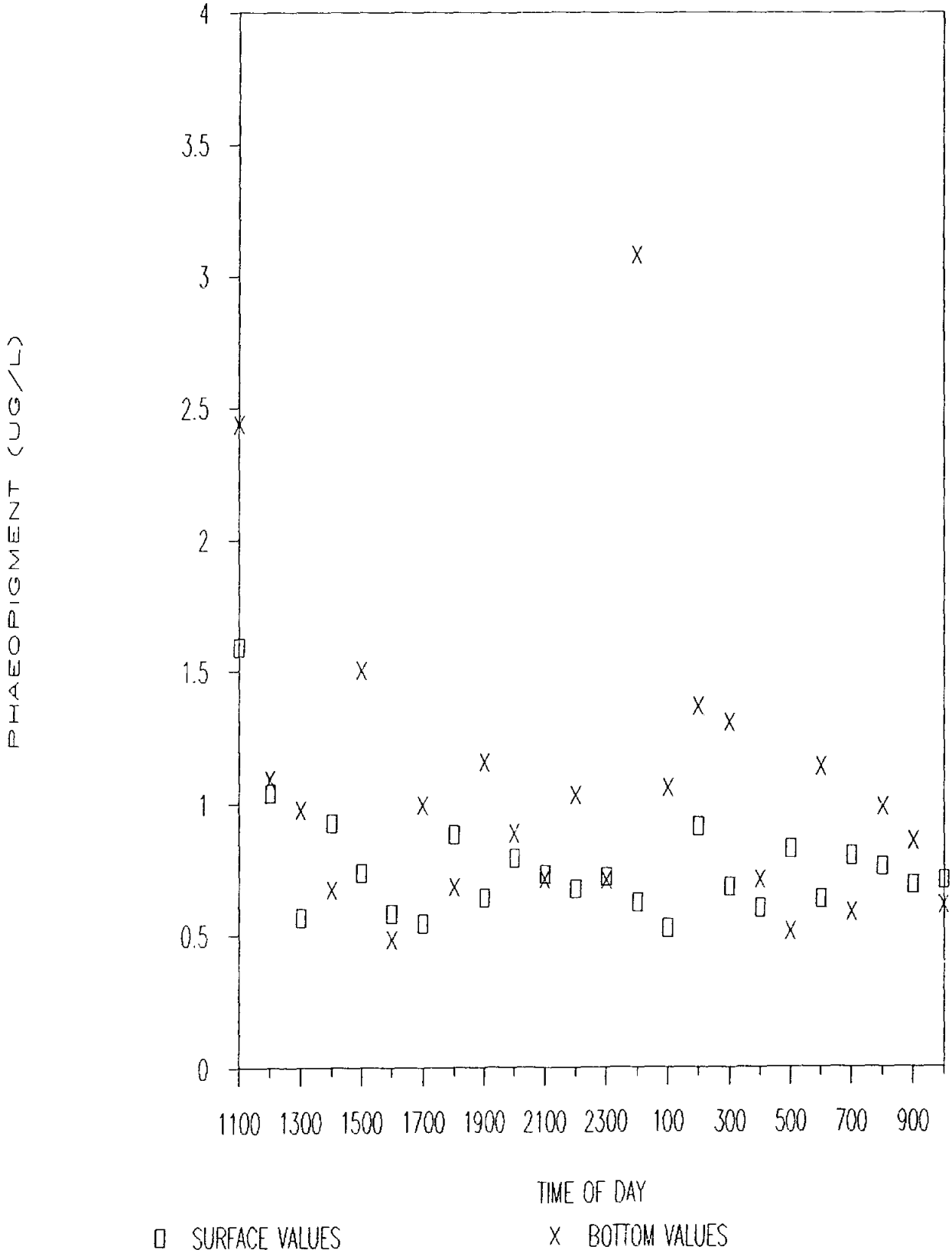

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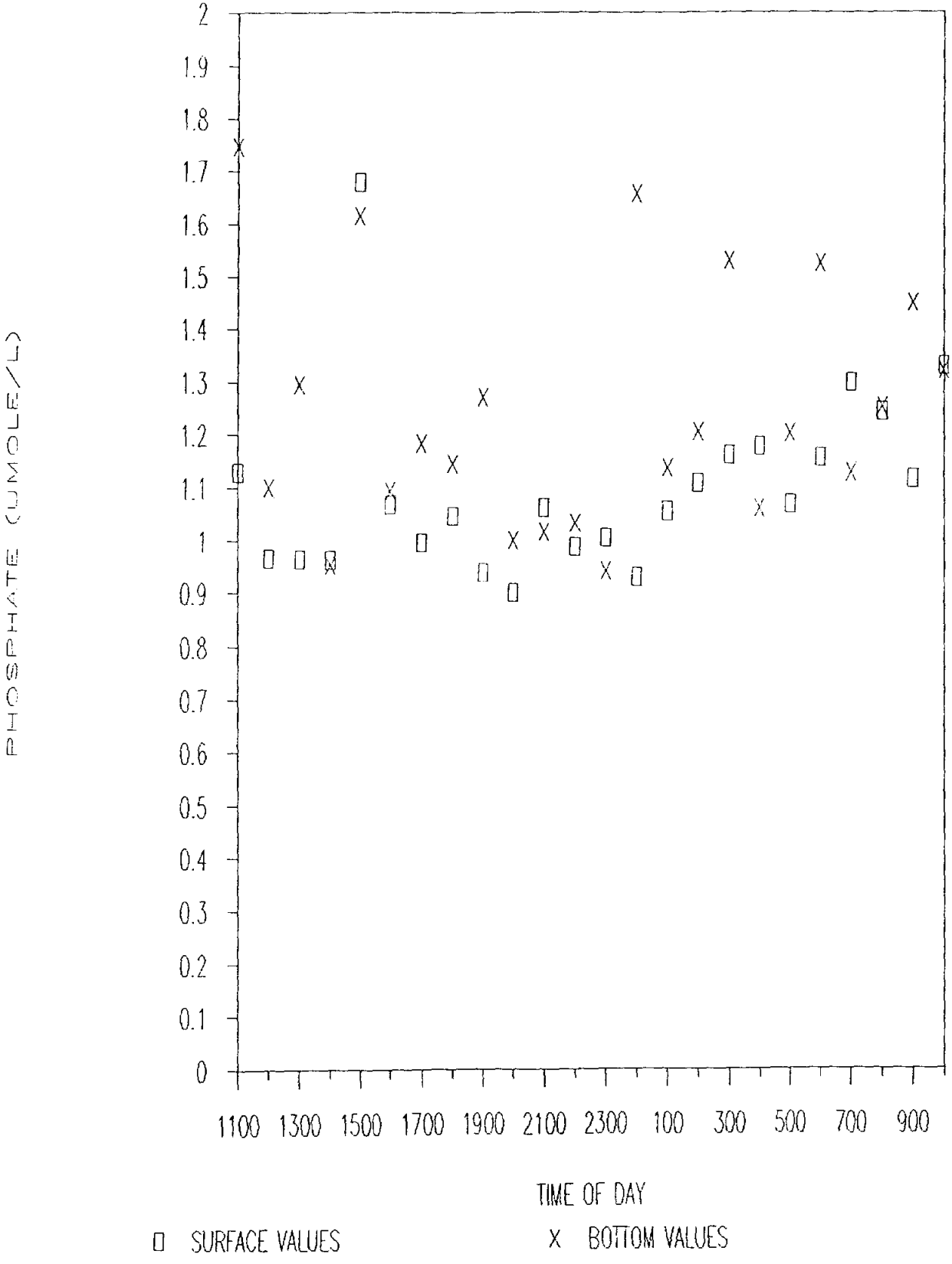

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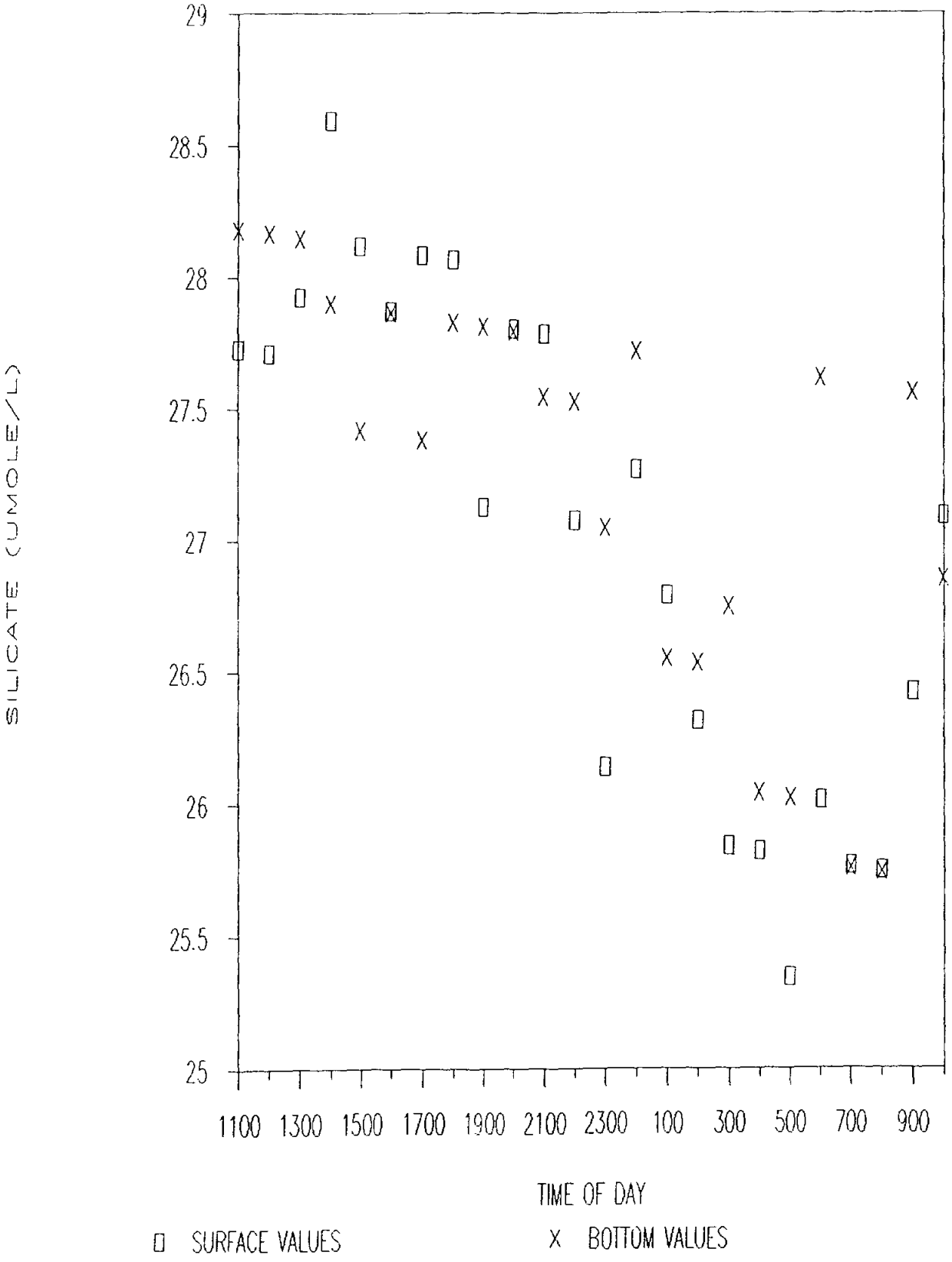

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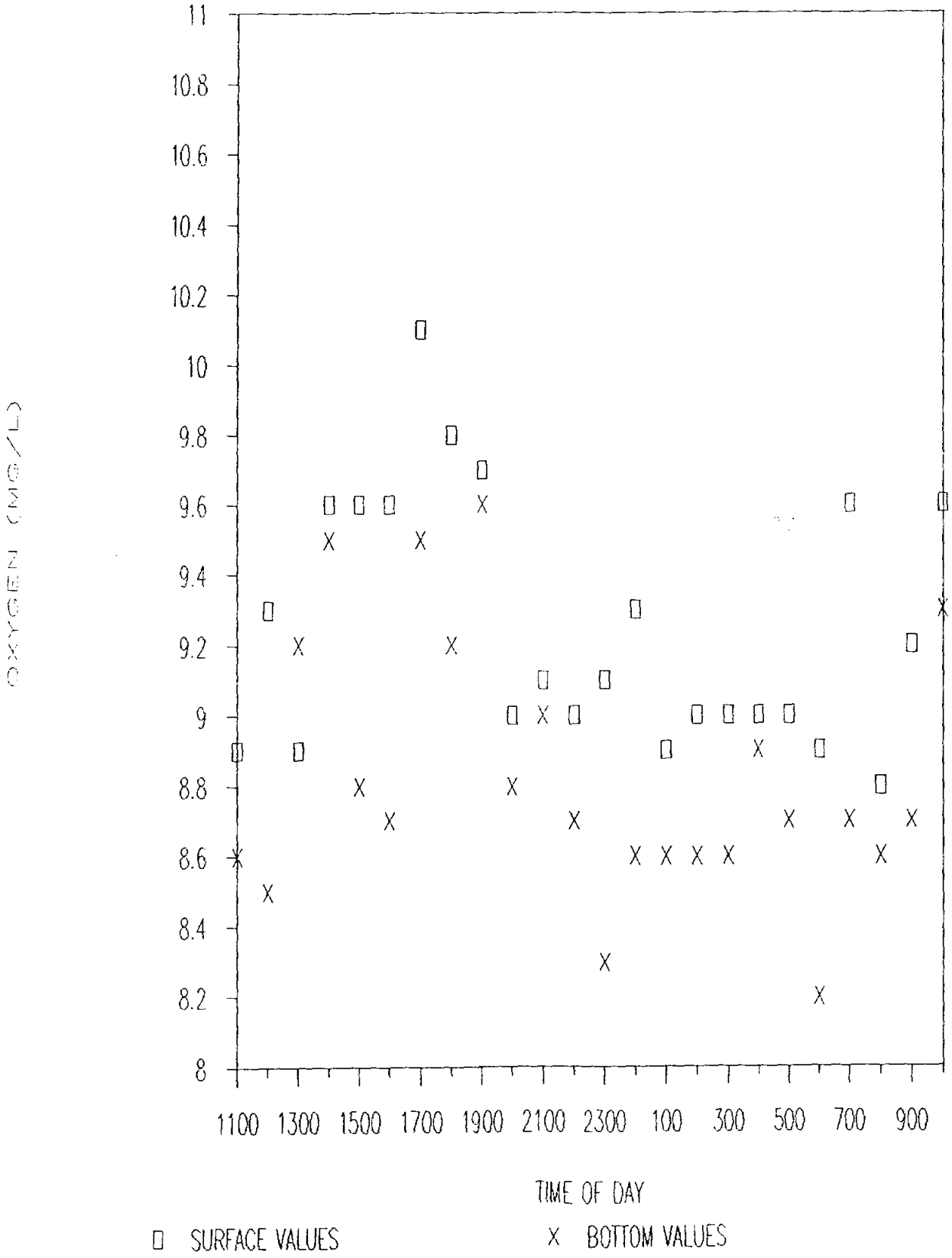

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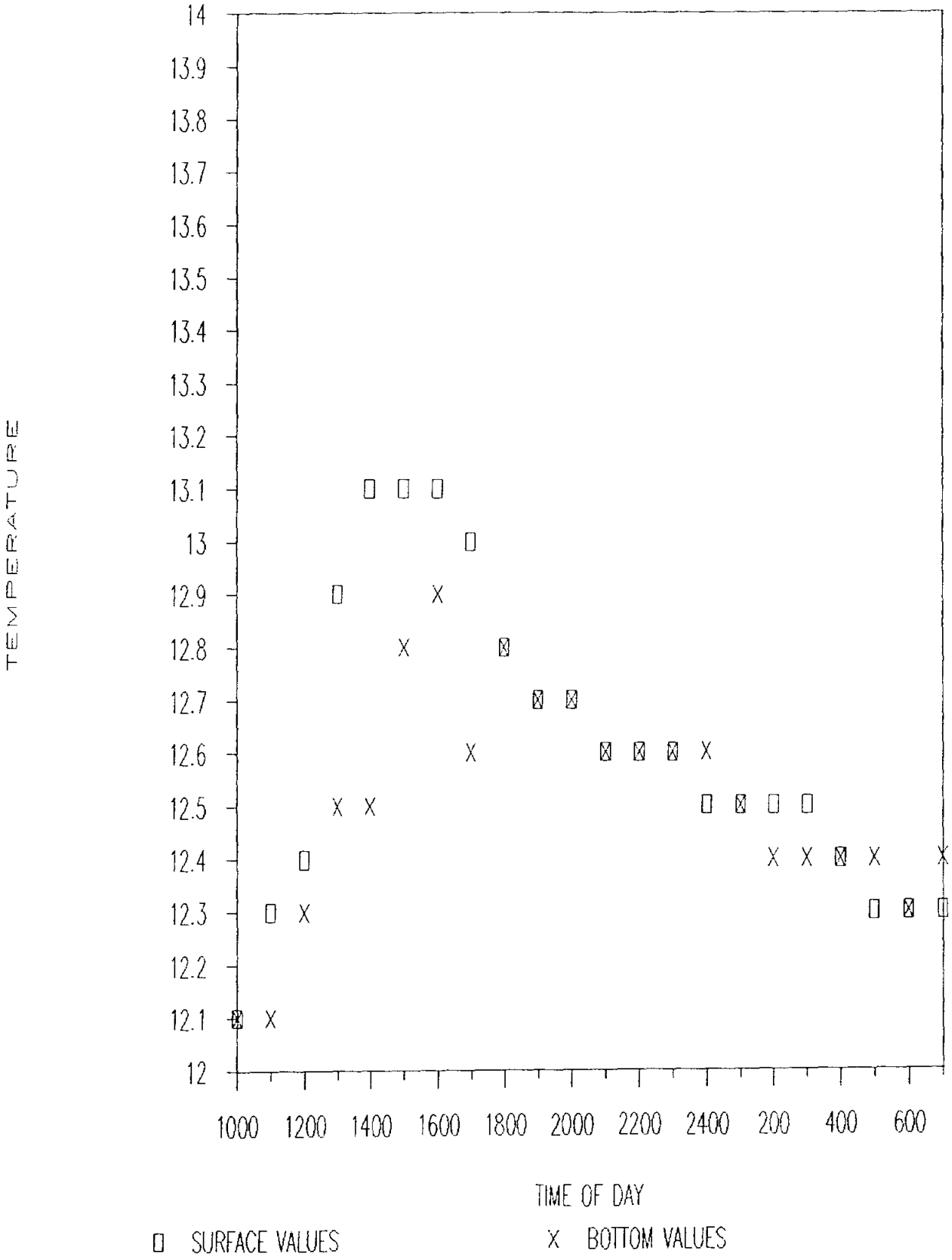

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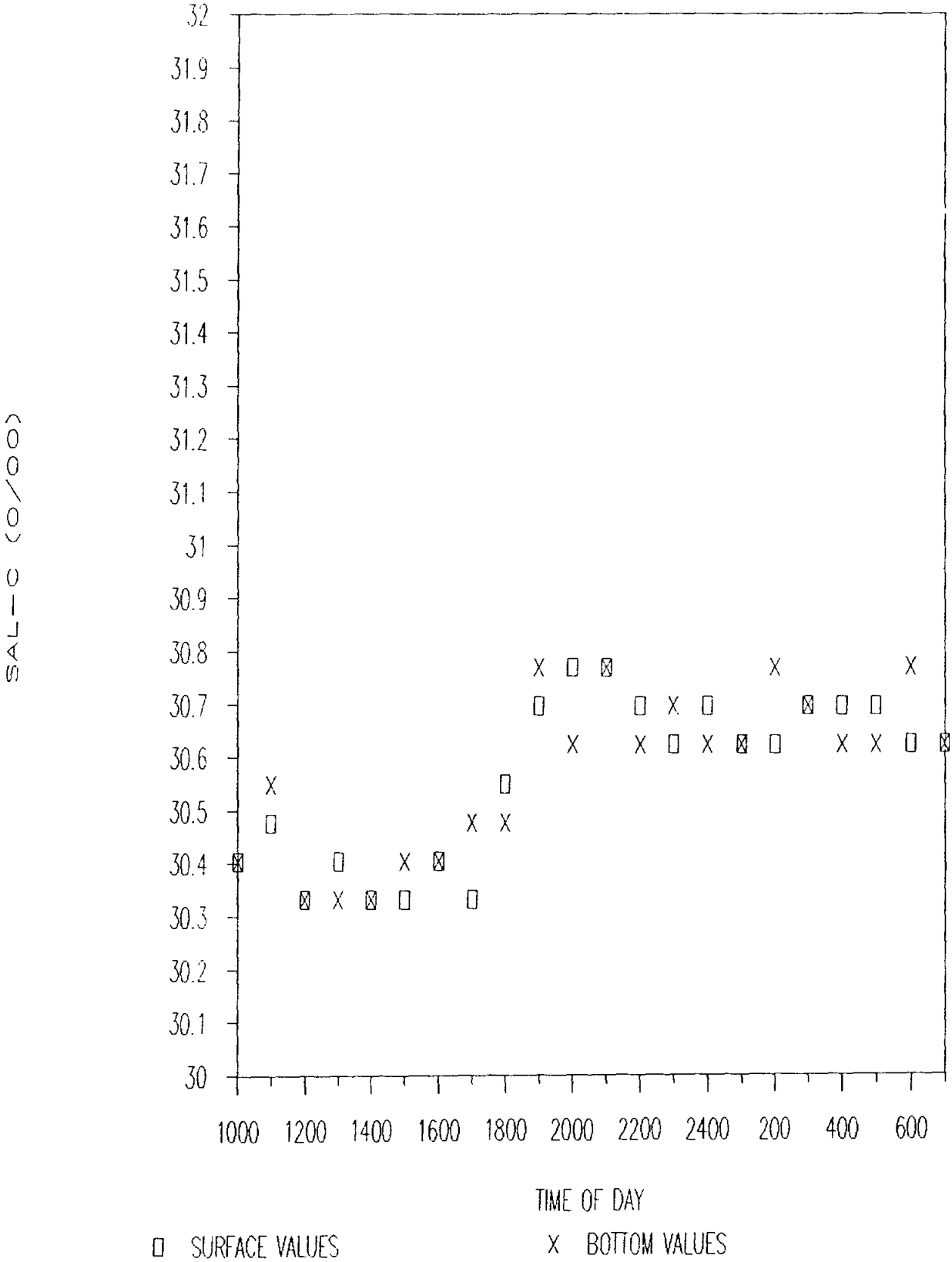

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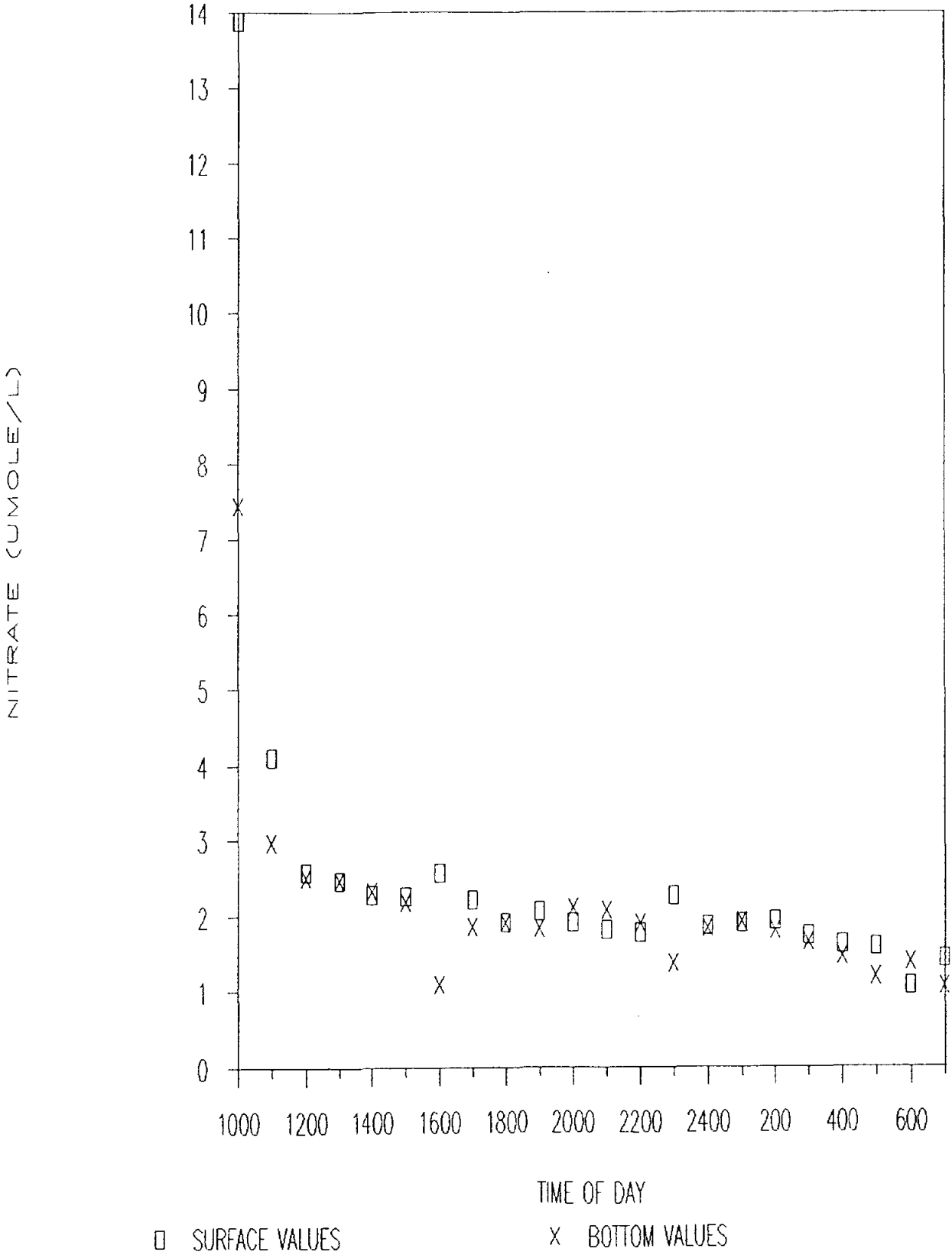

CORPUS CHRISTI/NUECES BAYS

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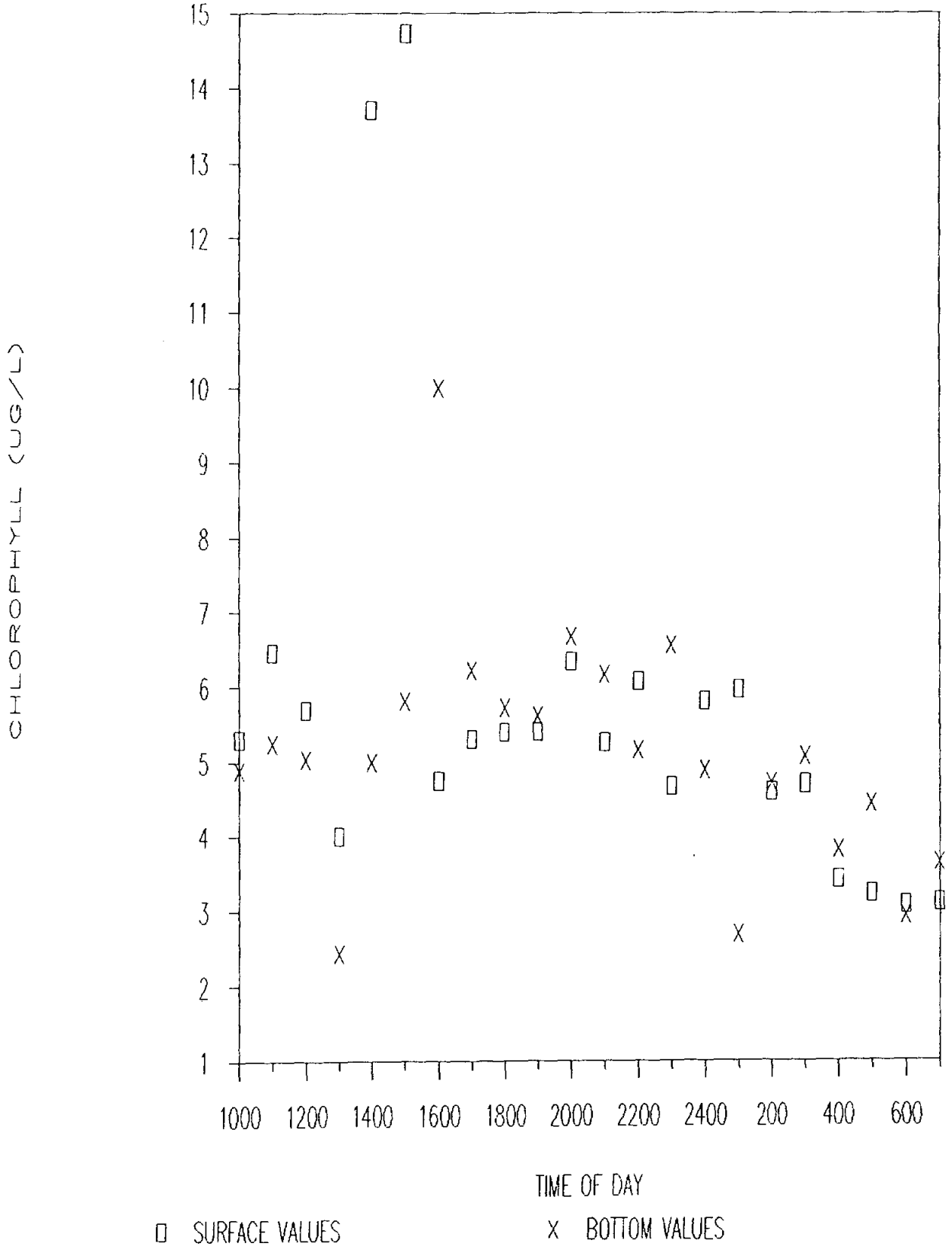
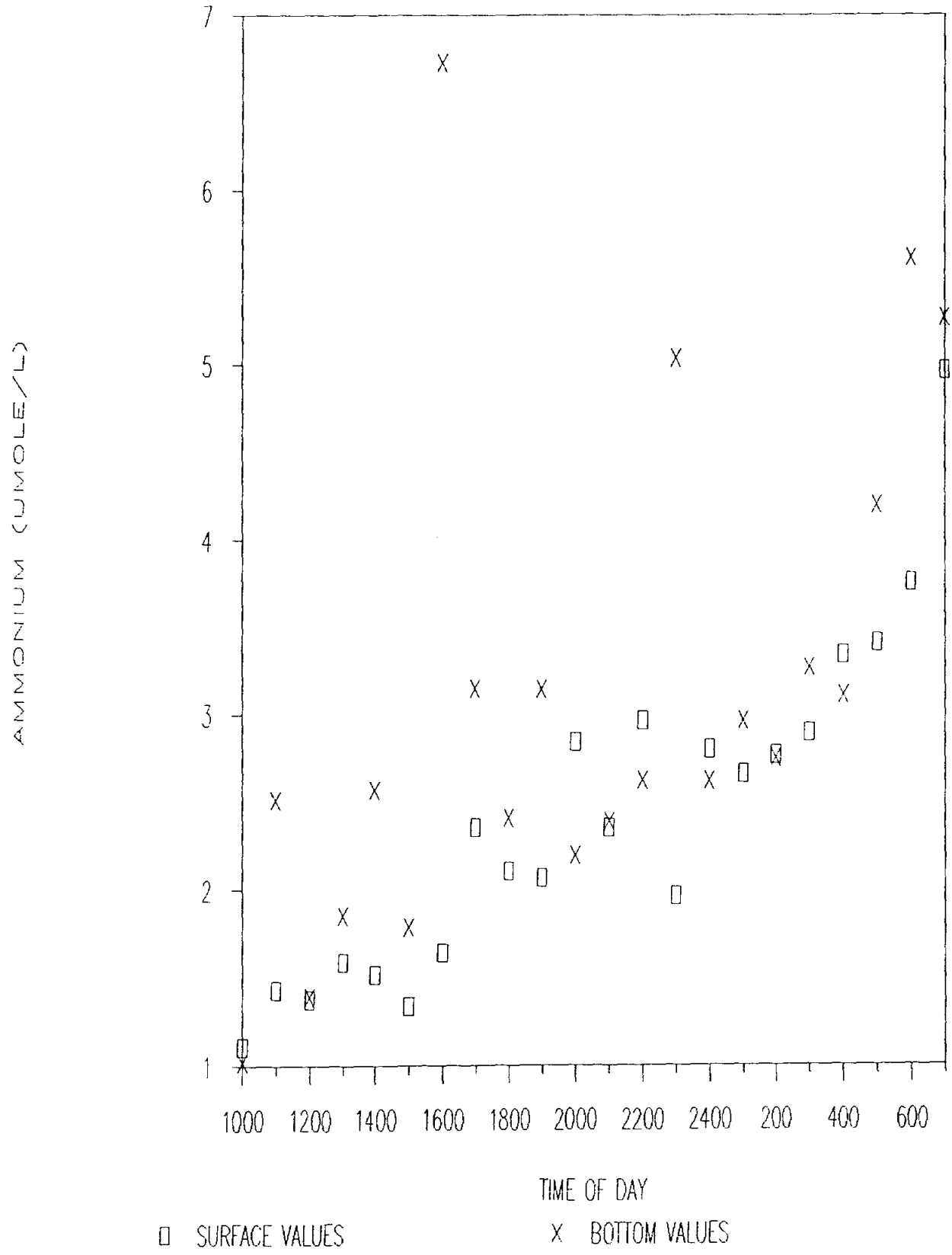


CORPUS CHRISTI/NUECES BAYS

FEB 1988 STATION C



CORPUS CHRISTI/NUECES BAYS

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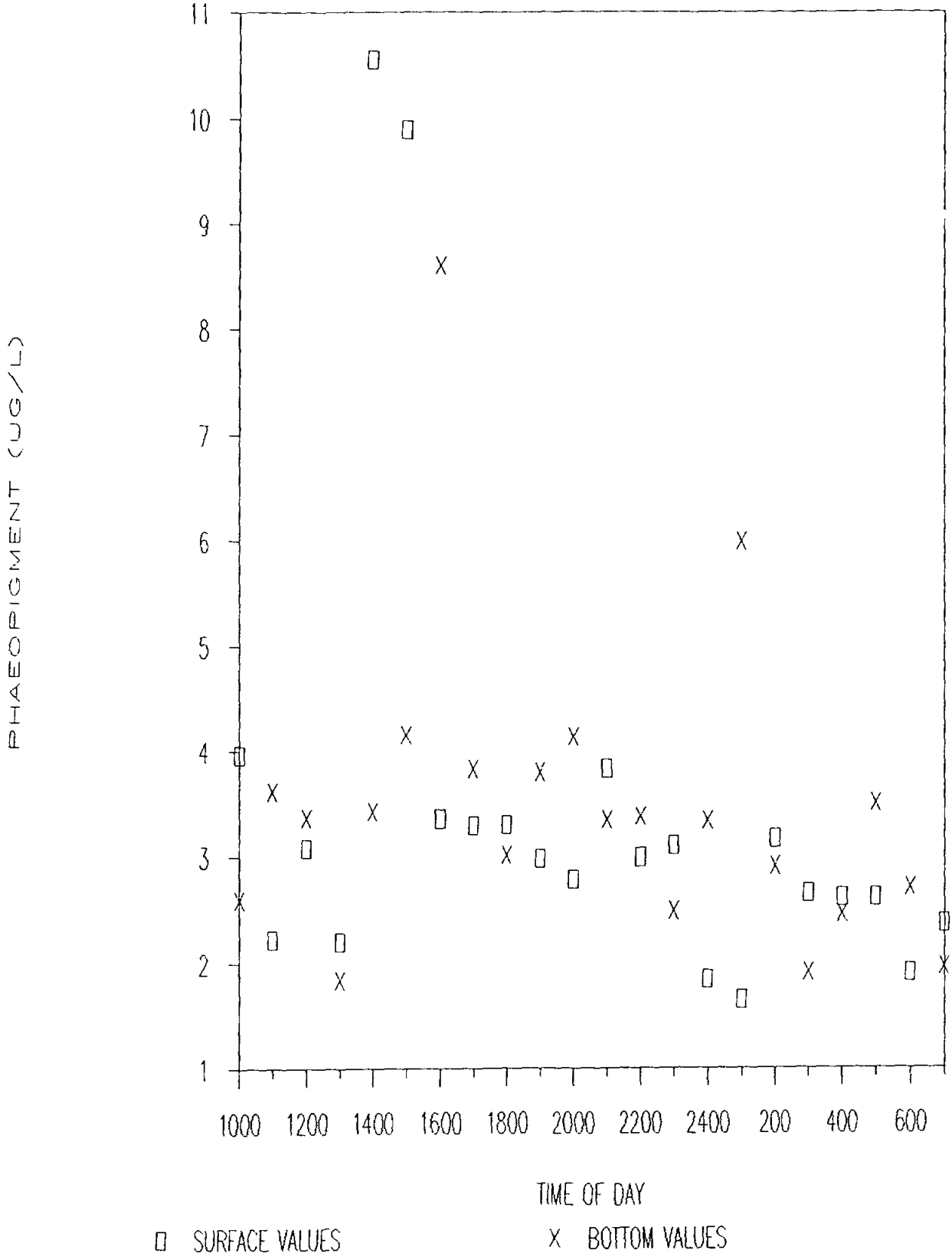

CORPUS CHRISTI/NUECES BAYS

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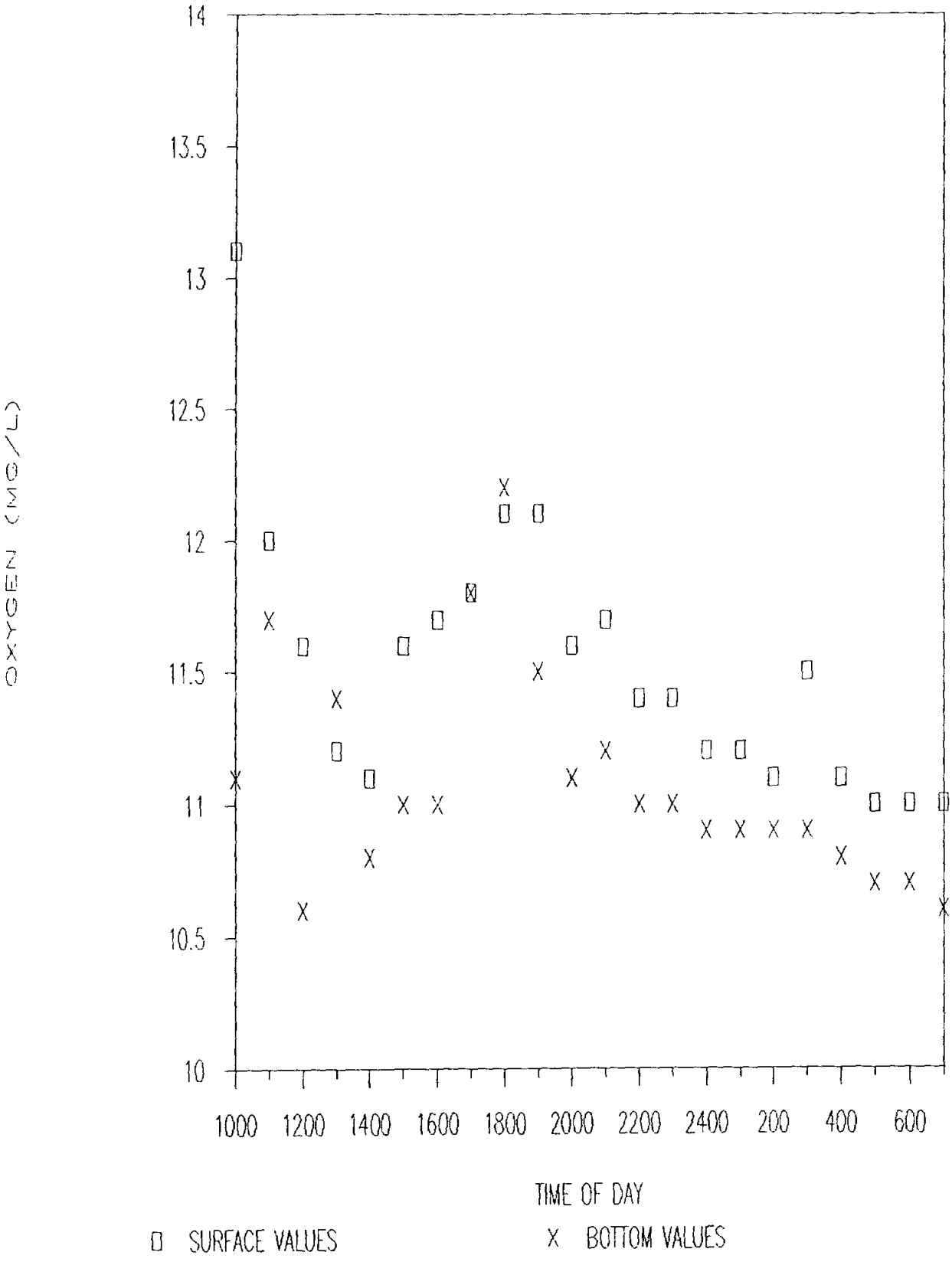

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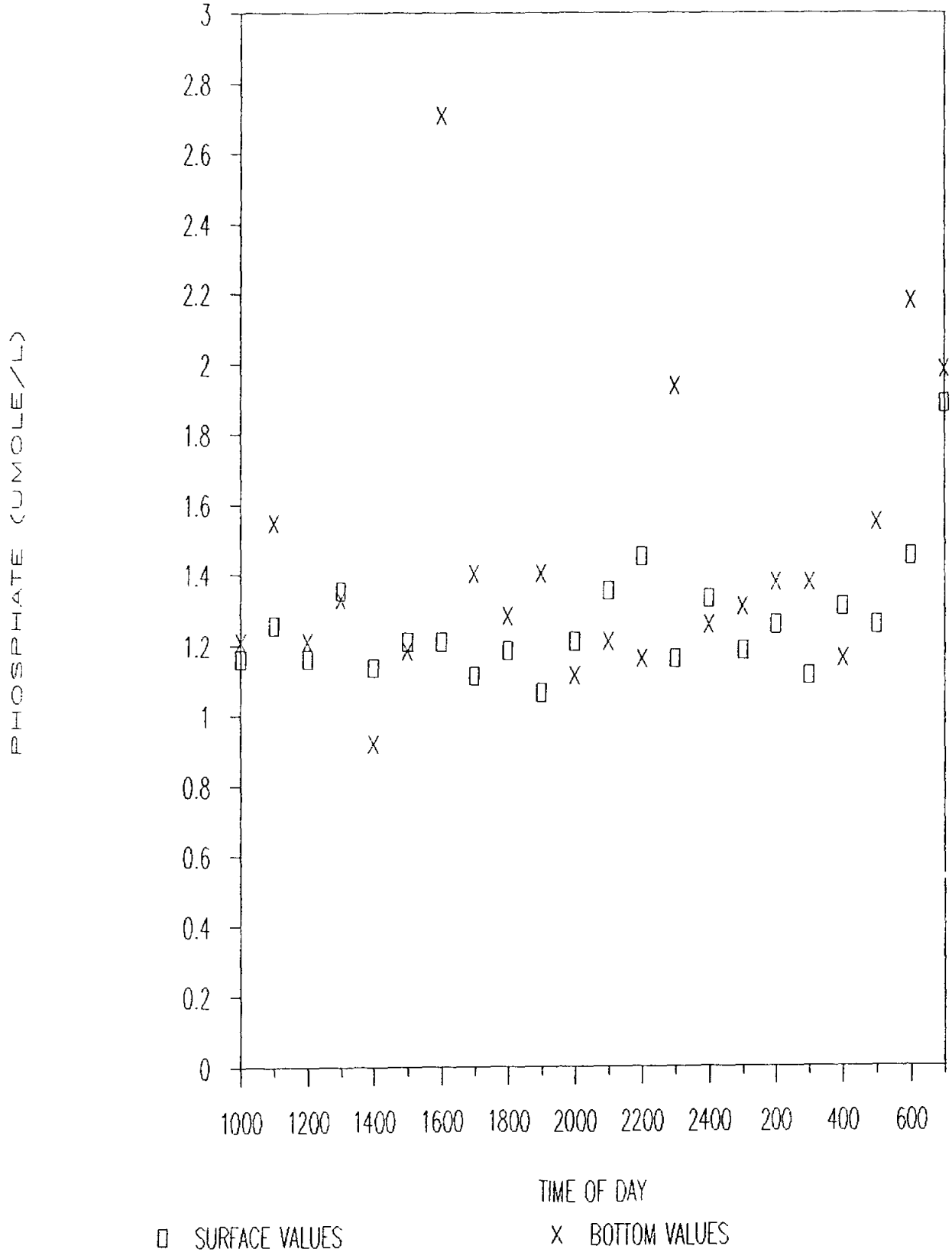

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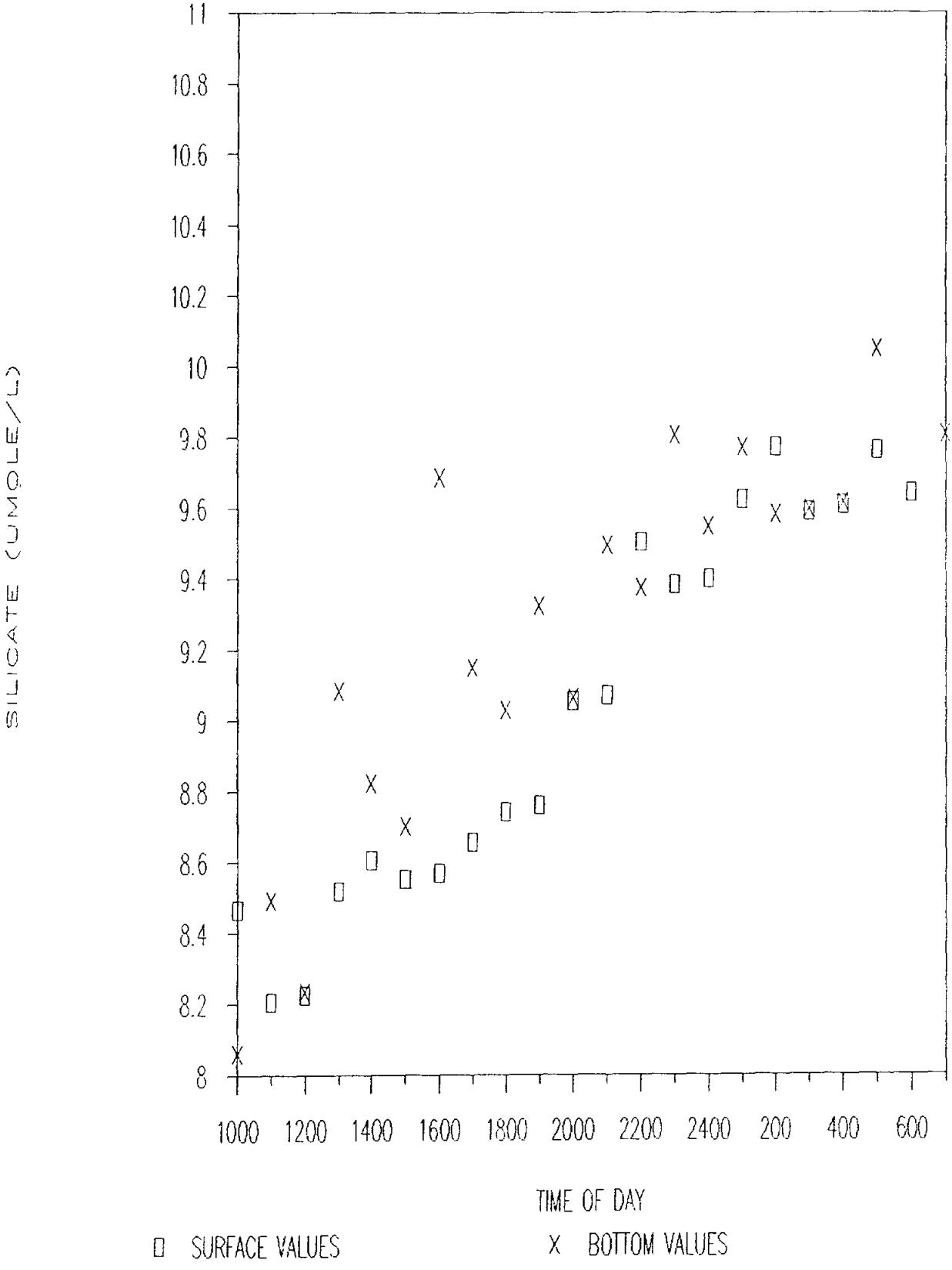

CORPUS CHRISTI/NUECES BAYS

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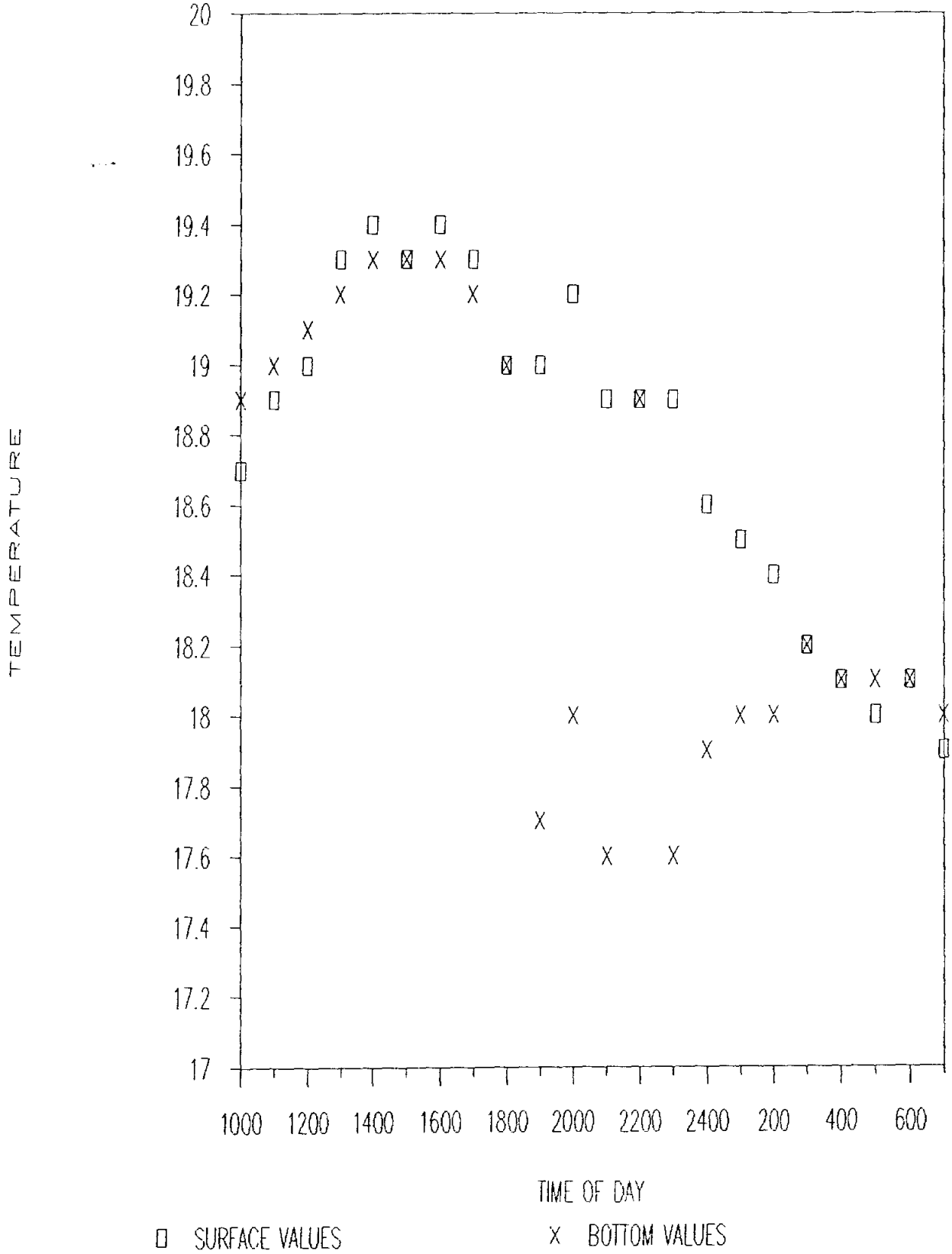

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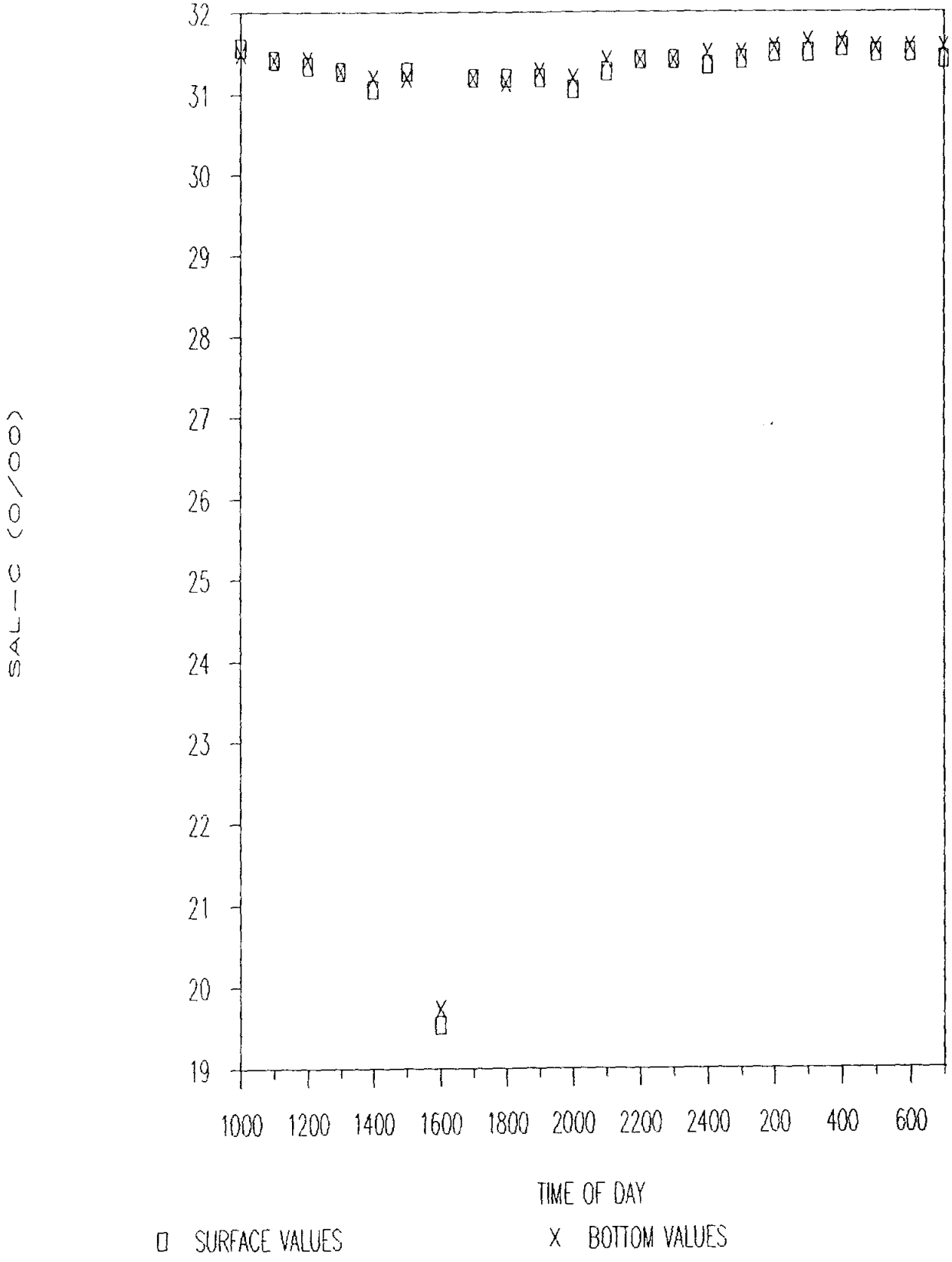

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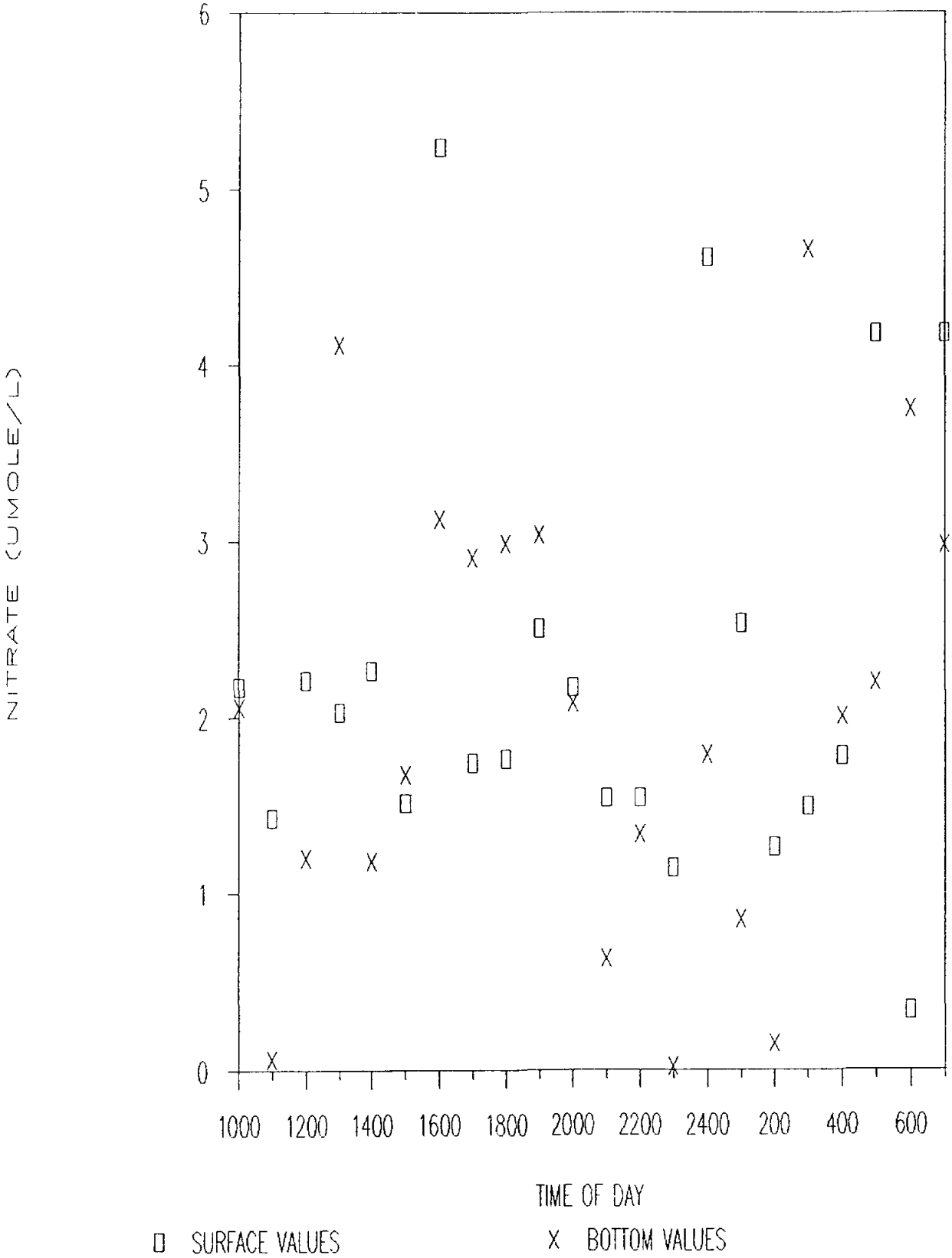

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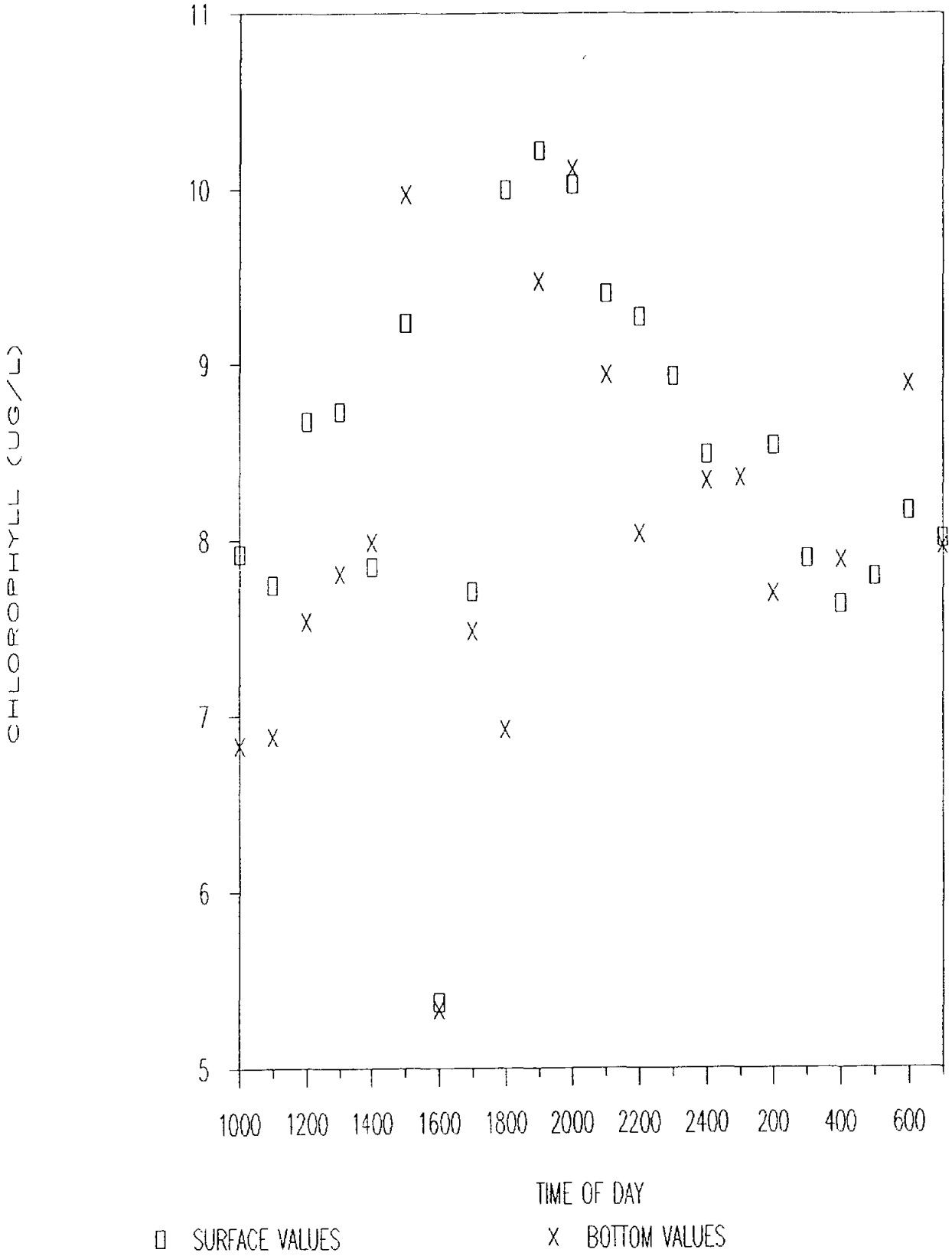

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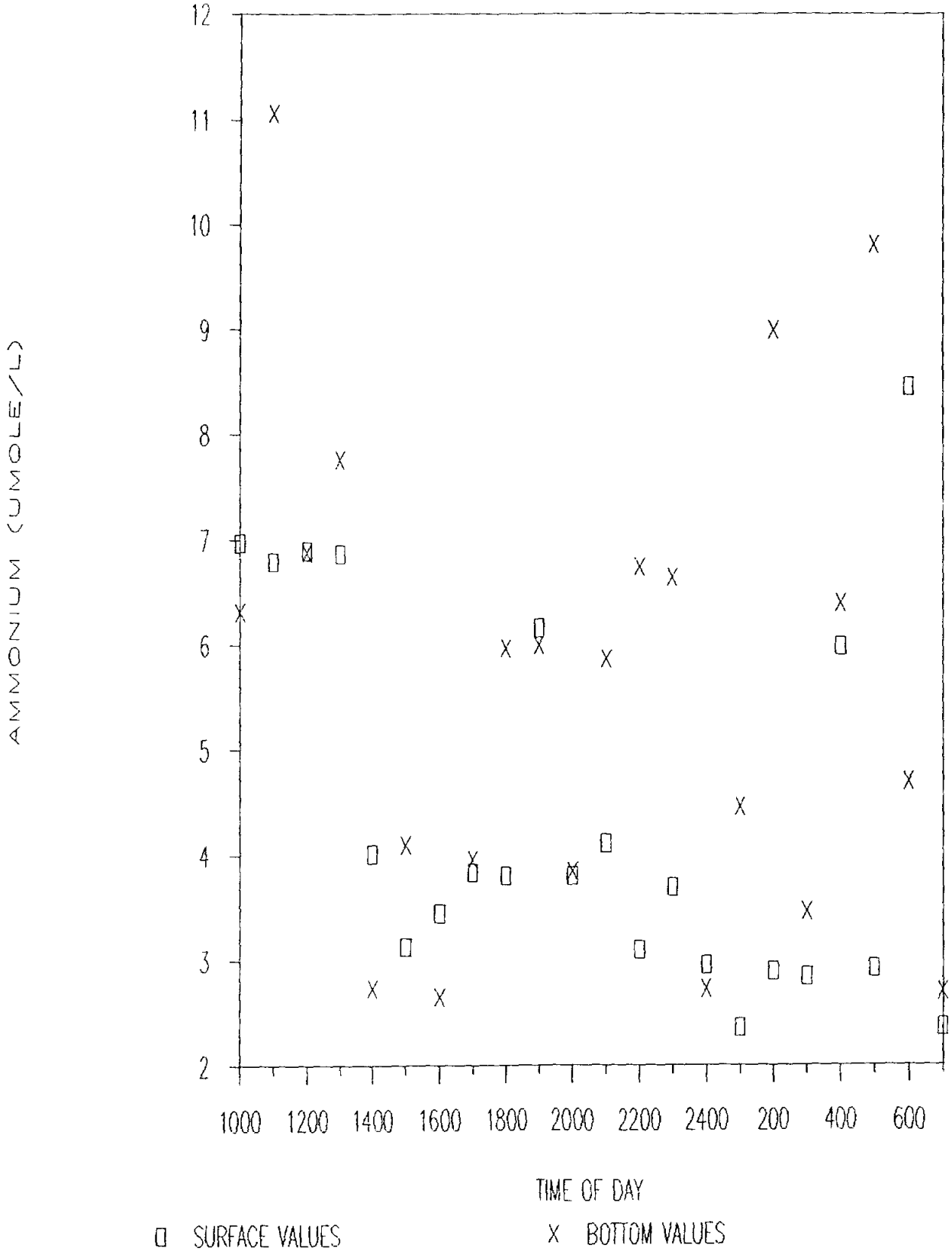

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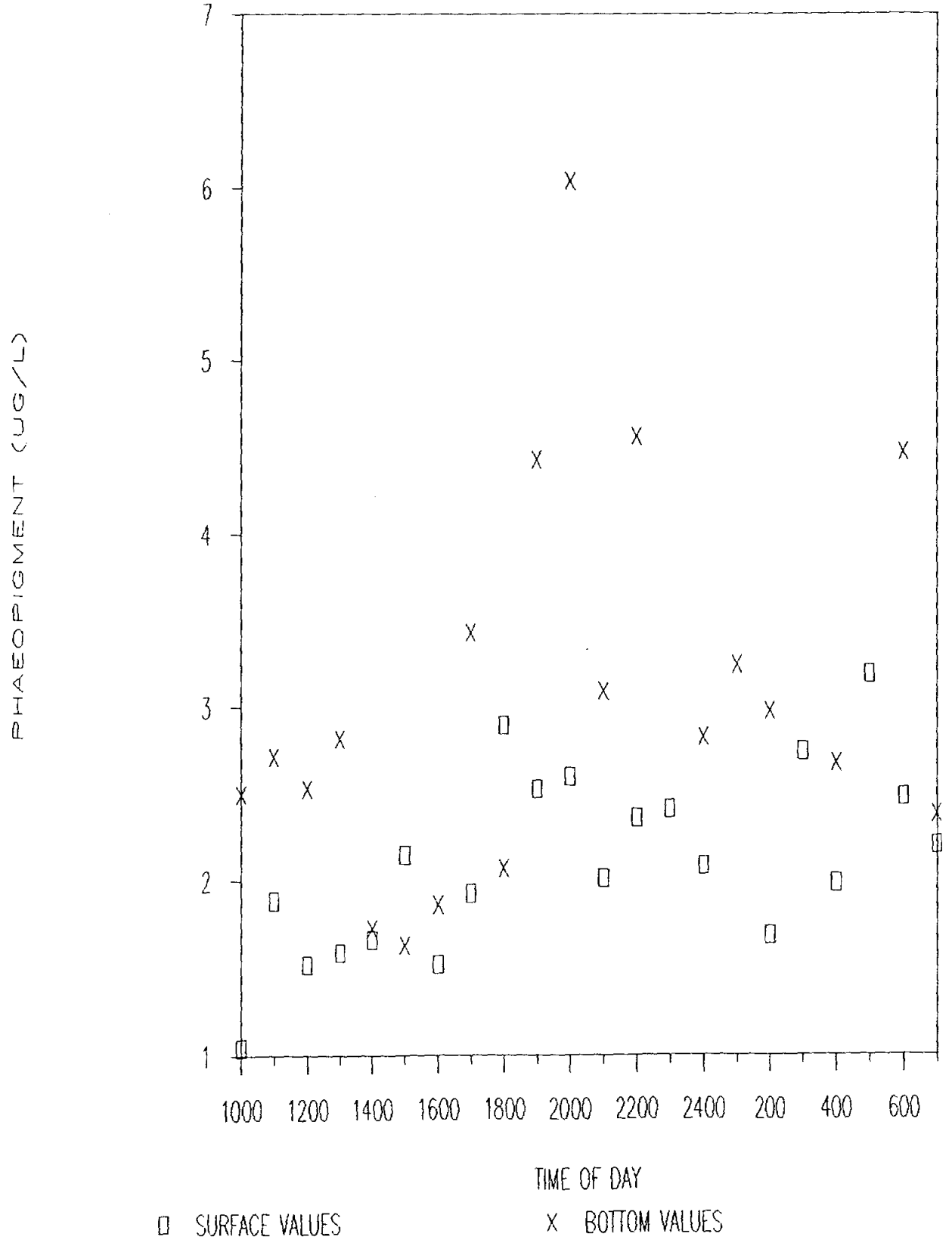

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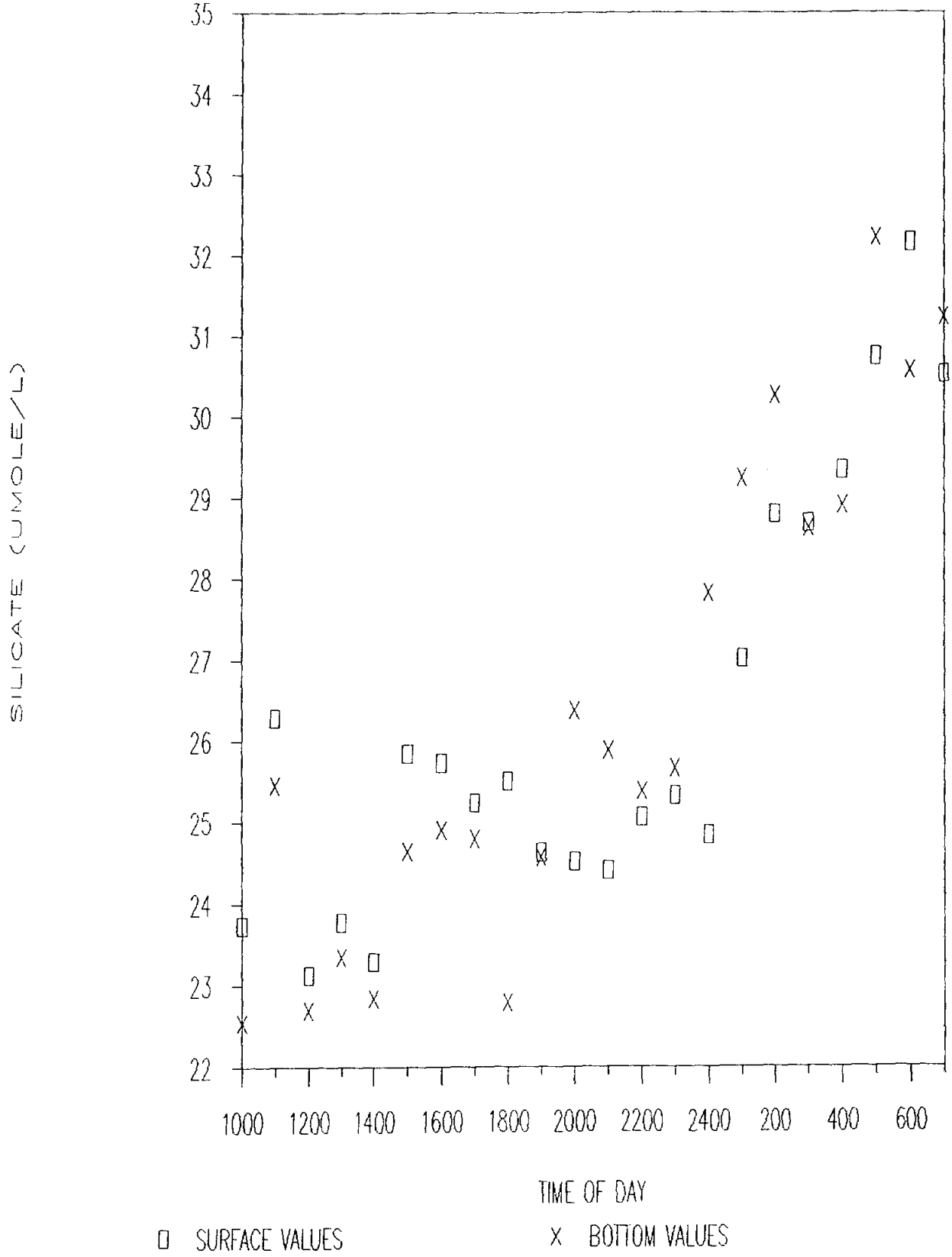

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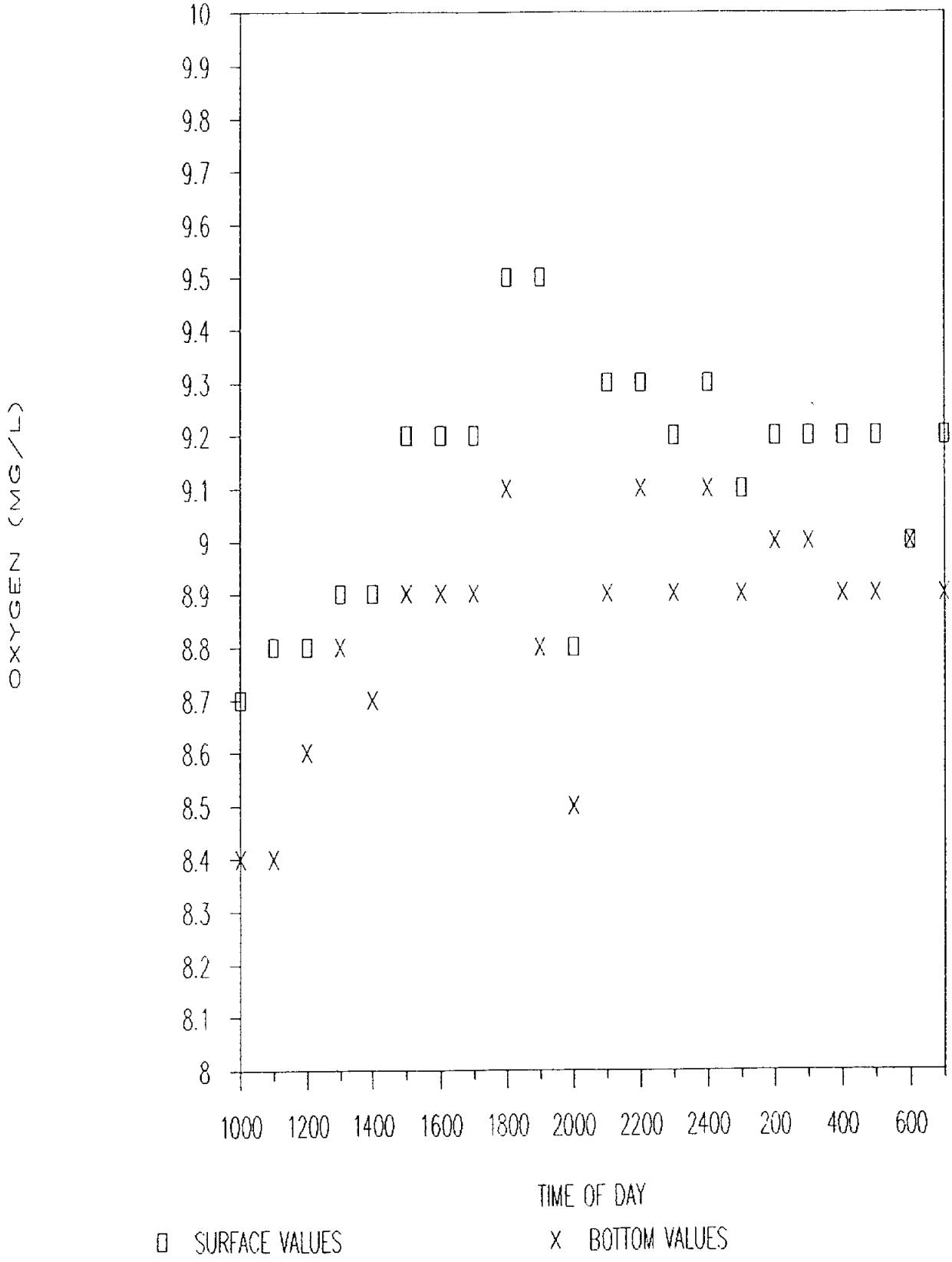

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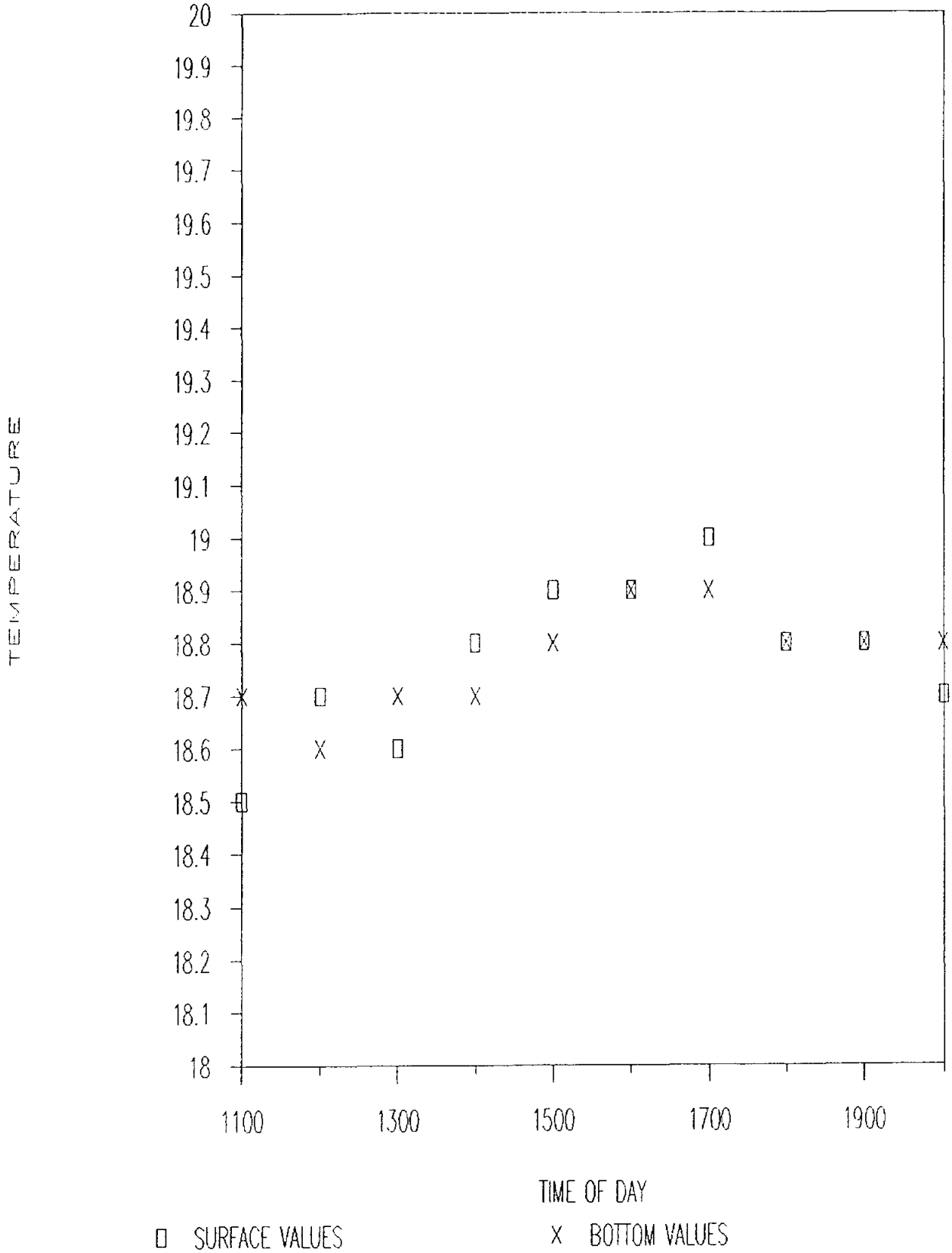
DEC 1987 STATION D



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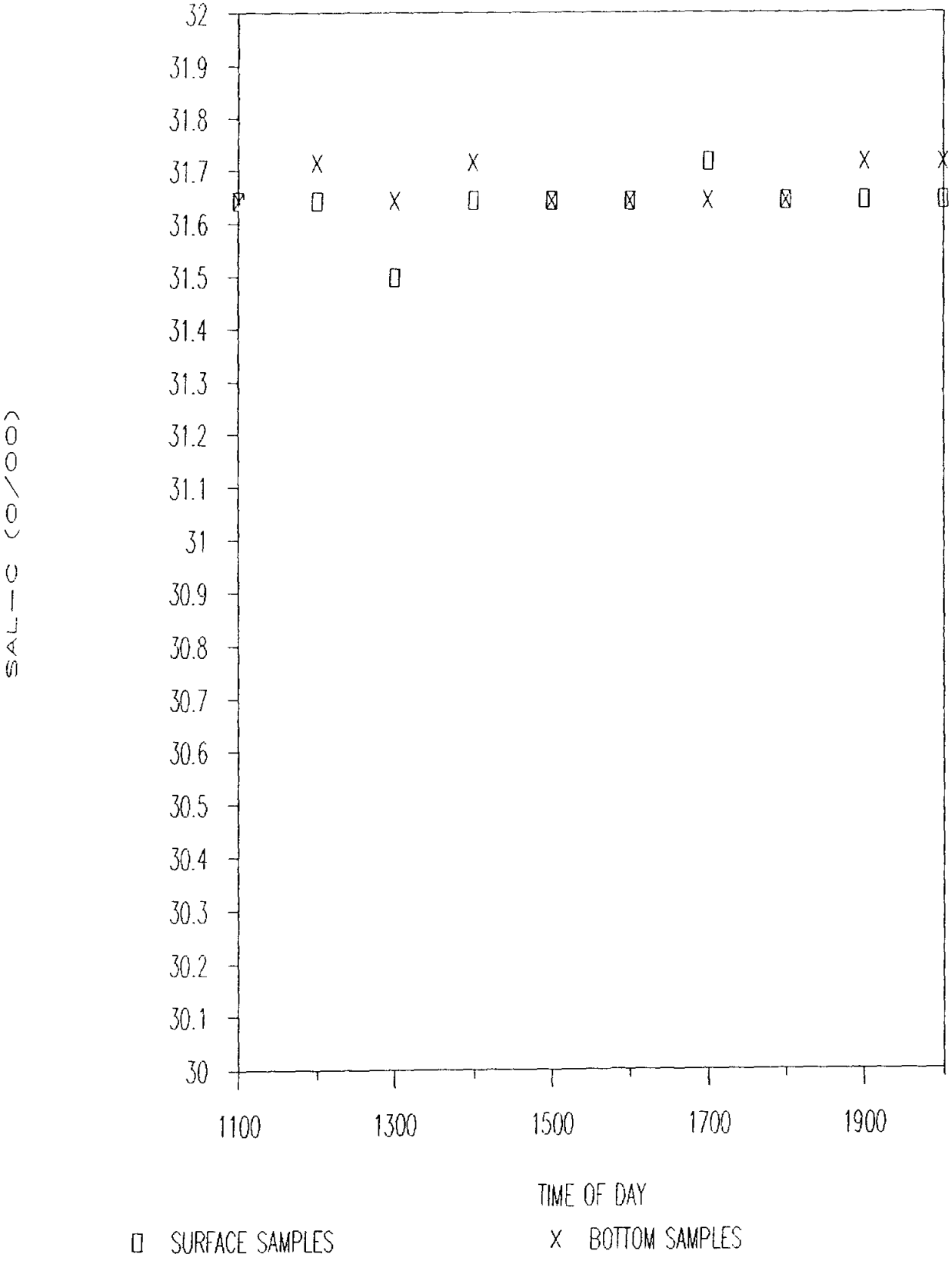

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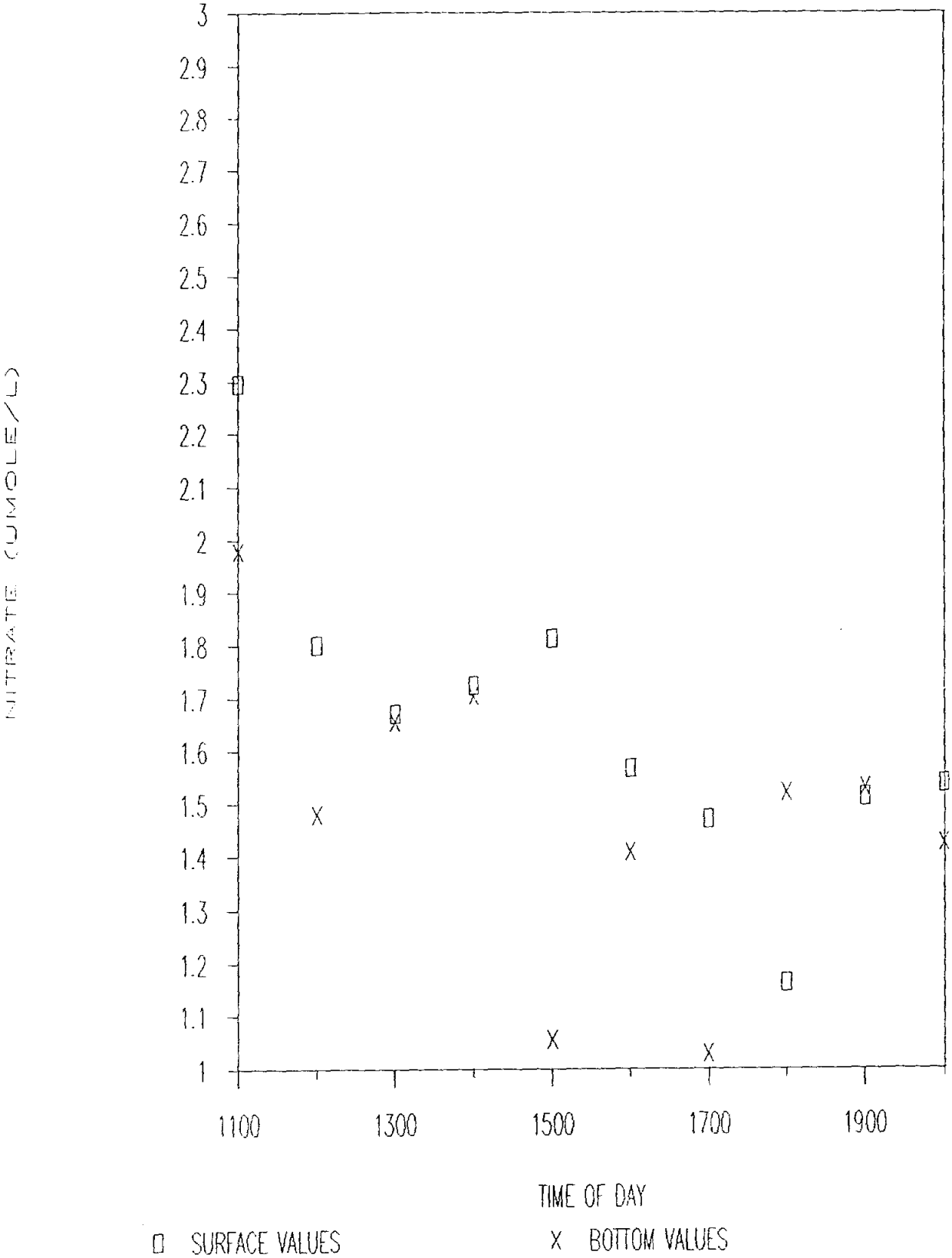

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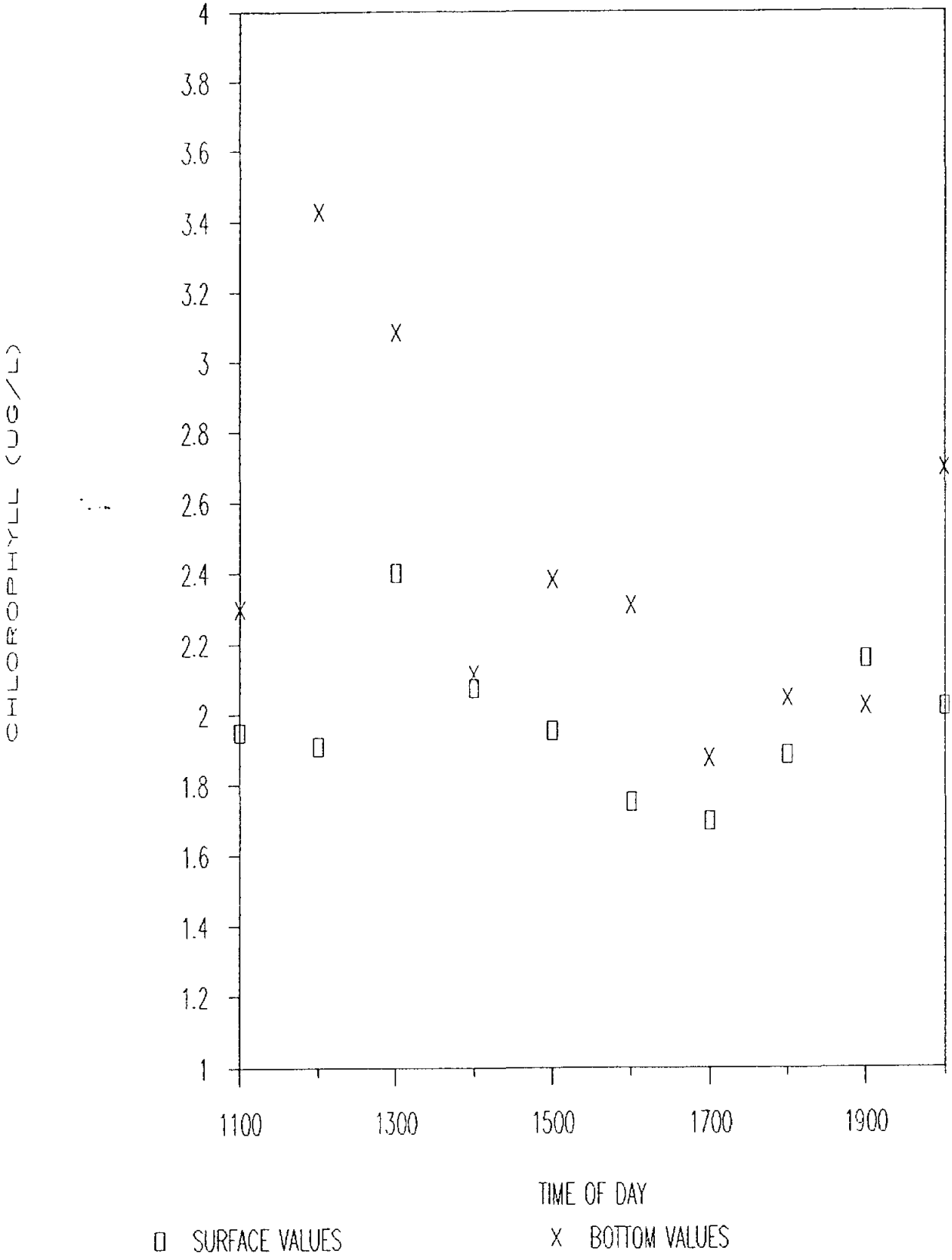

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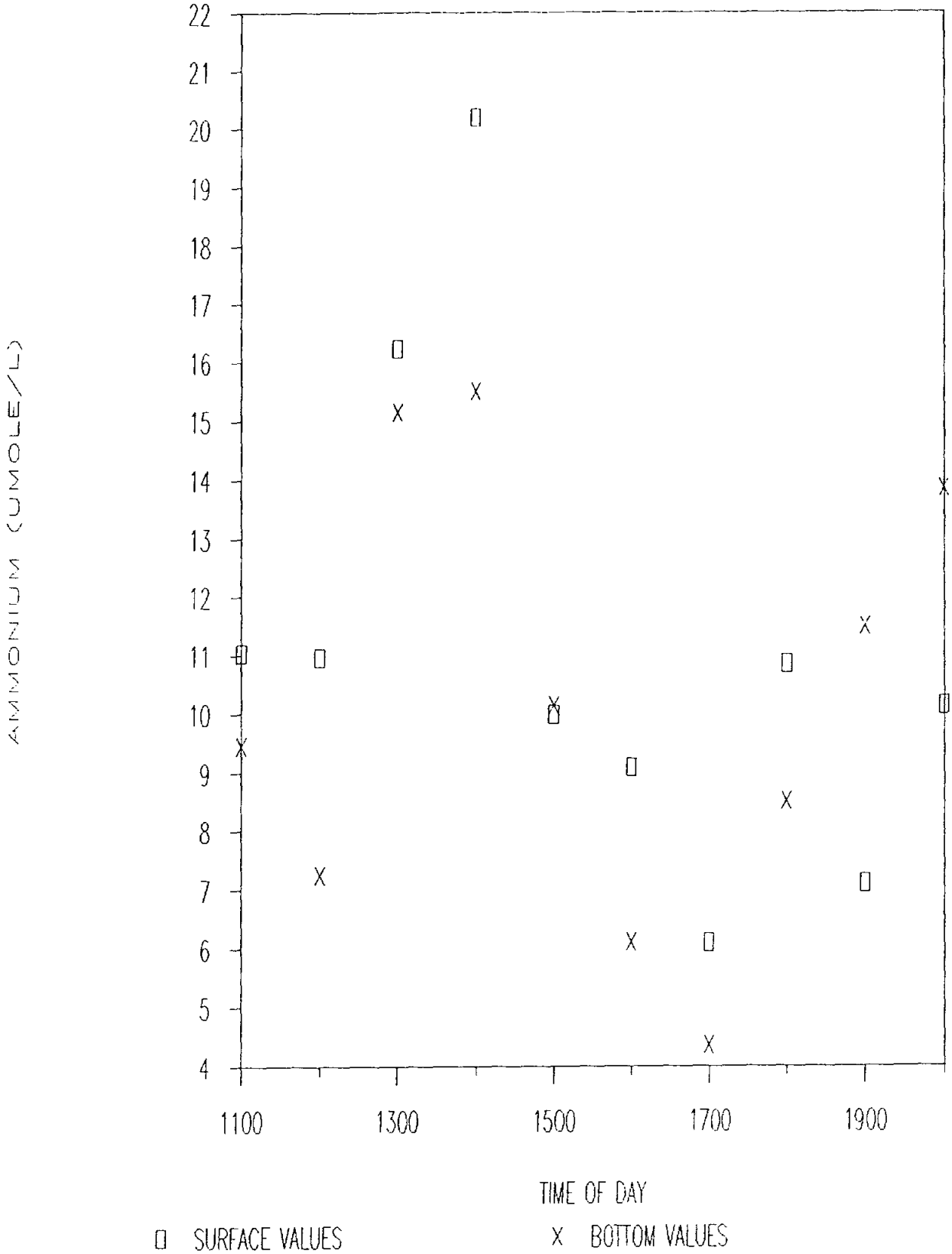

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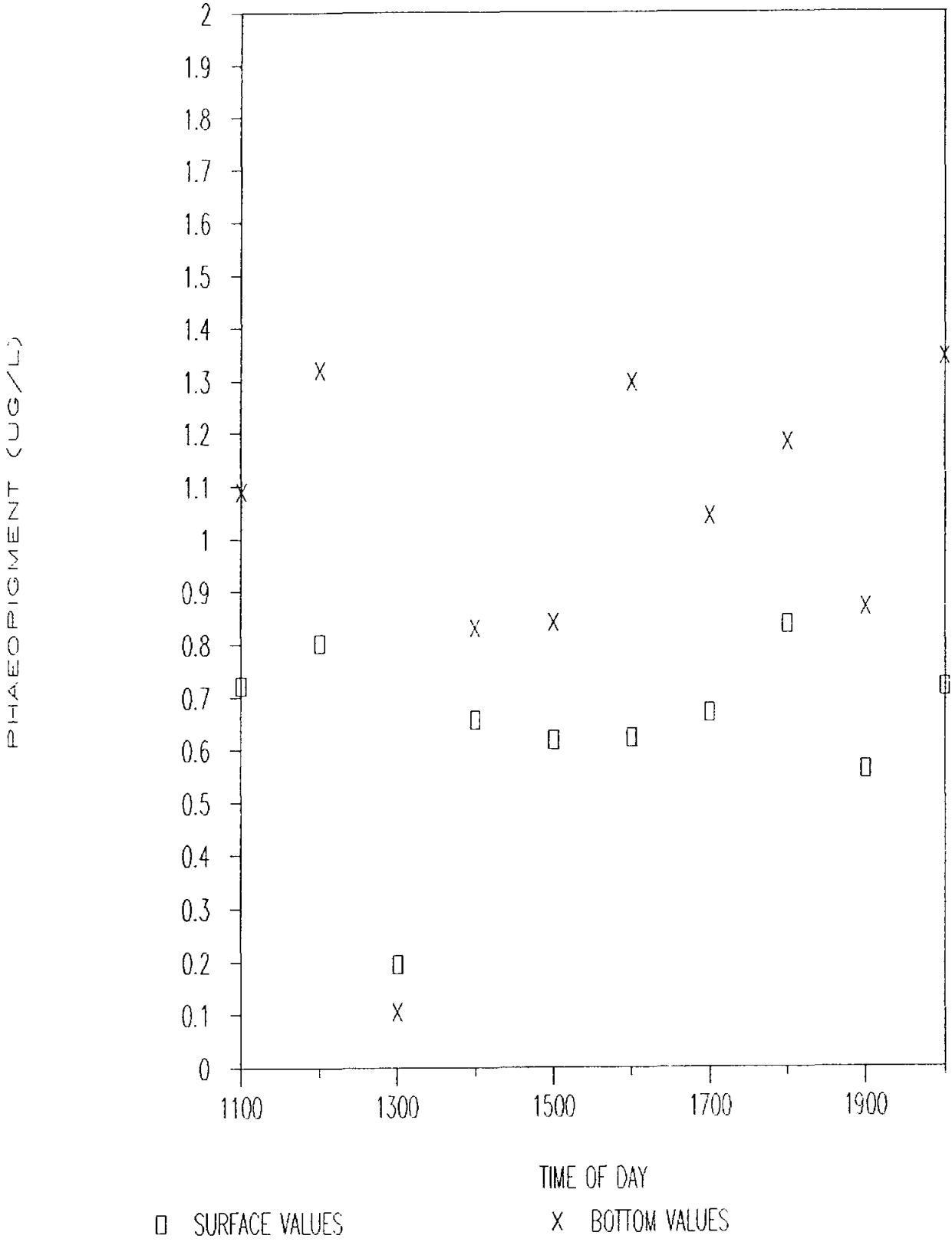

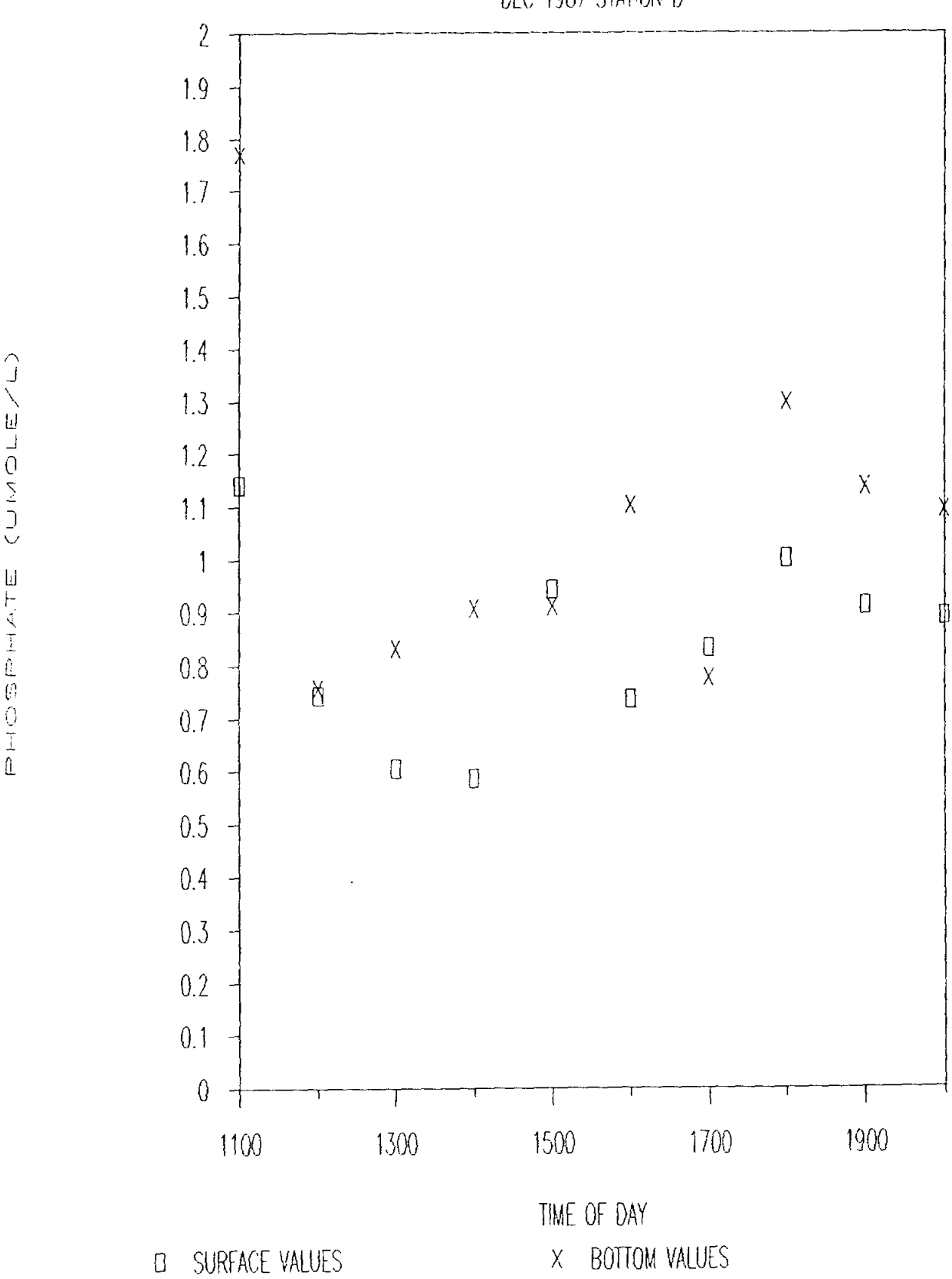
DEC 1987 STATION D
PHOSPHATE (UMOLE/L)
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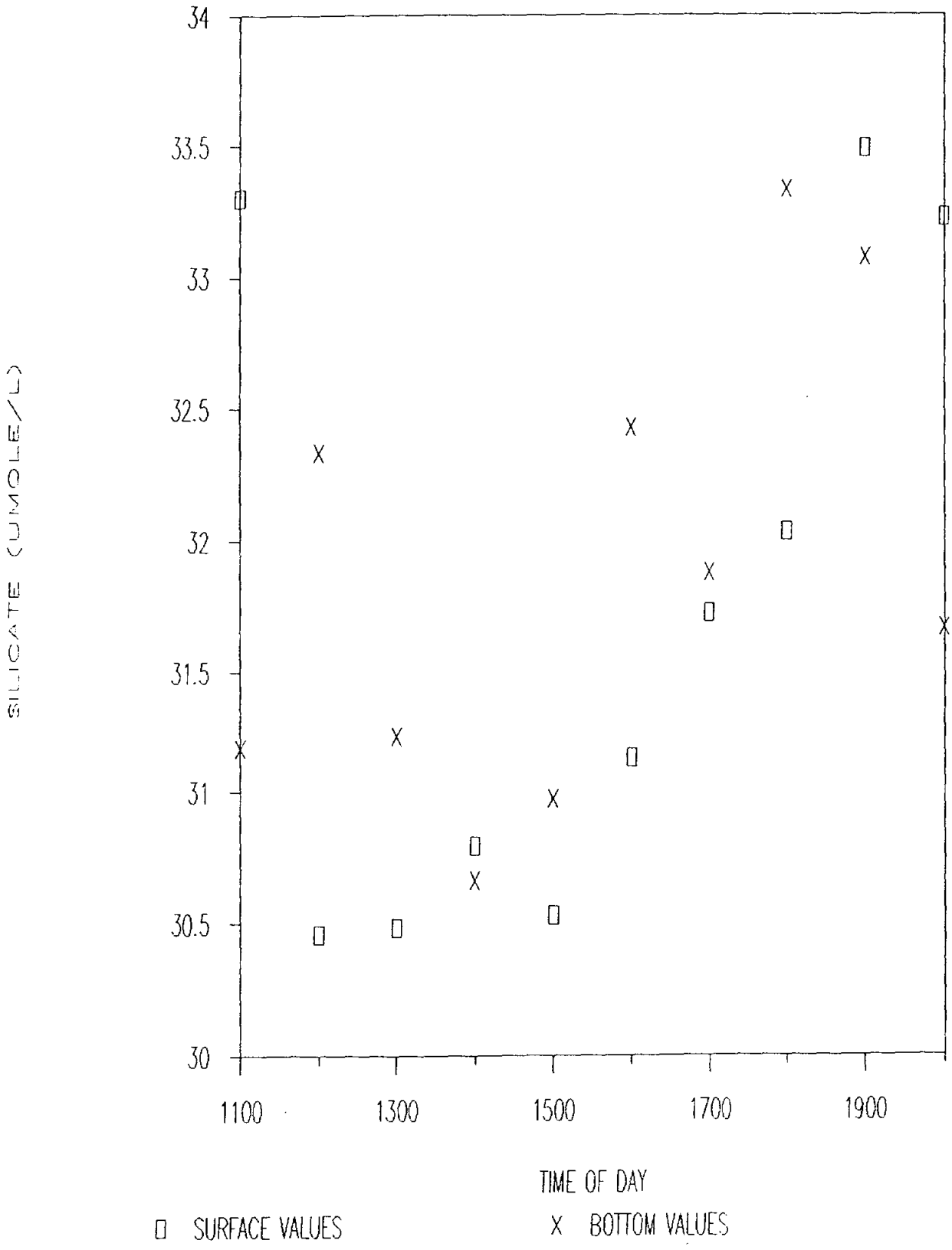
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1100
1300
1500
1700
1900
TIME OF DAY
SURFACE VALUES
X BOTTOM VALUES

CORPUS CHRISTI/NUECES BAYS

DEC 1987 STATION D



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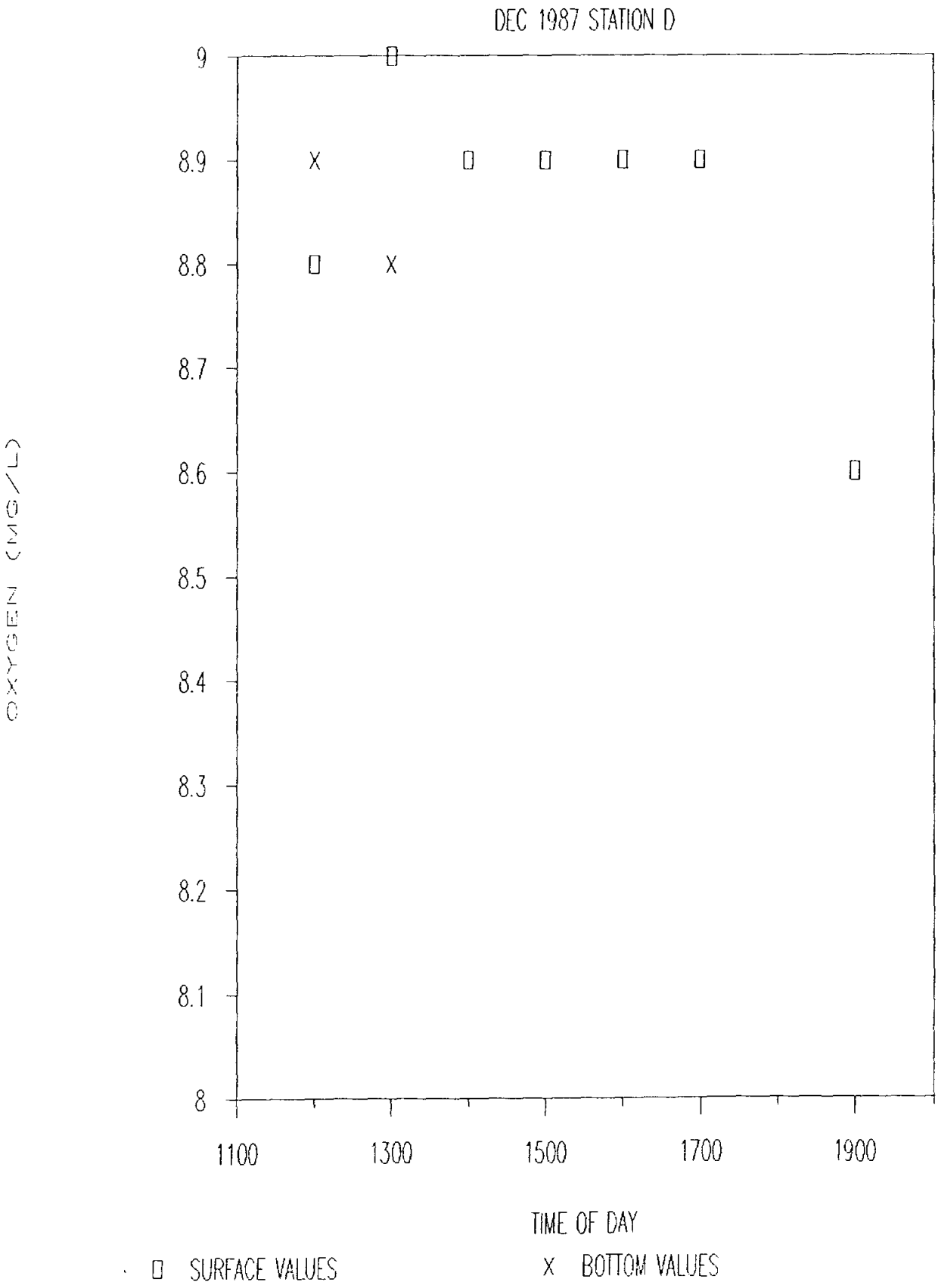
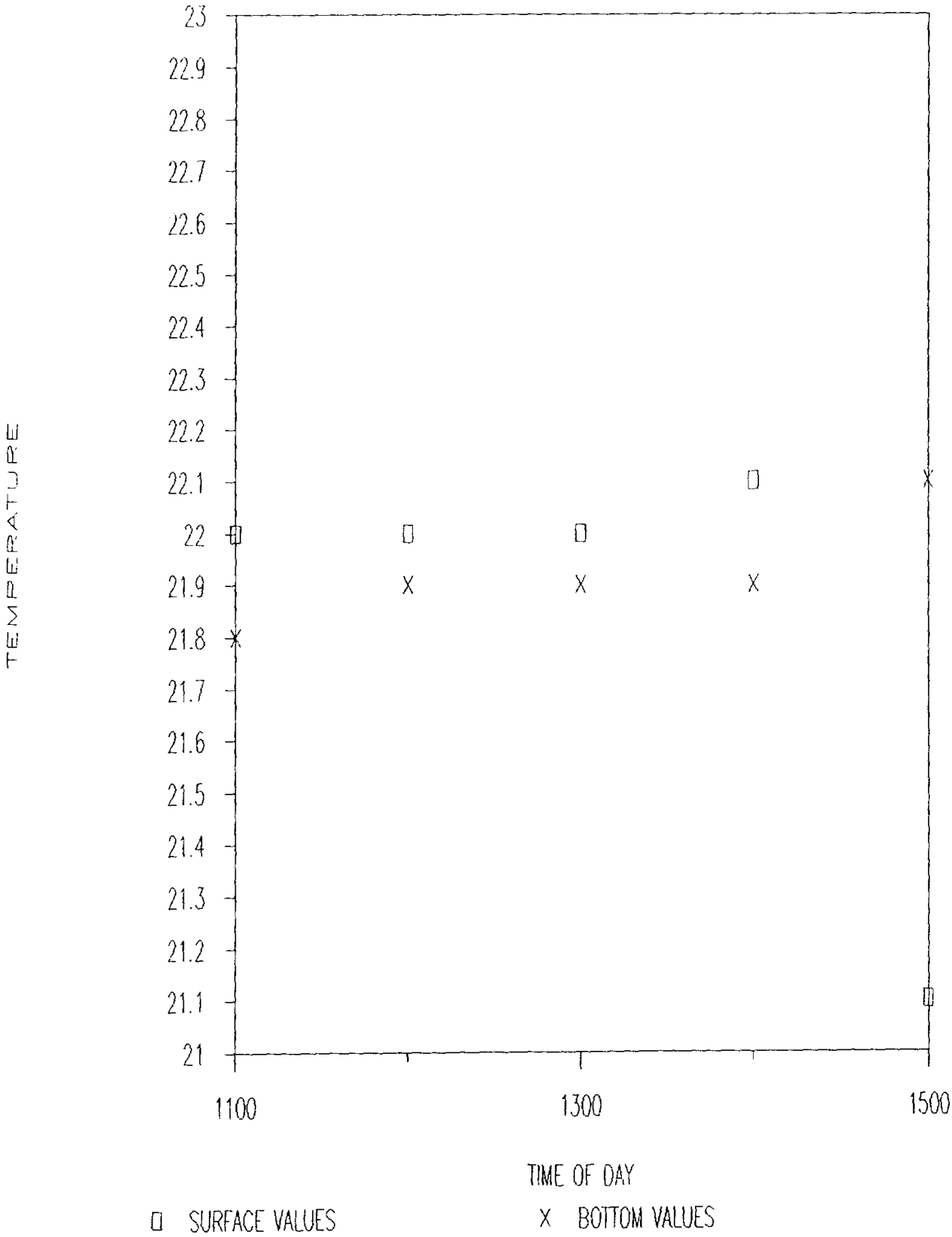


CORPUS CHRISTI/NUECES BAYS

OCT 1987 STATION D



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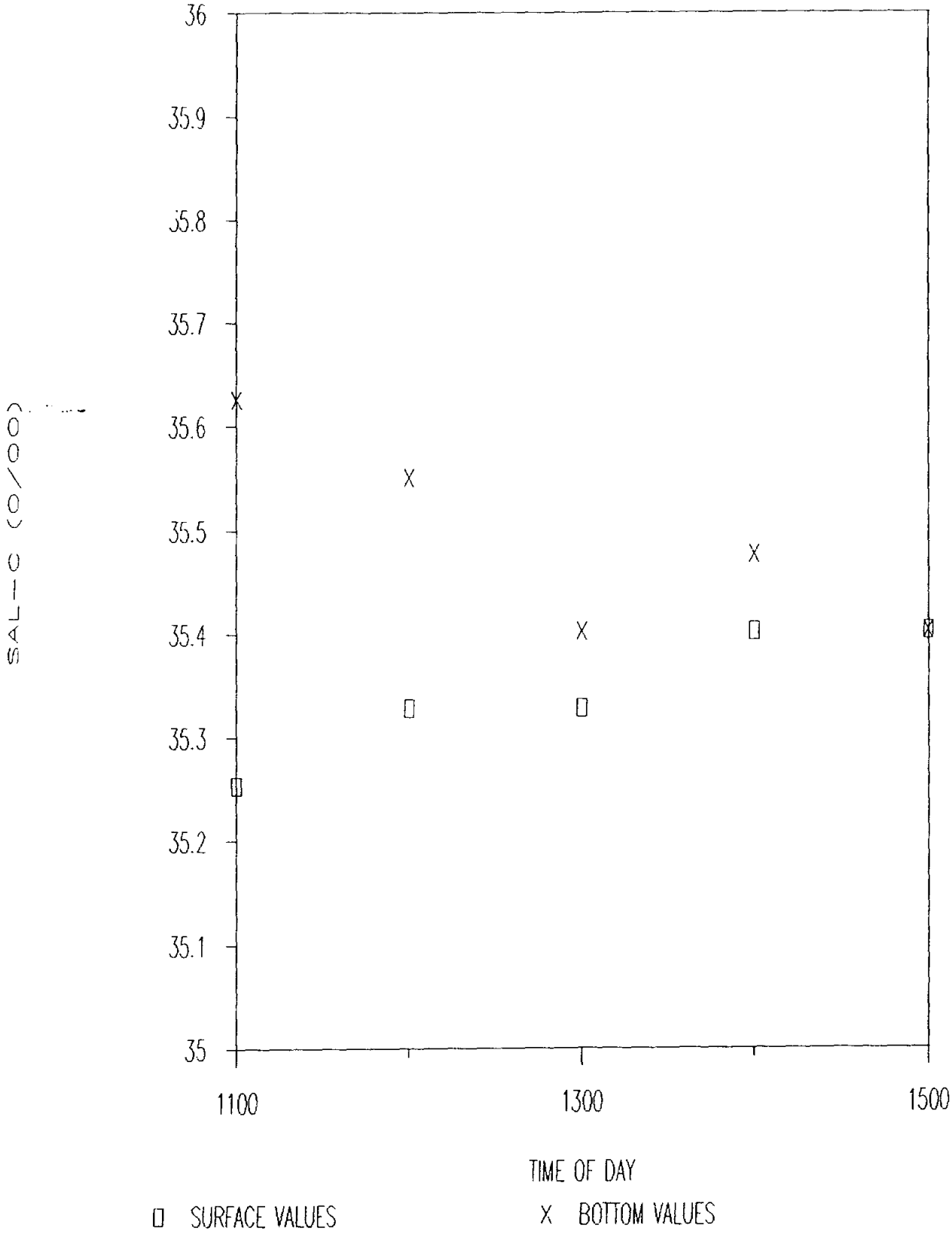

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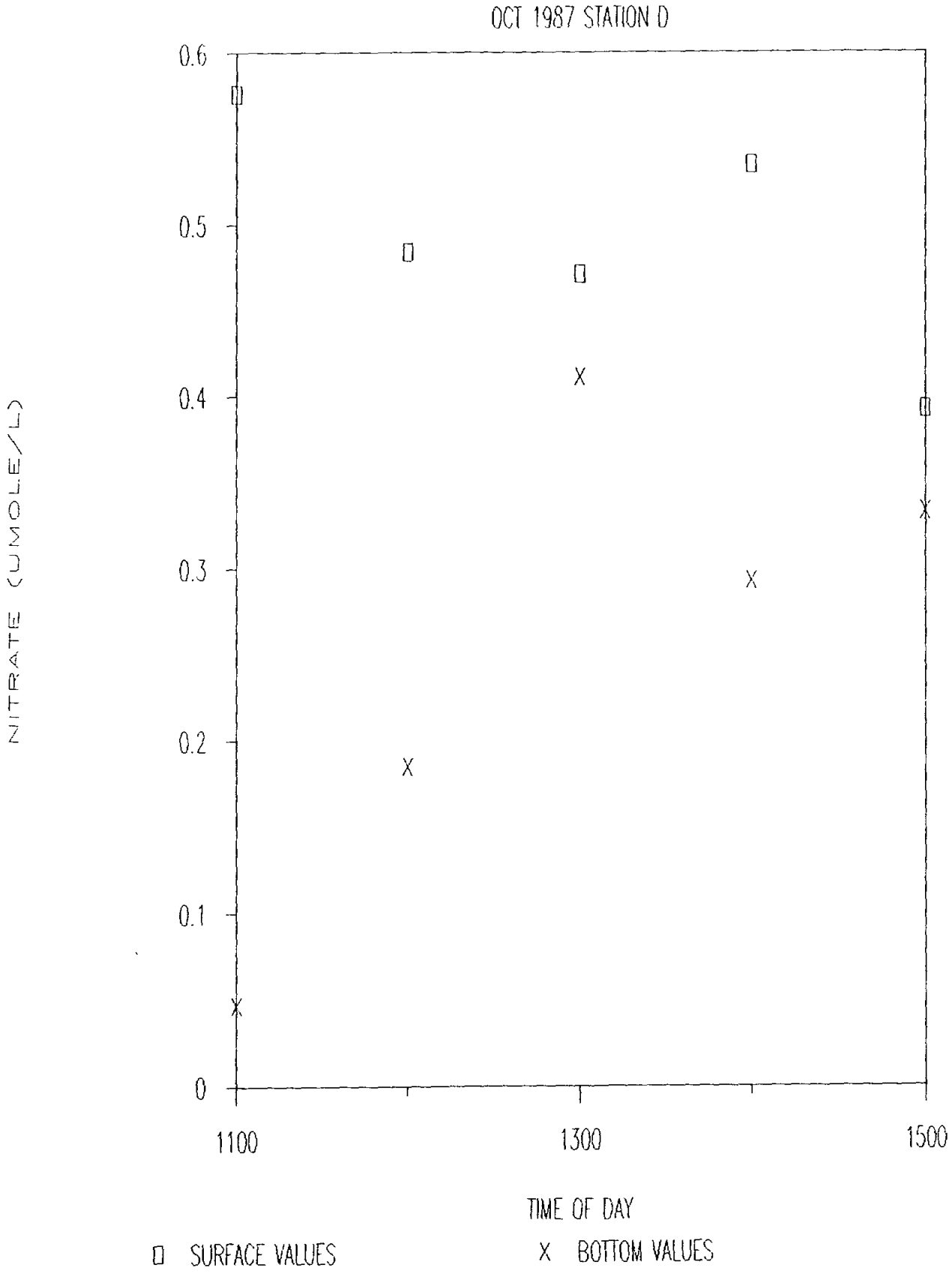

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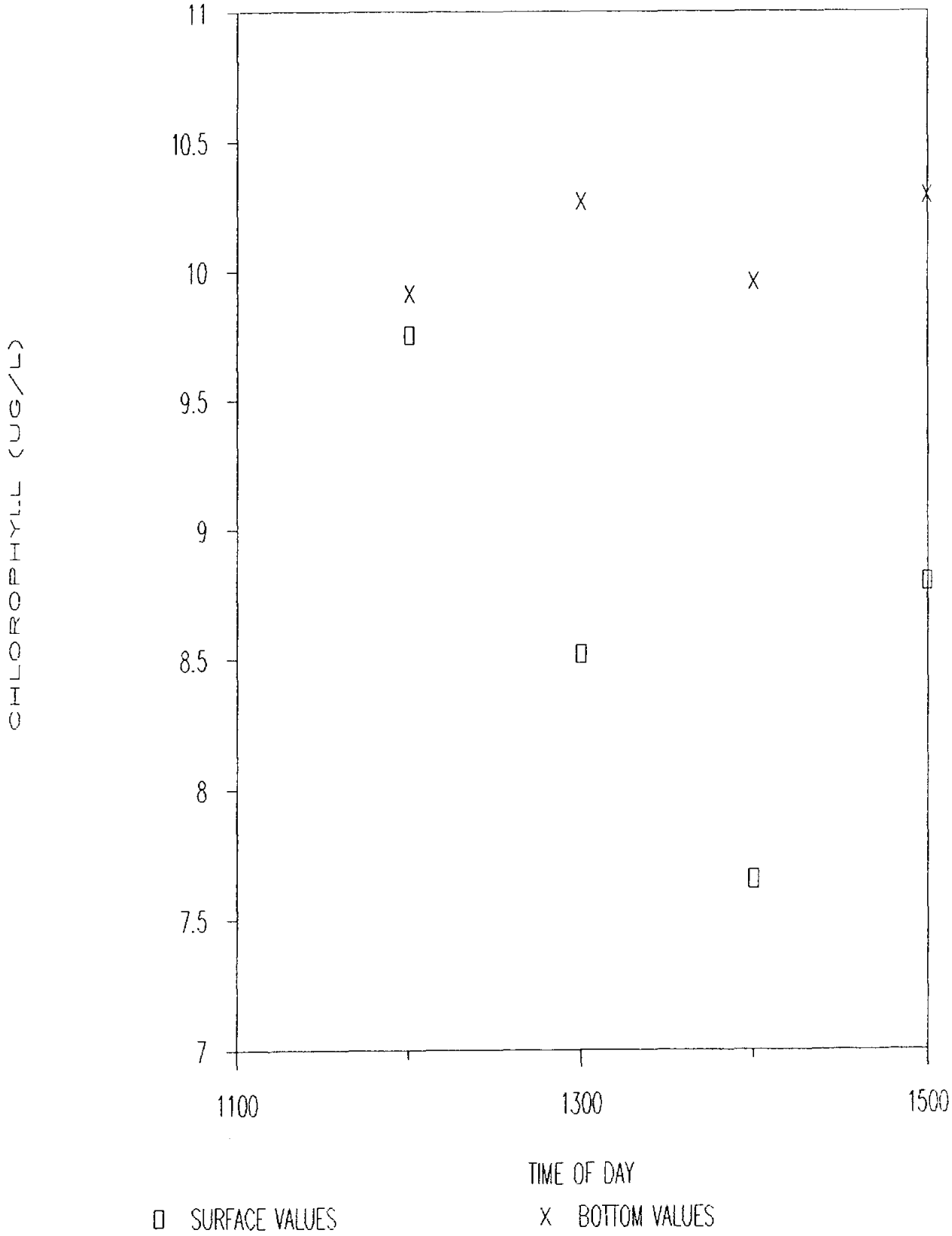

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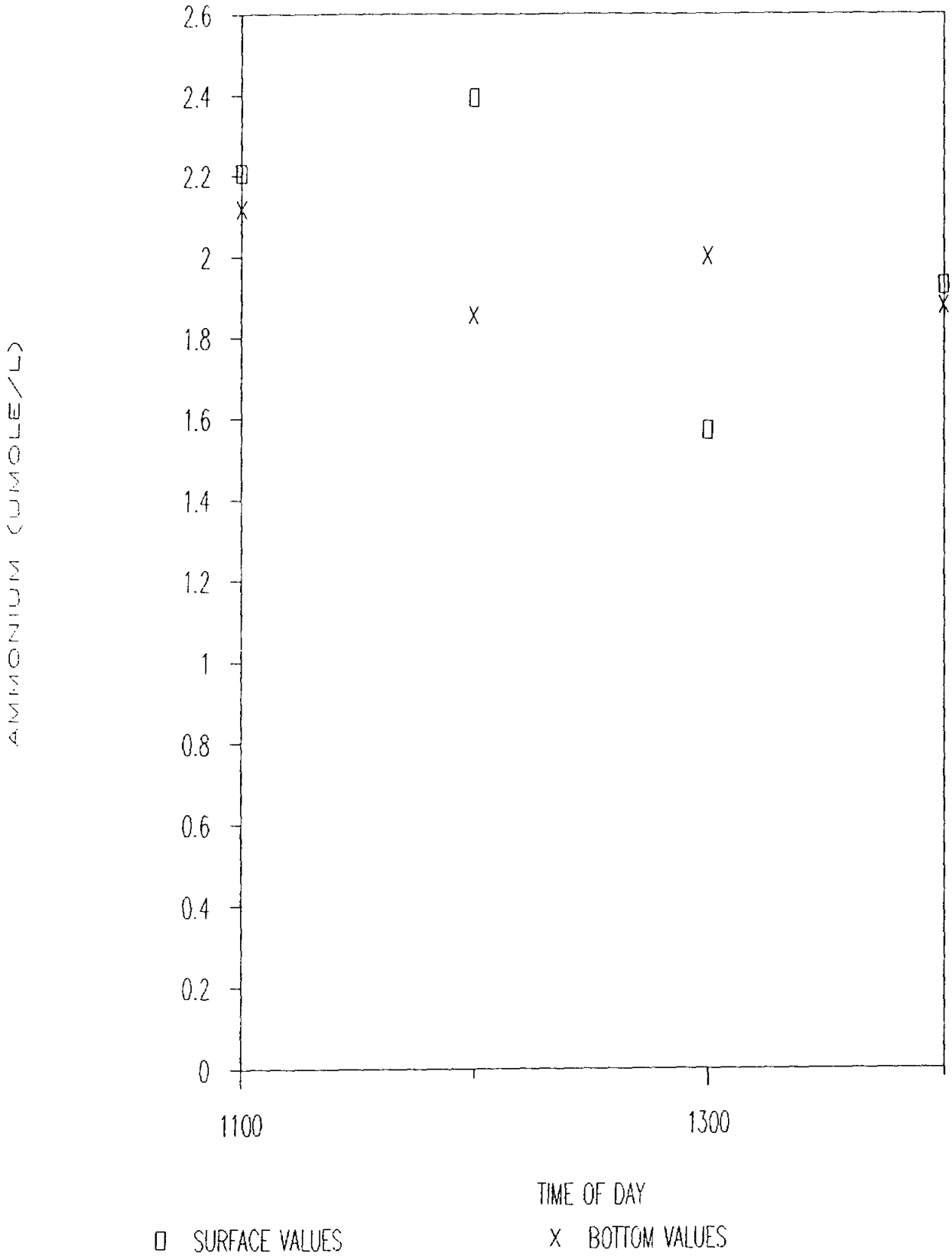

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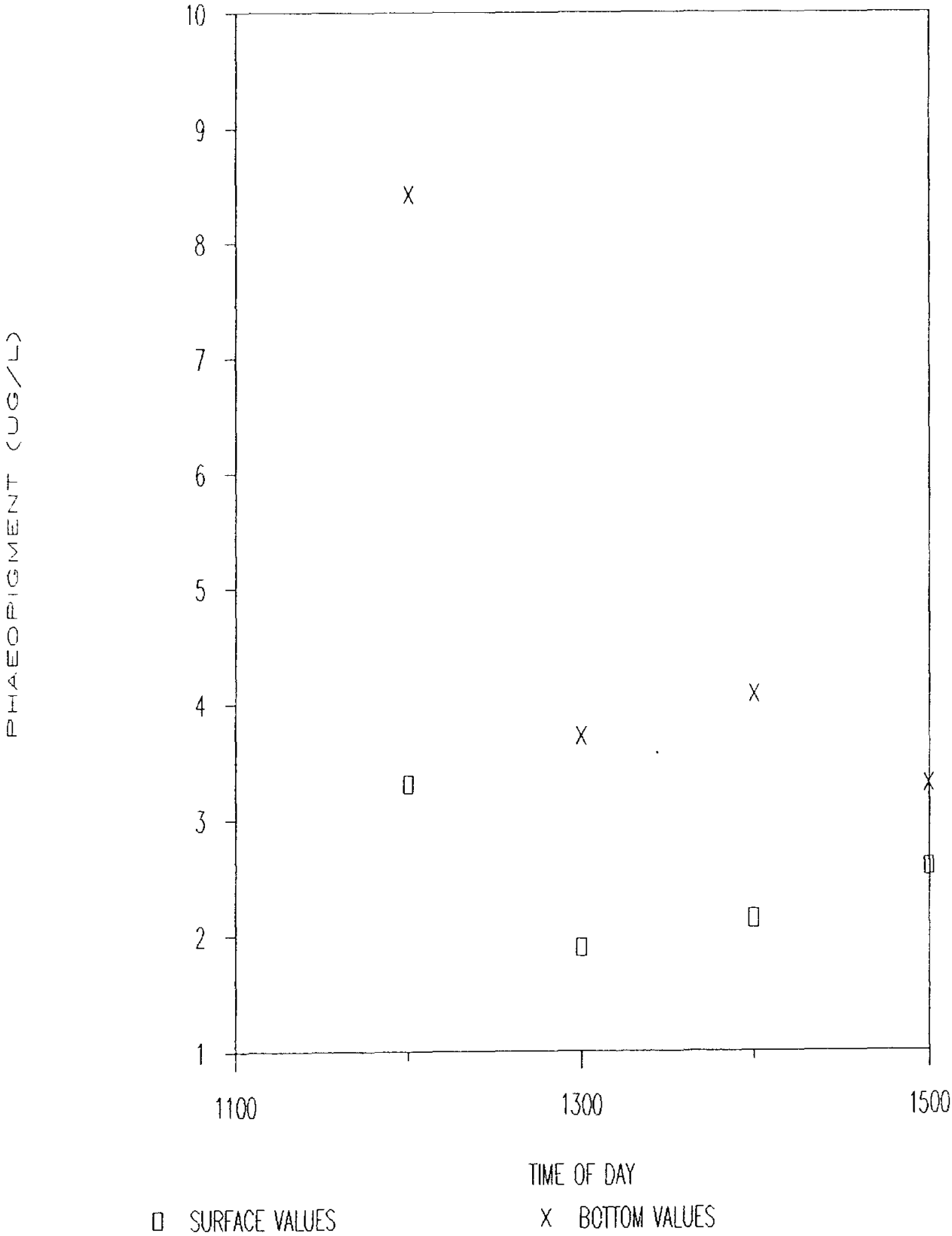

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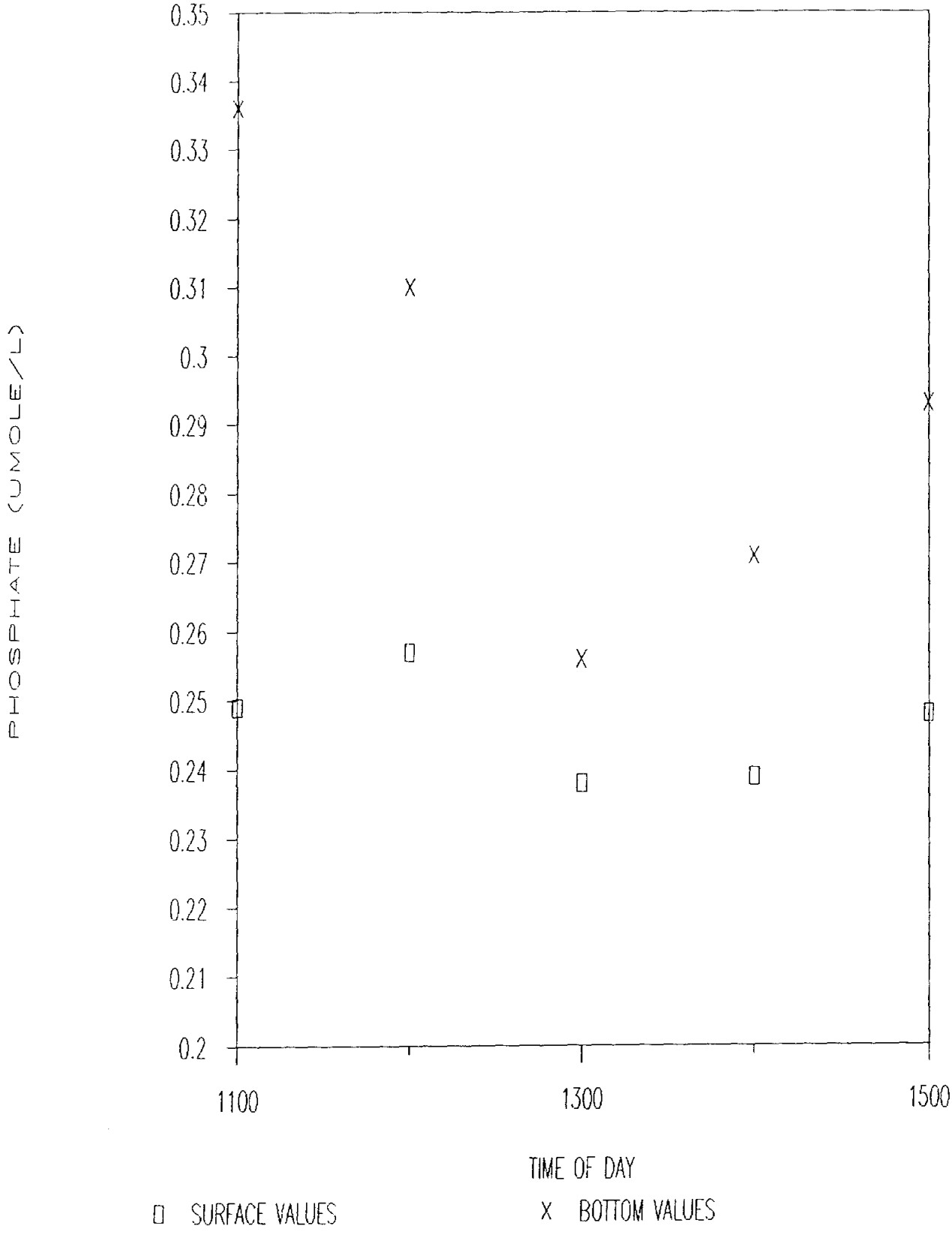

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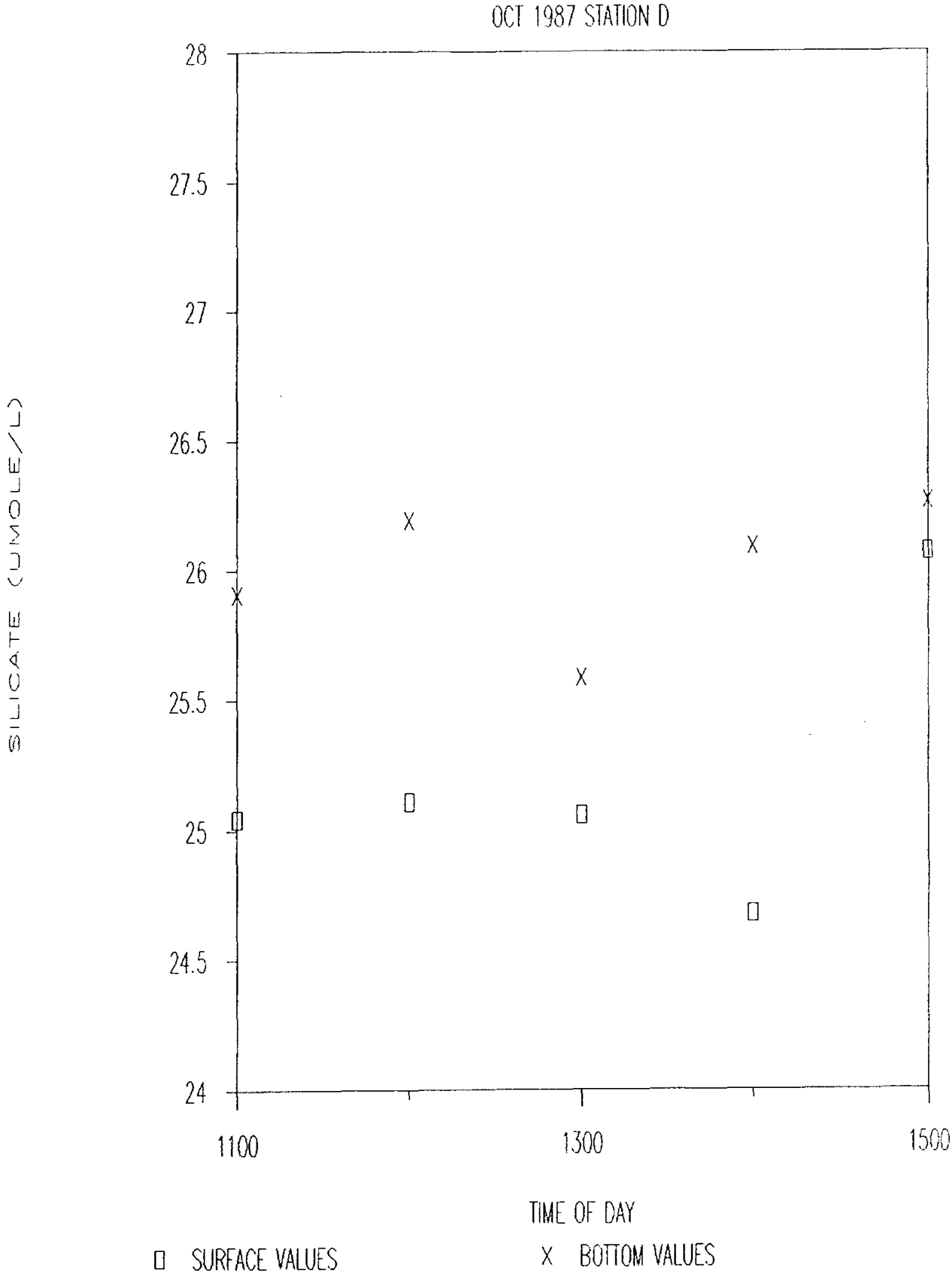

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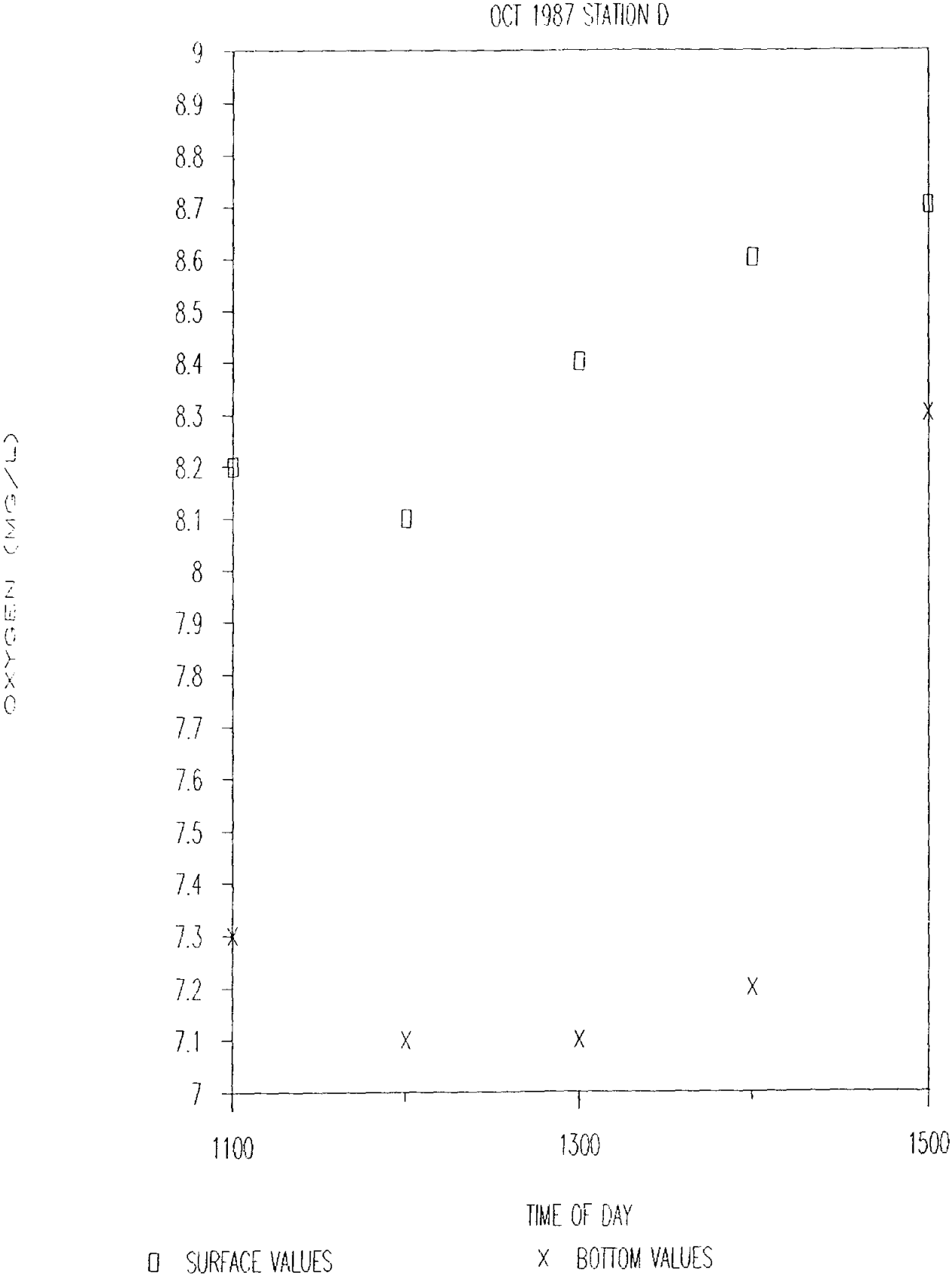

CORPUS CHRISTI/NUECES BAYS

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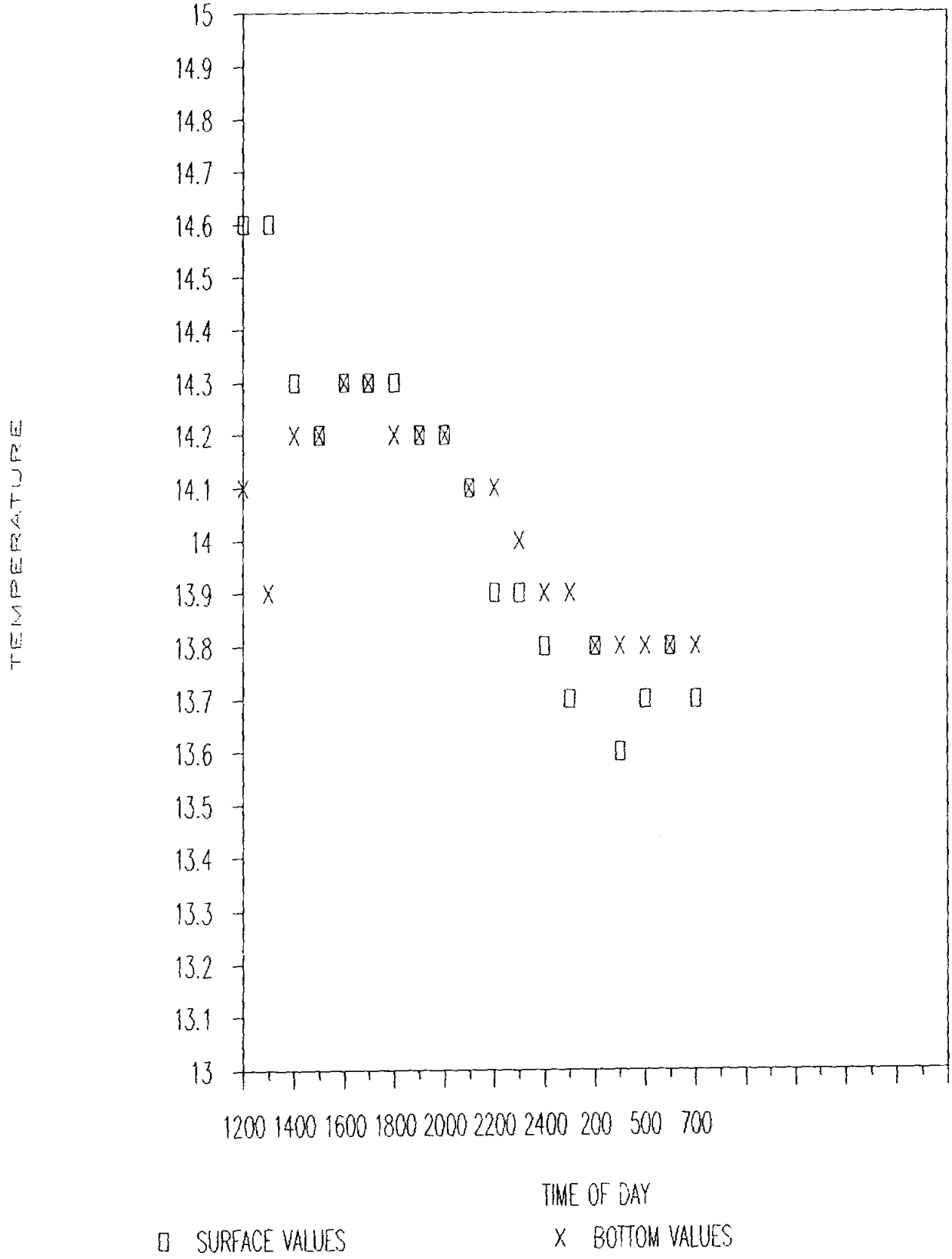

CORPUS CHRISTI/NUECES BAYS

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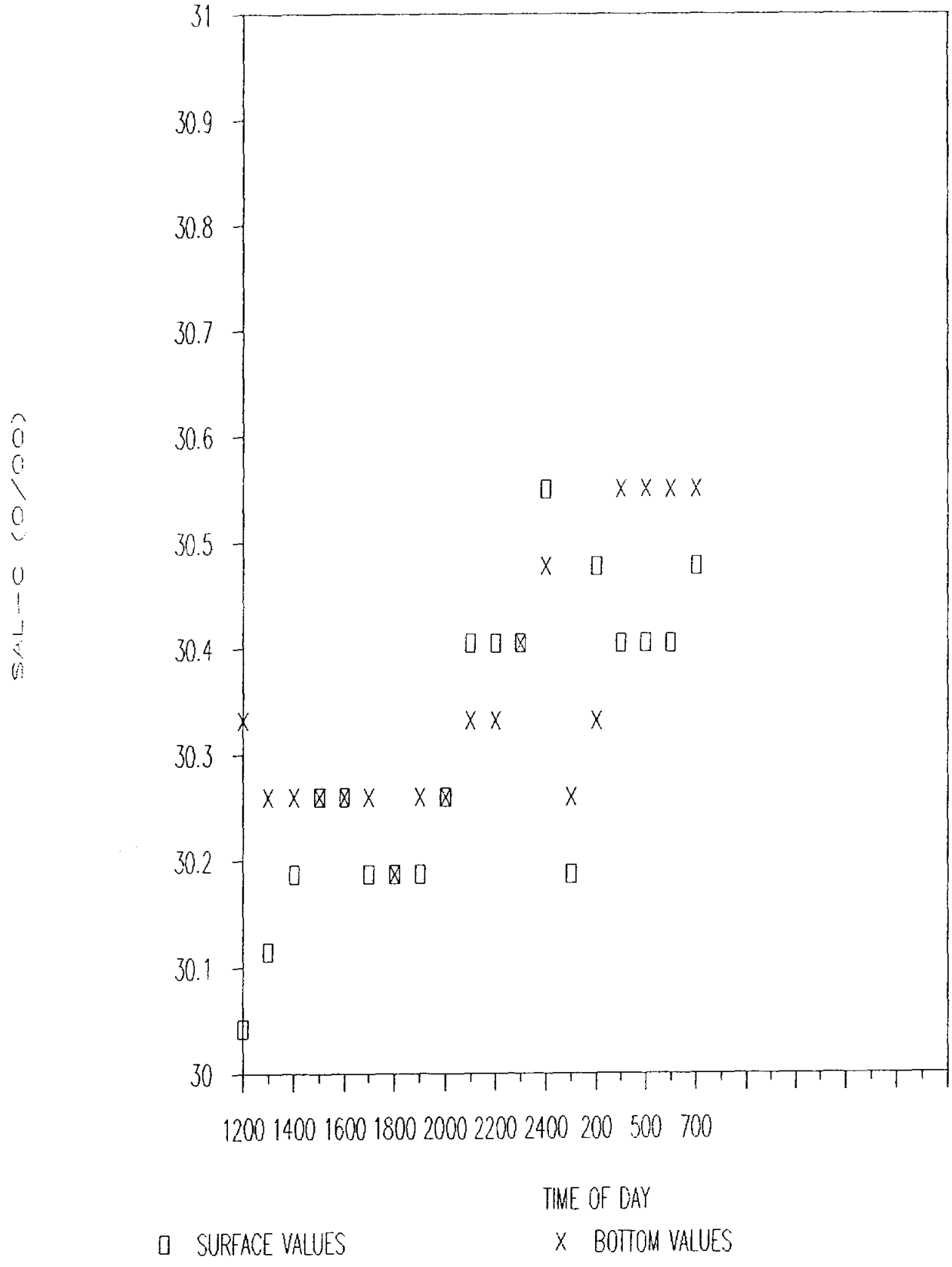

CORPUS CHRISTI/NUECES BAYS

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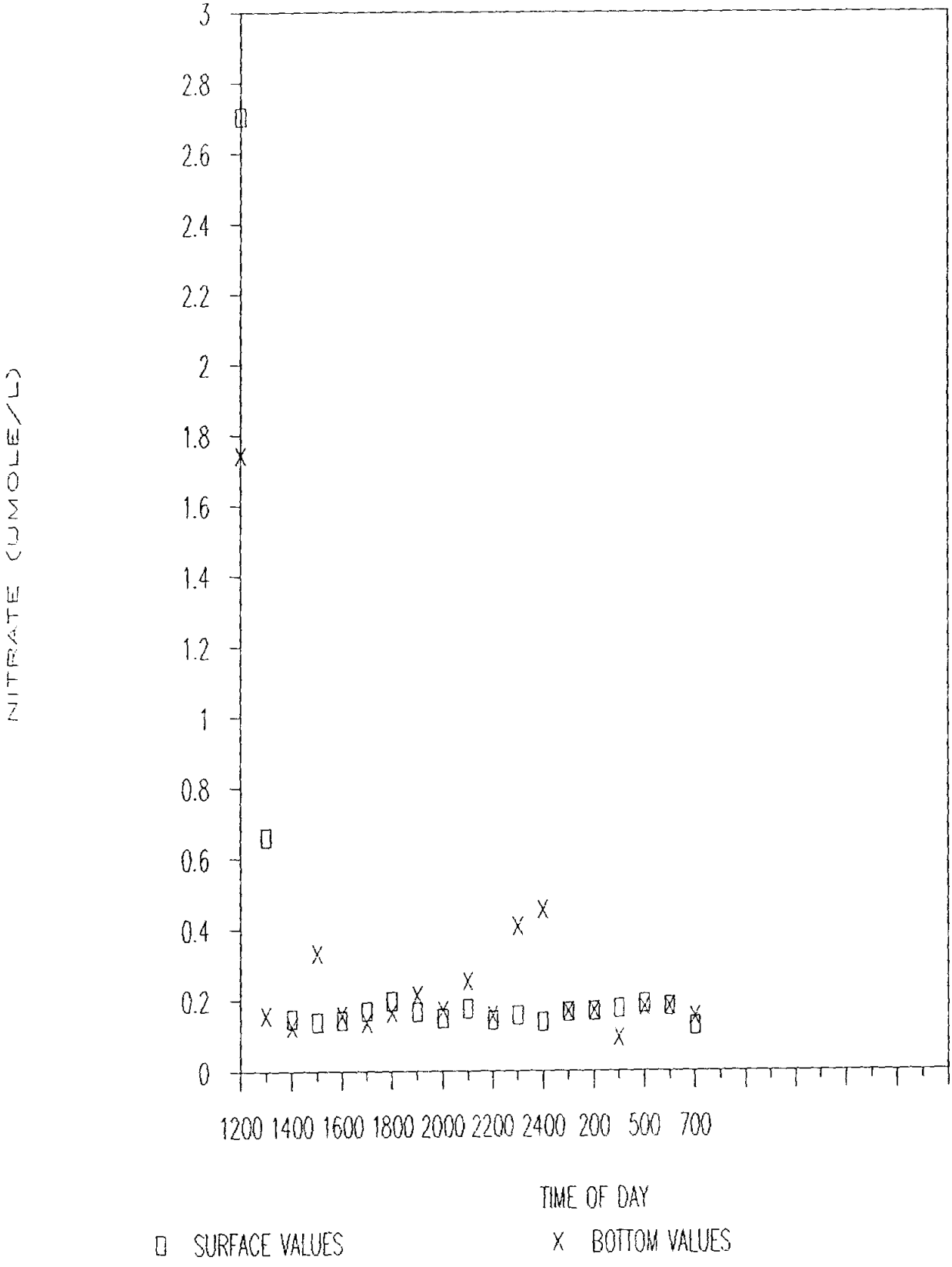

CORPUS CHRISTI/NUECES BAYS

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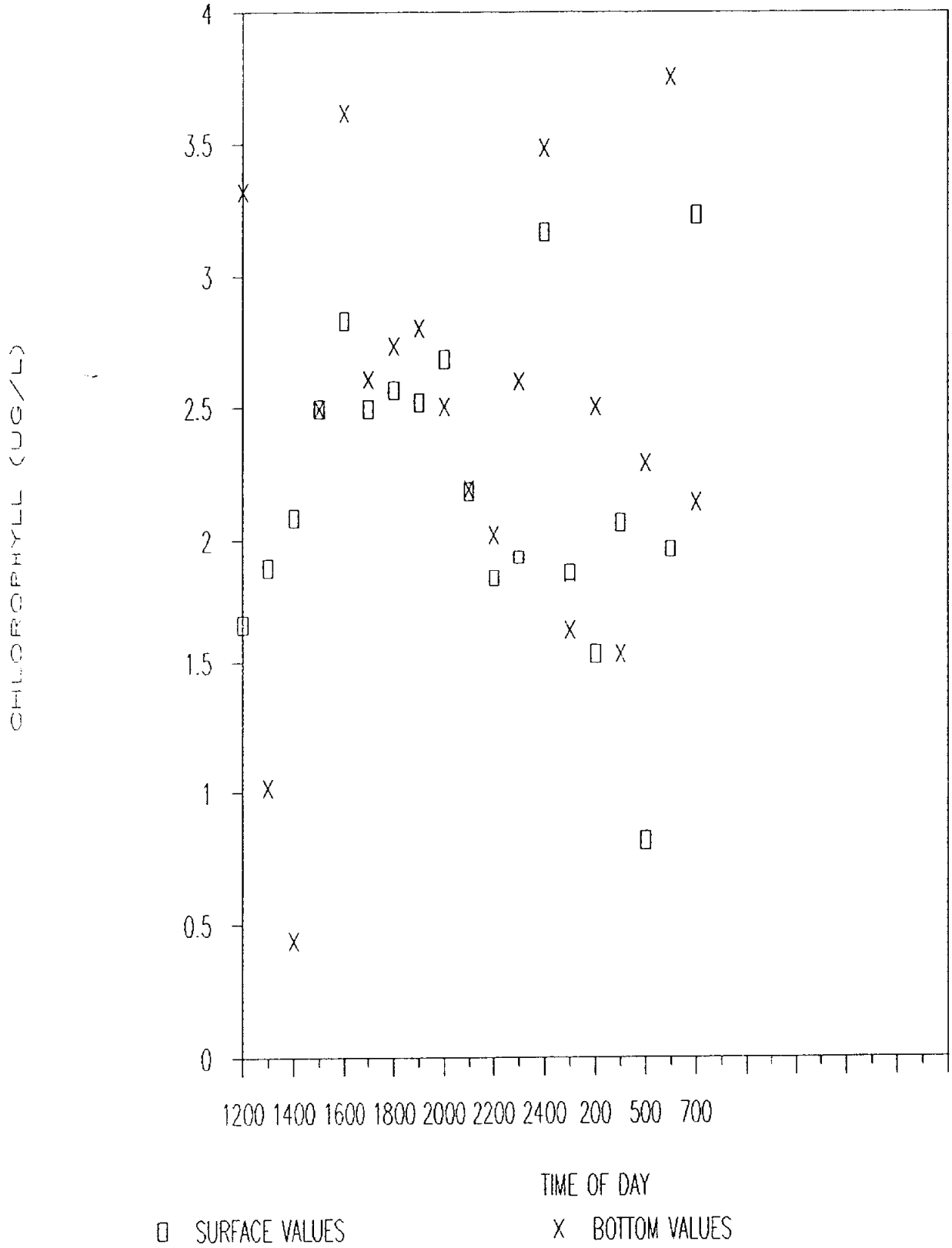

CORPUS CHRISTI/NUECES BAYS

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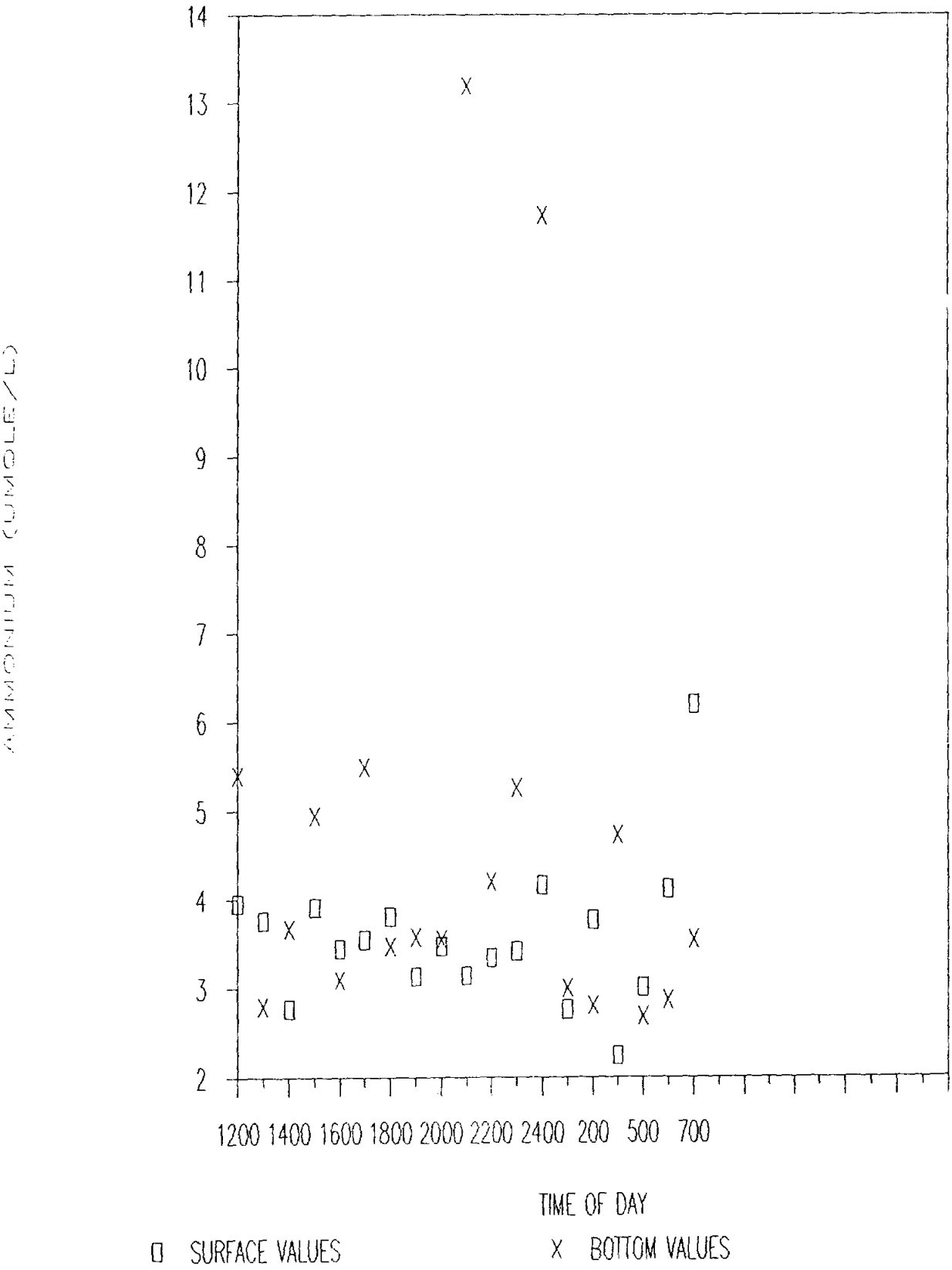

CORPUS CHRISTI/NUECES BAYS

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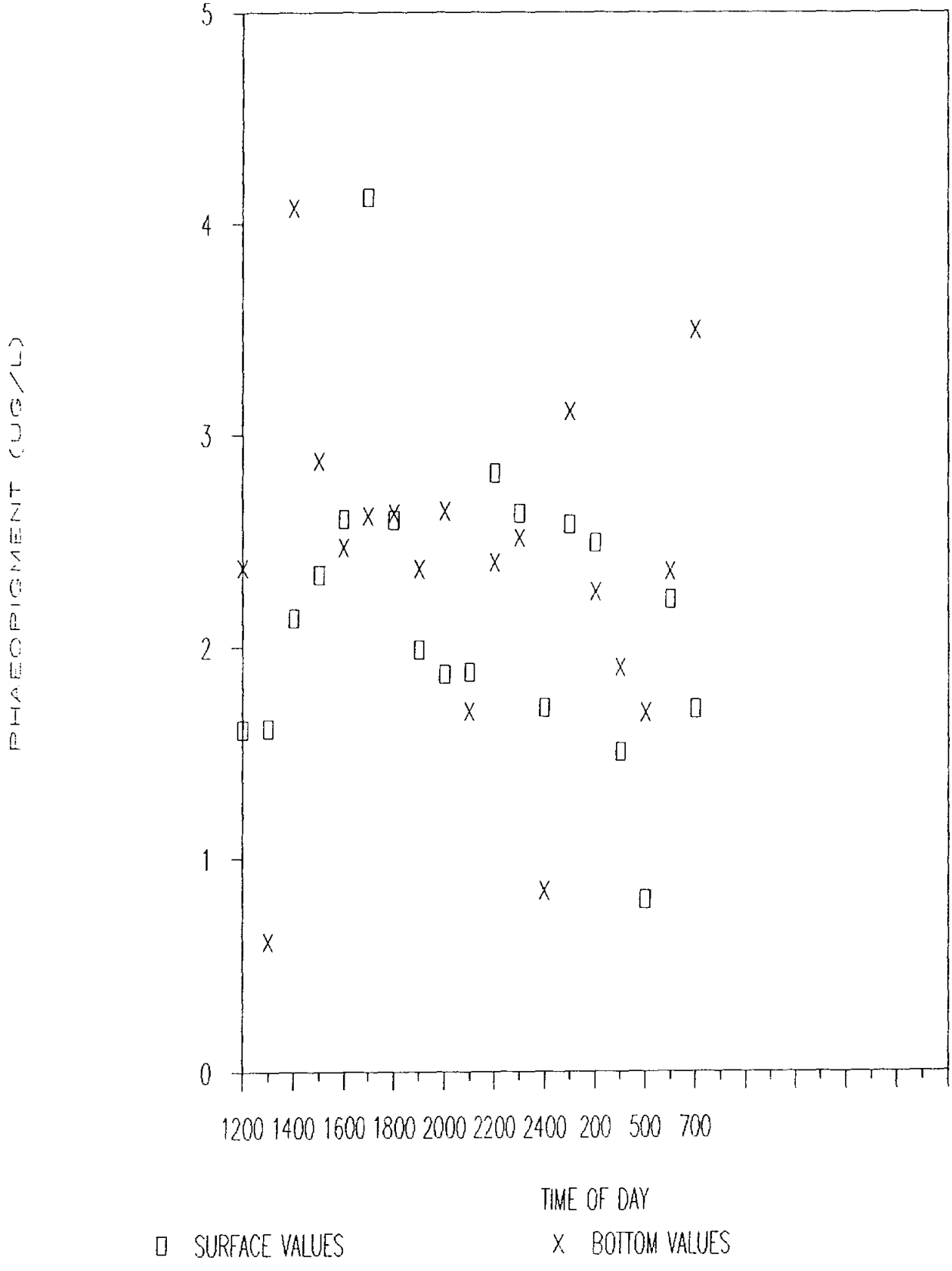

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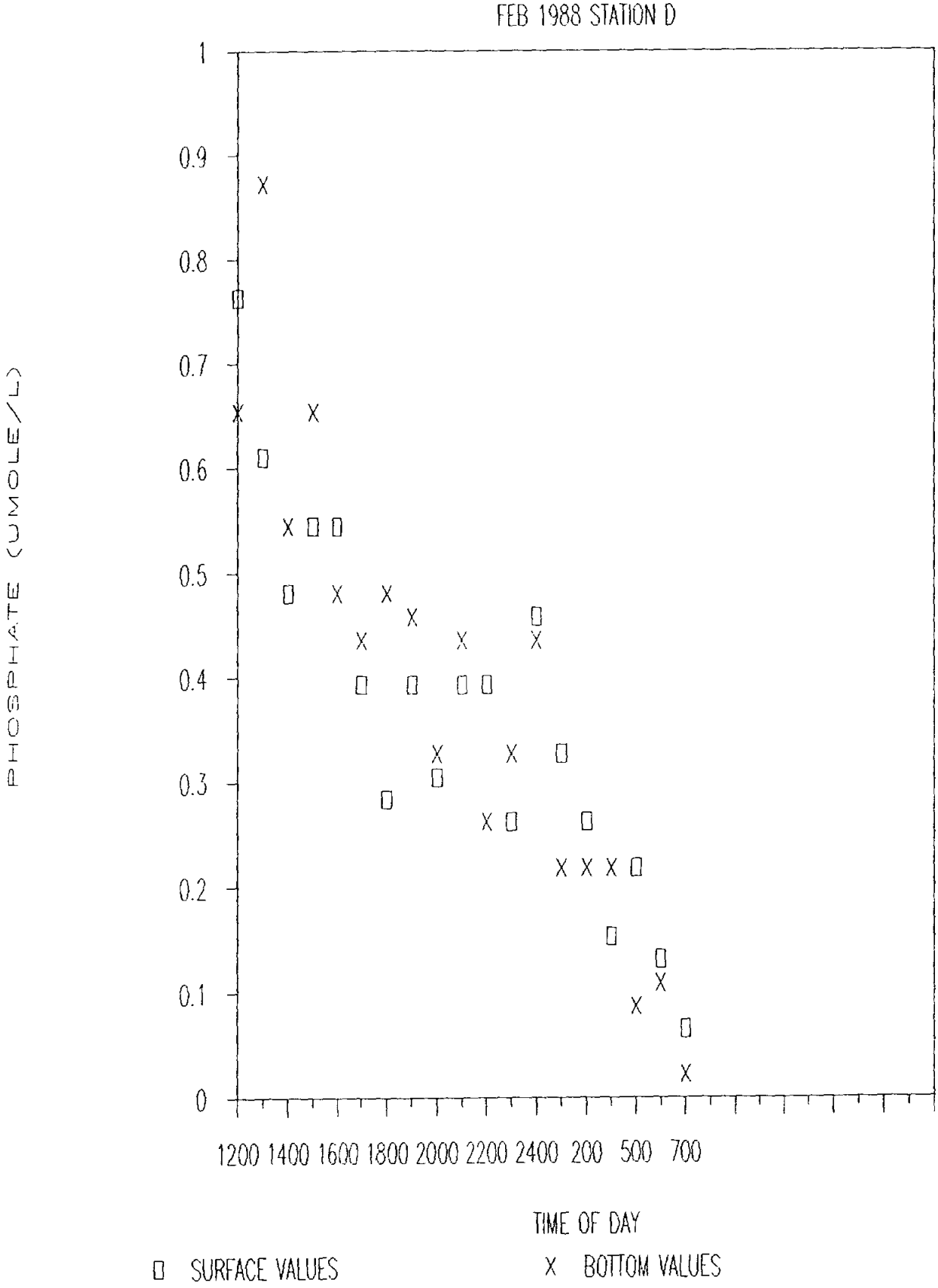

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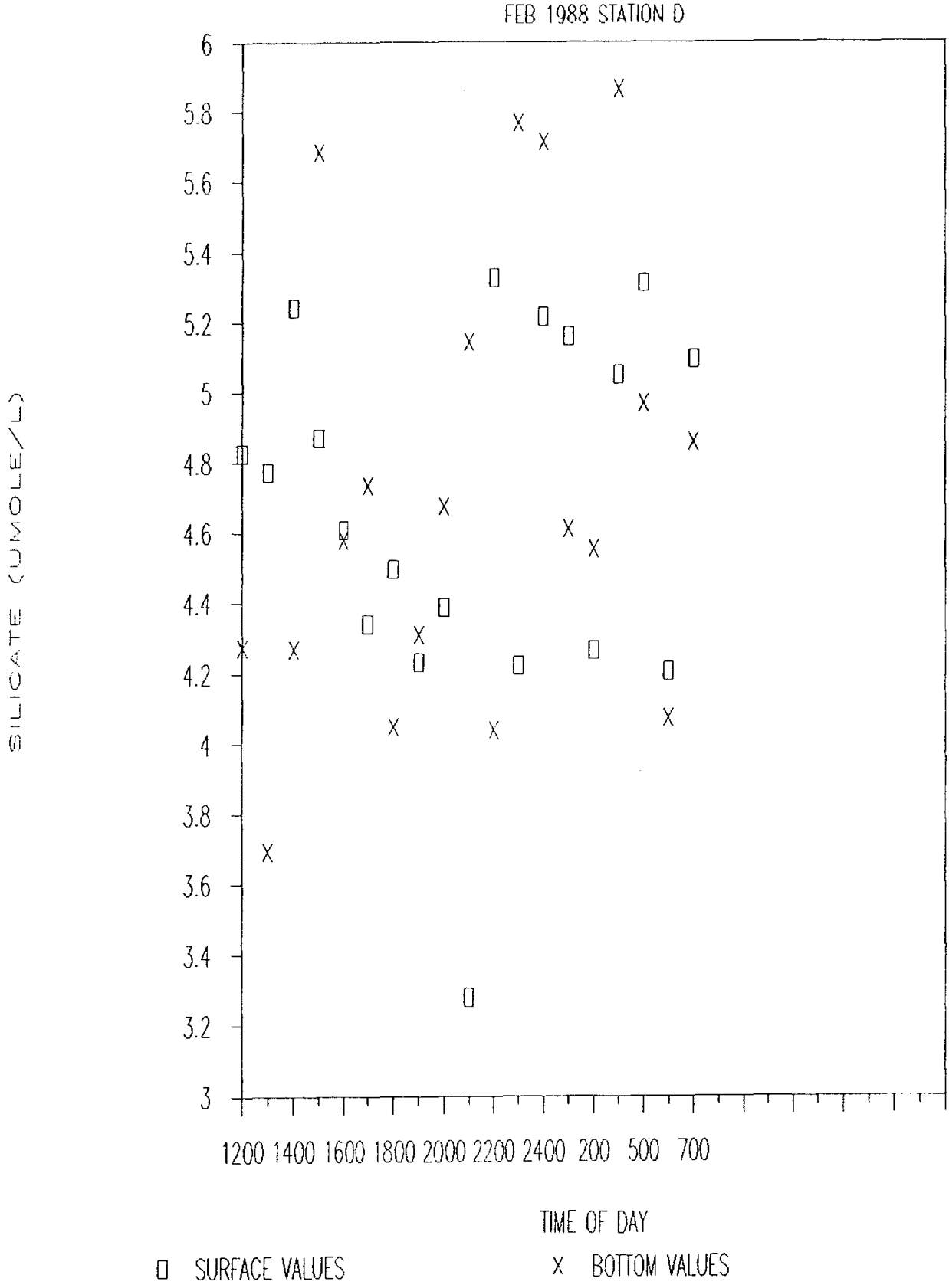

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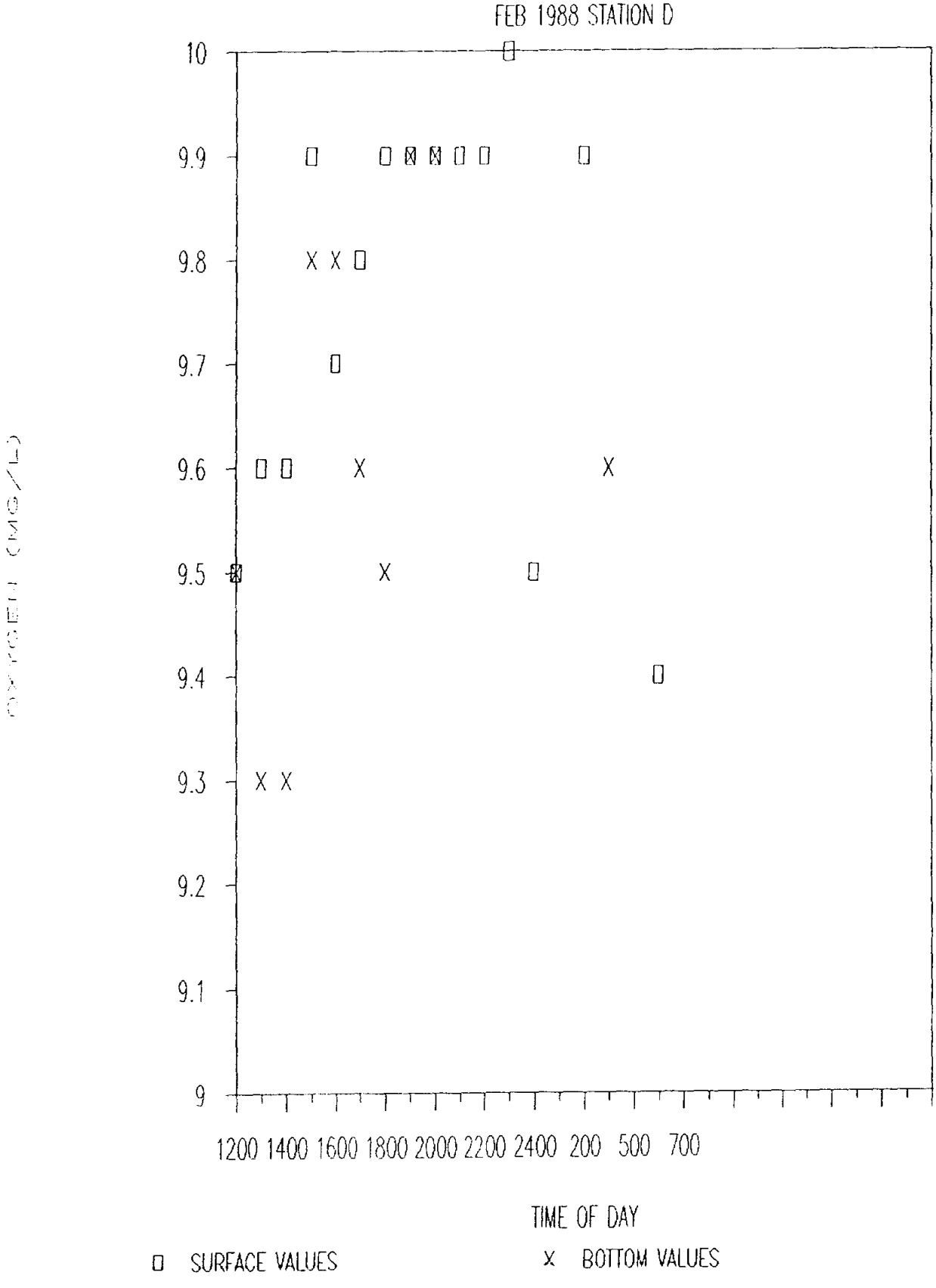

CORPUS CHRISTI/NUECES BAYS

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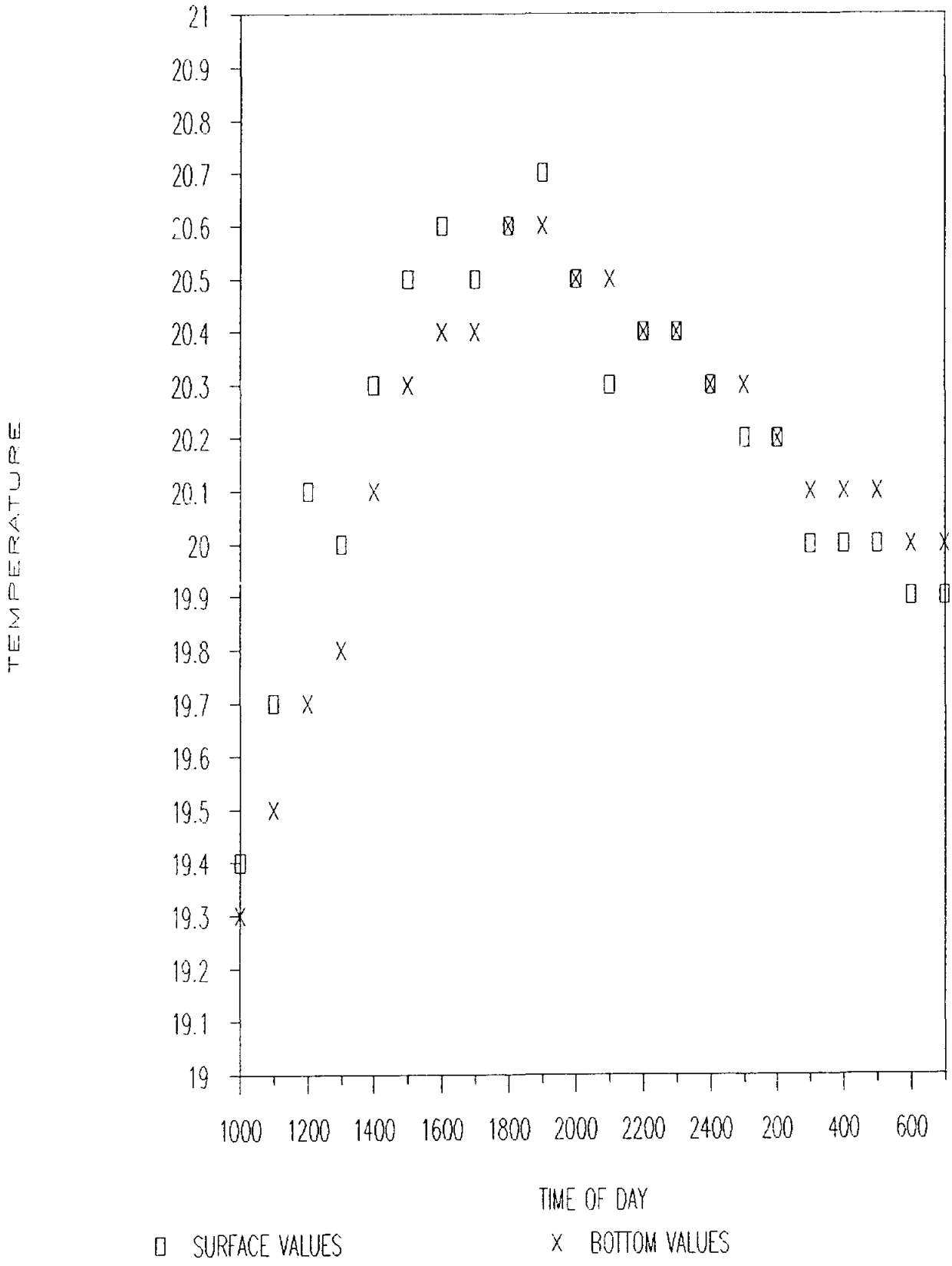

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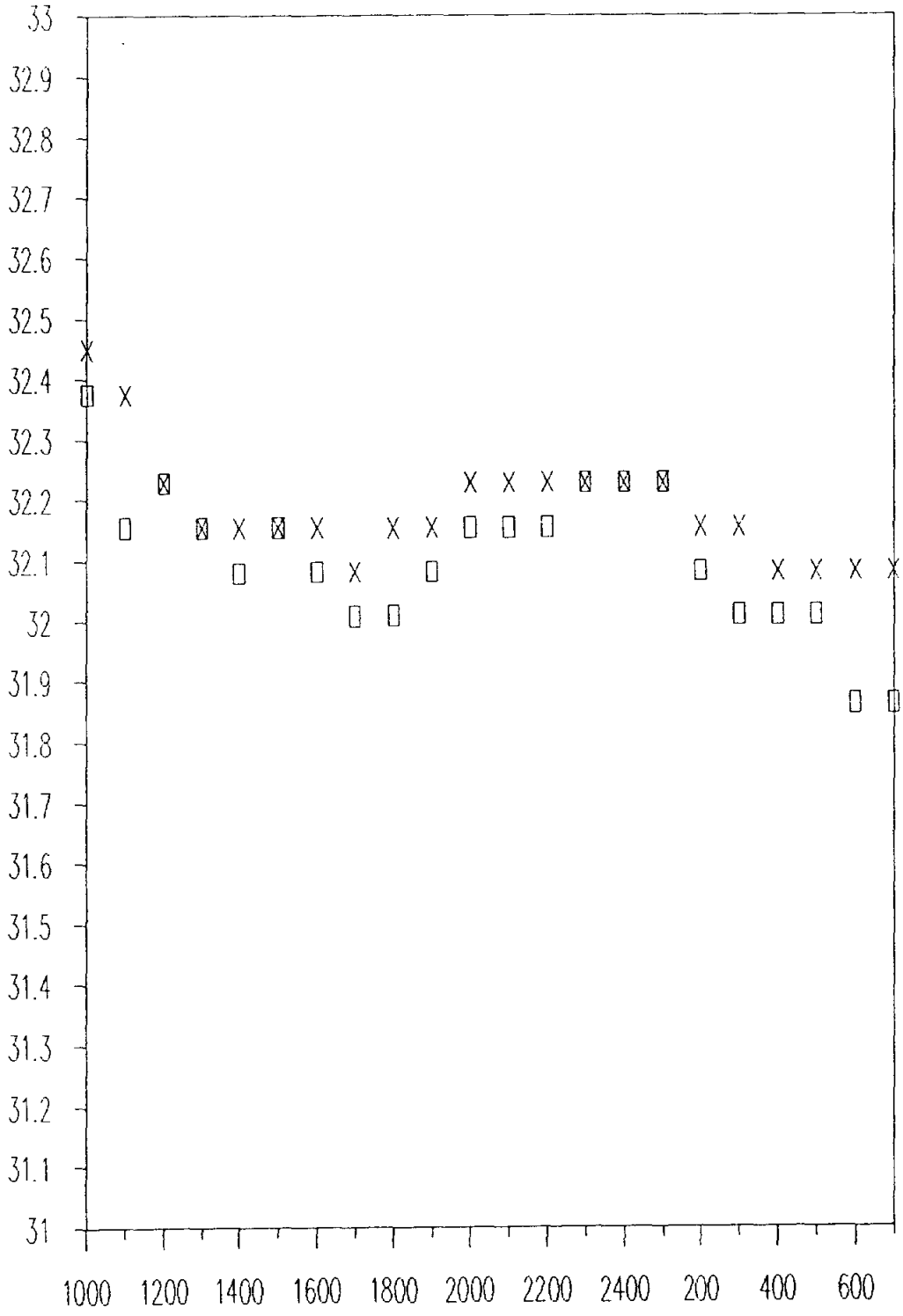

CORPUS CHRISTI/NUECES BAYS

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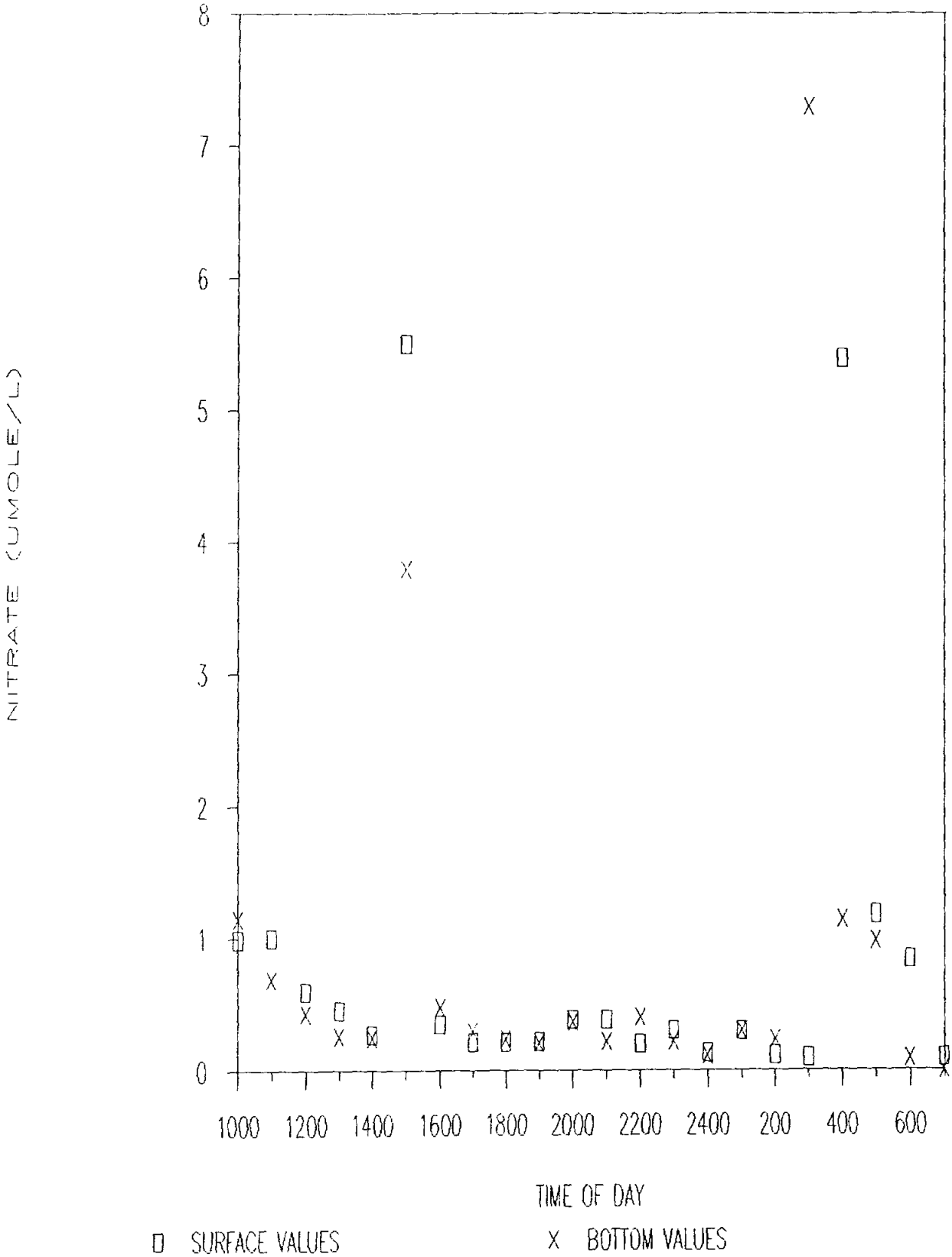

CORPUS CHRISTI/NUECES BAYS

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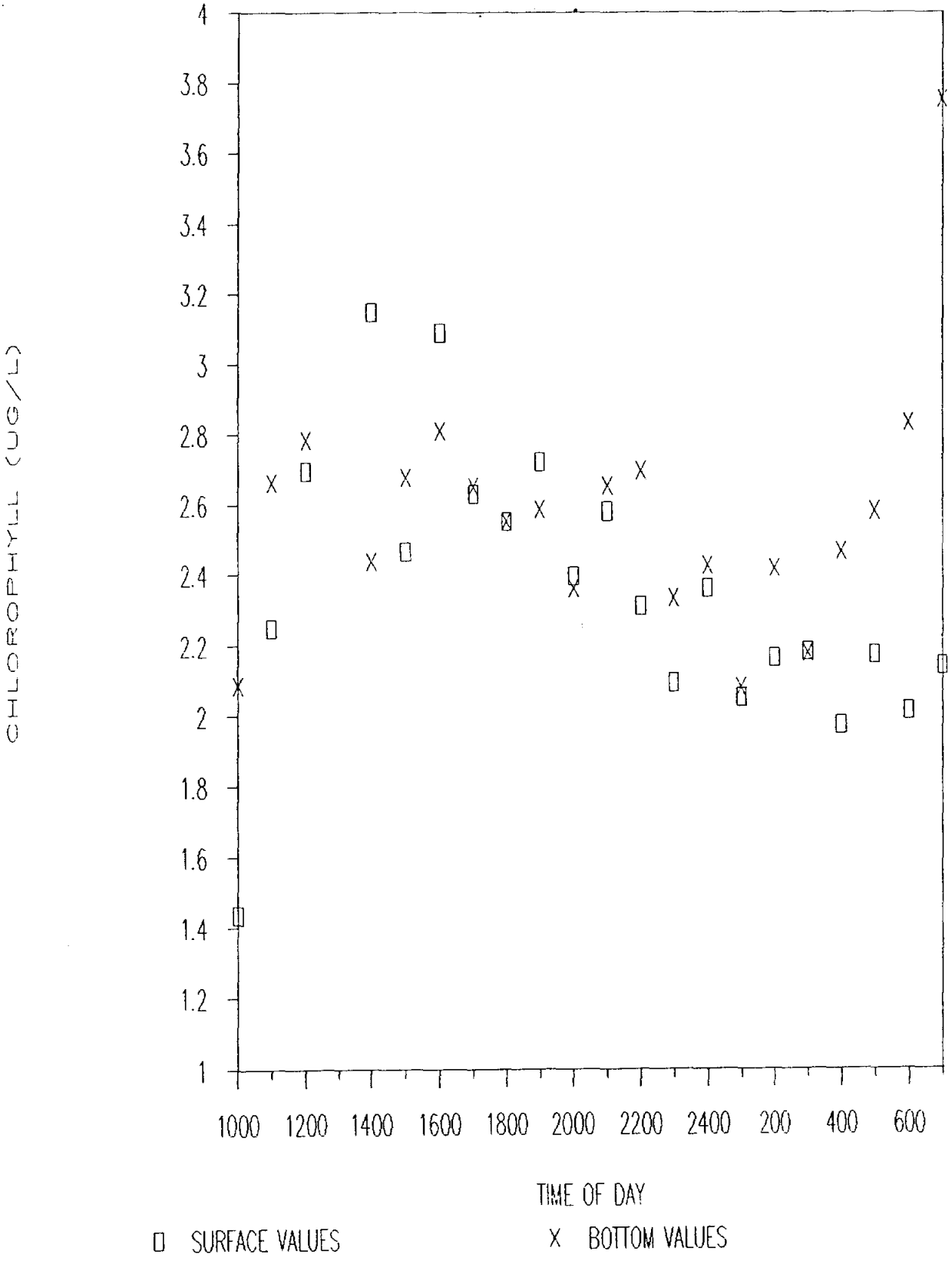

CORPUS CHRISTI/NUECES BAYS

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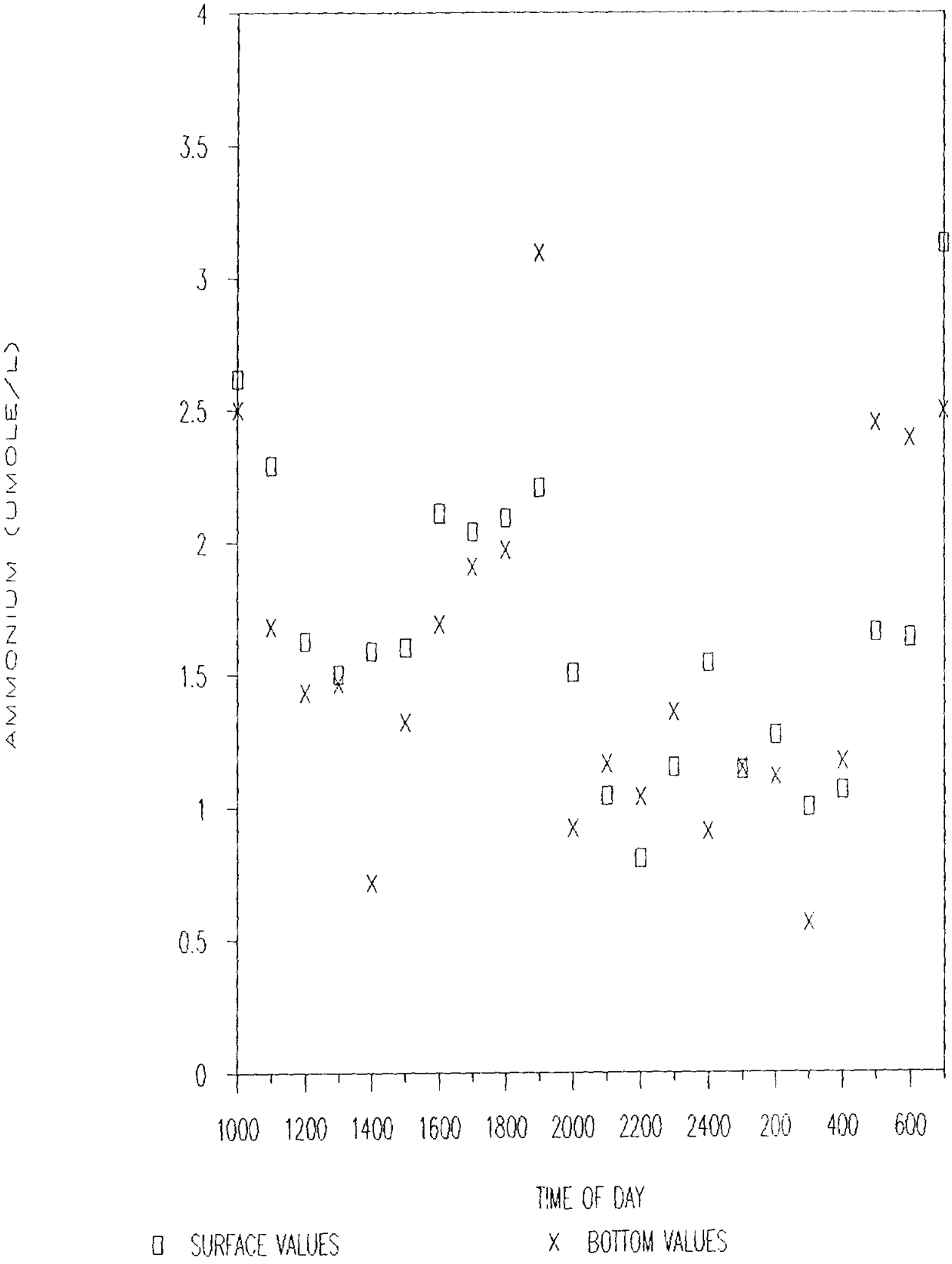

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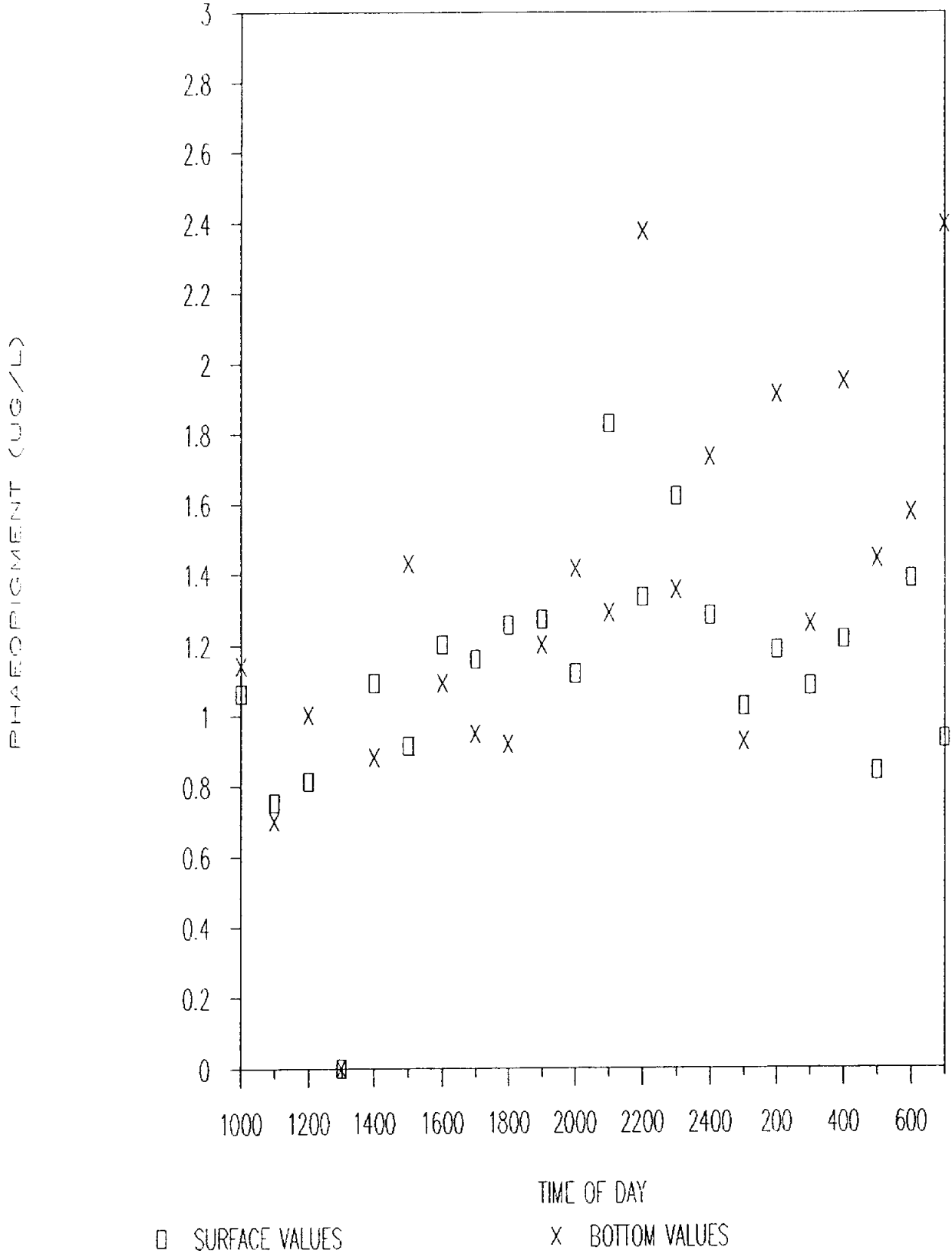

CORPUS CHRISTI/NUECES BAYS

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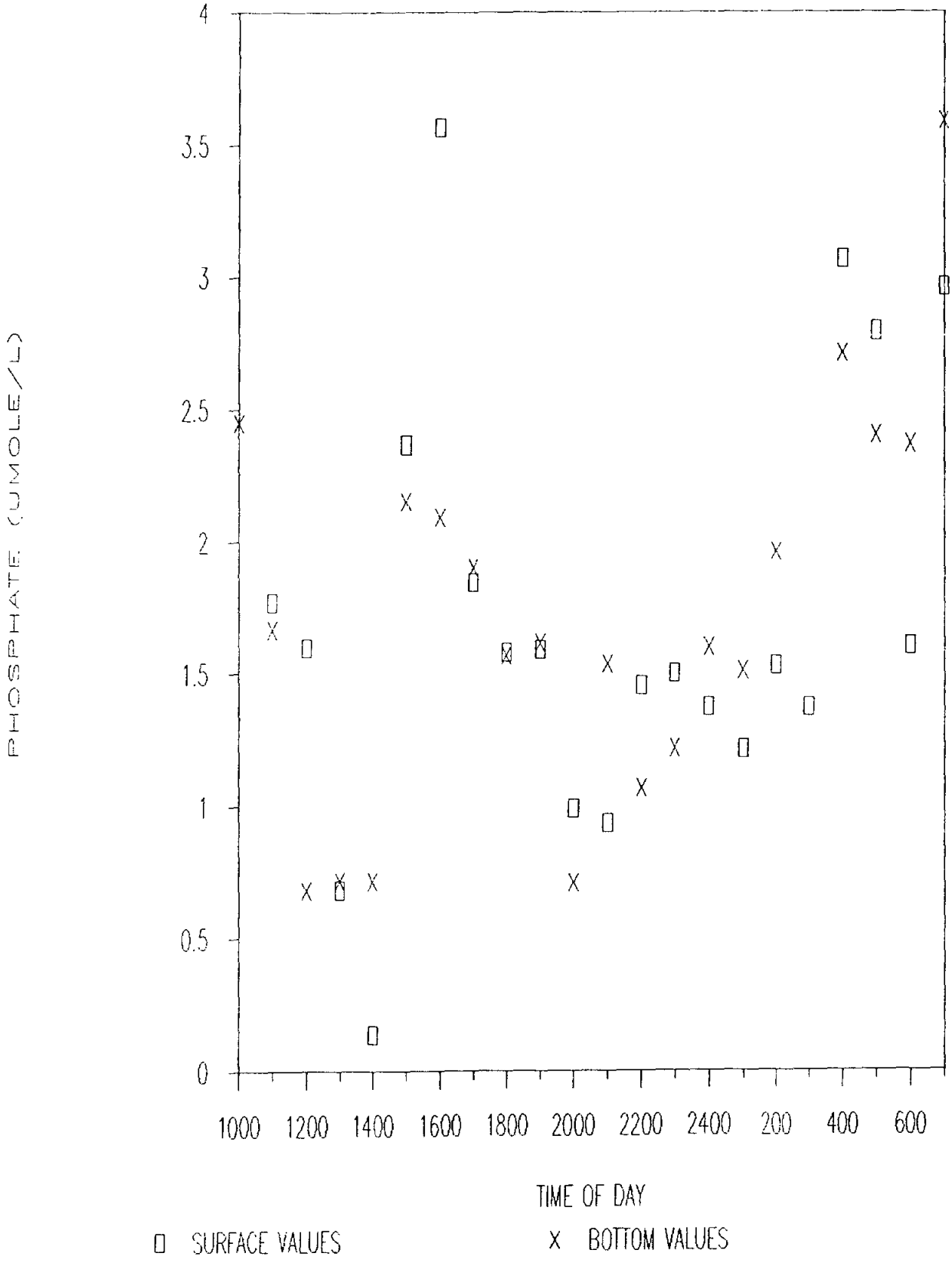

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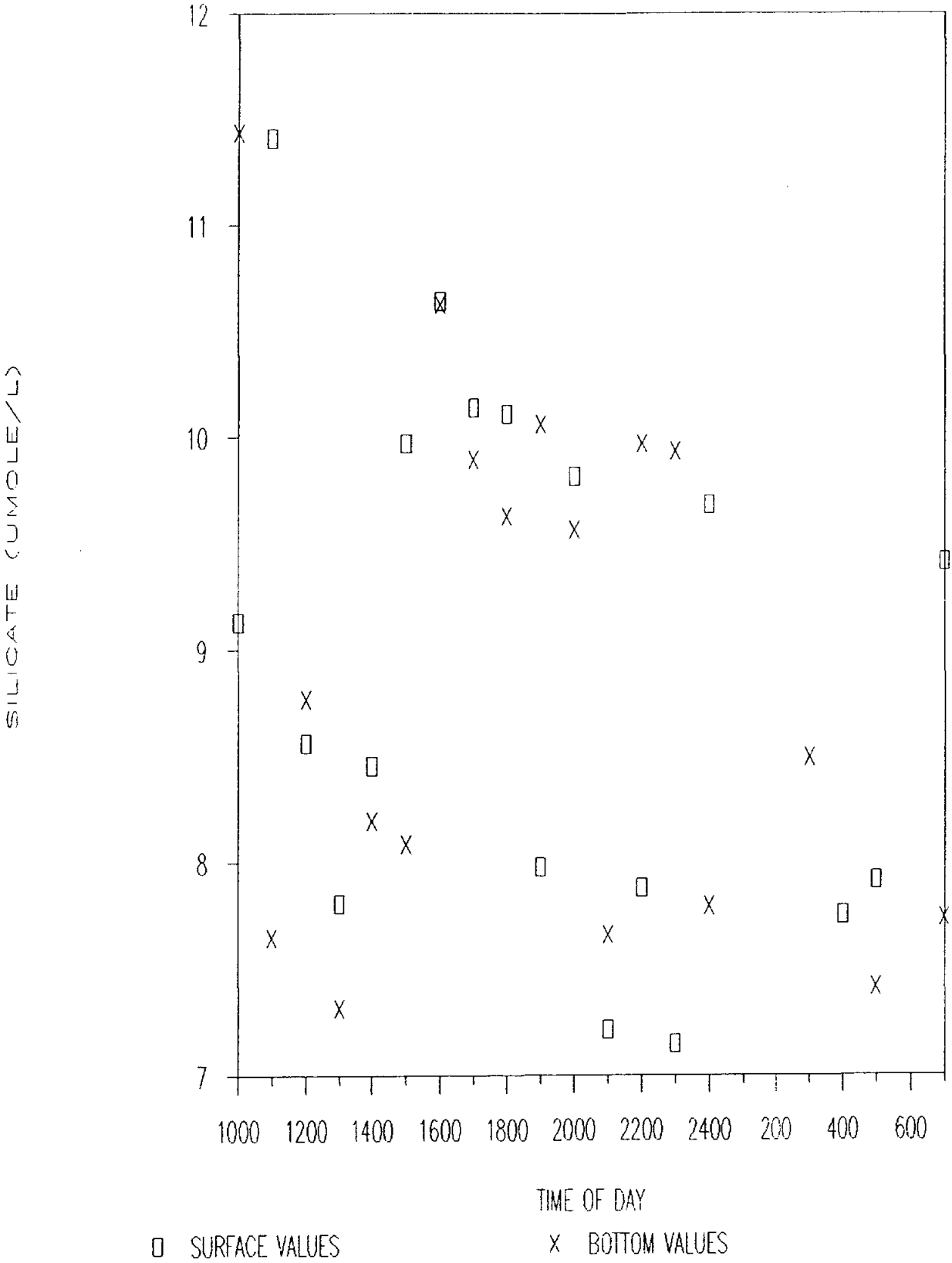
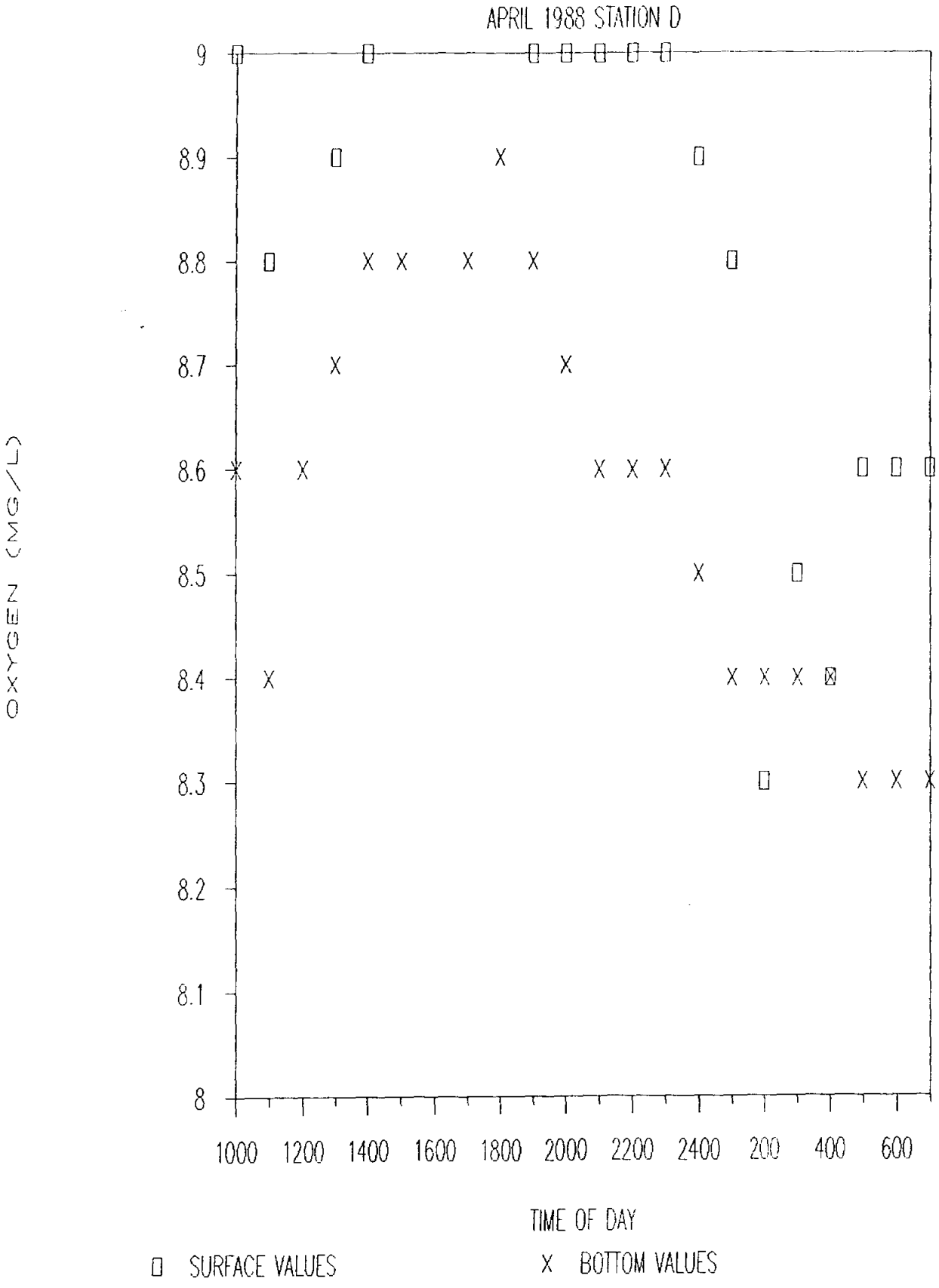
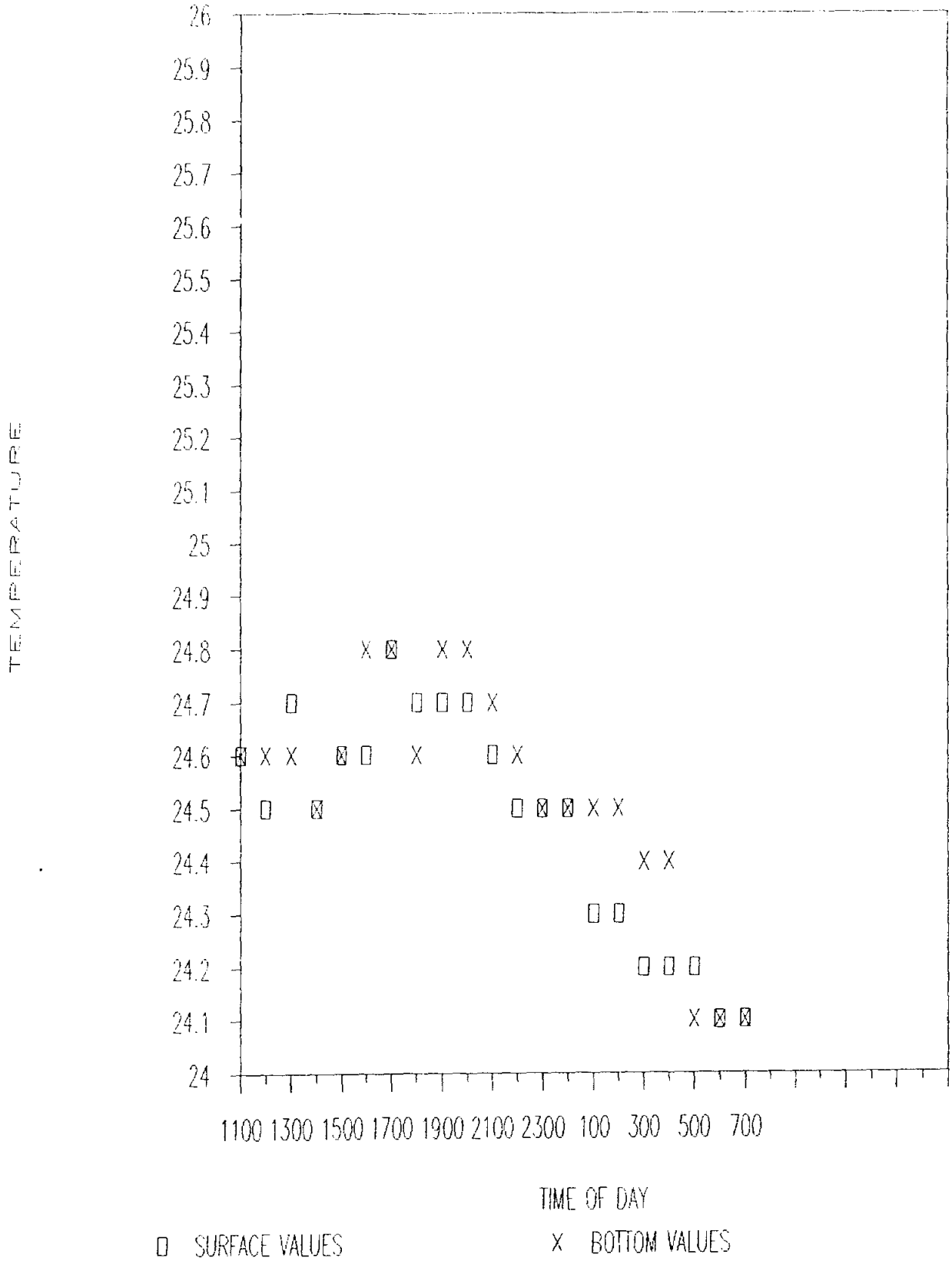


CORPUS CHRISTI/NUECES BAYS



CORPUS CHRISTI/NUECES BAYS

MAY 1988 STATION D



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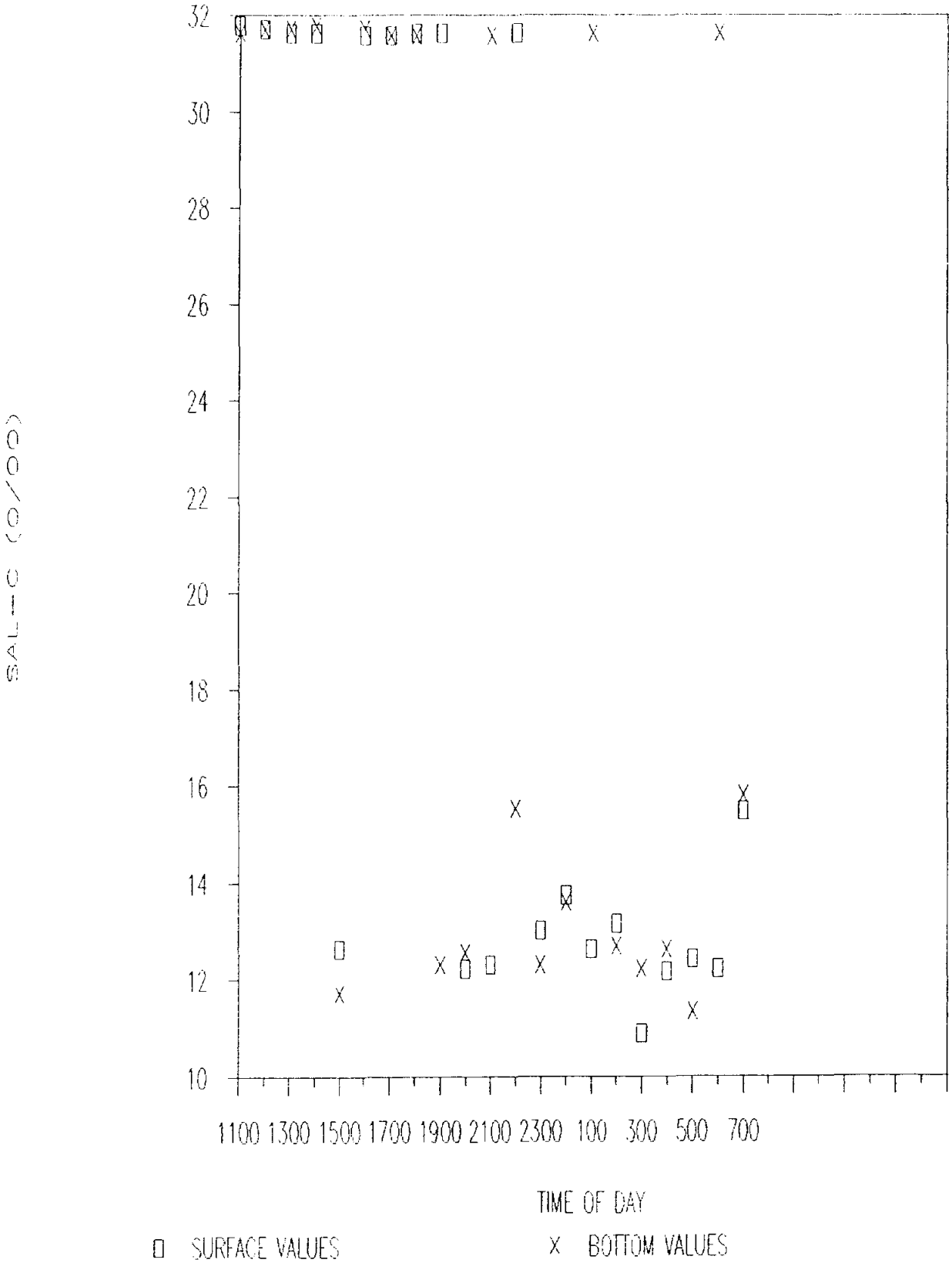

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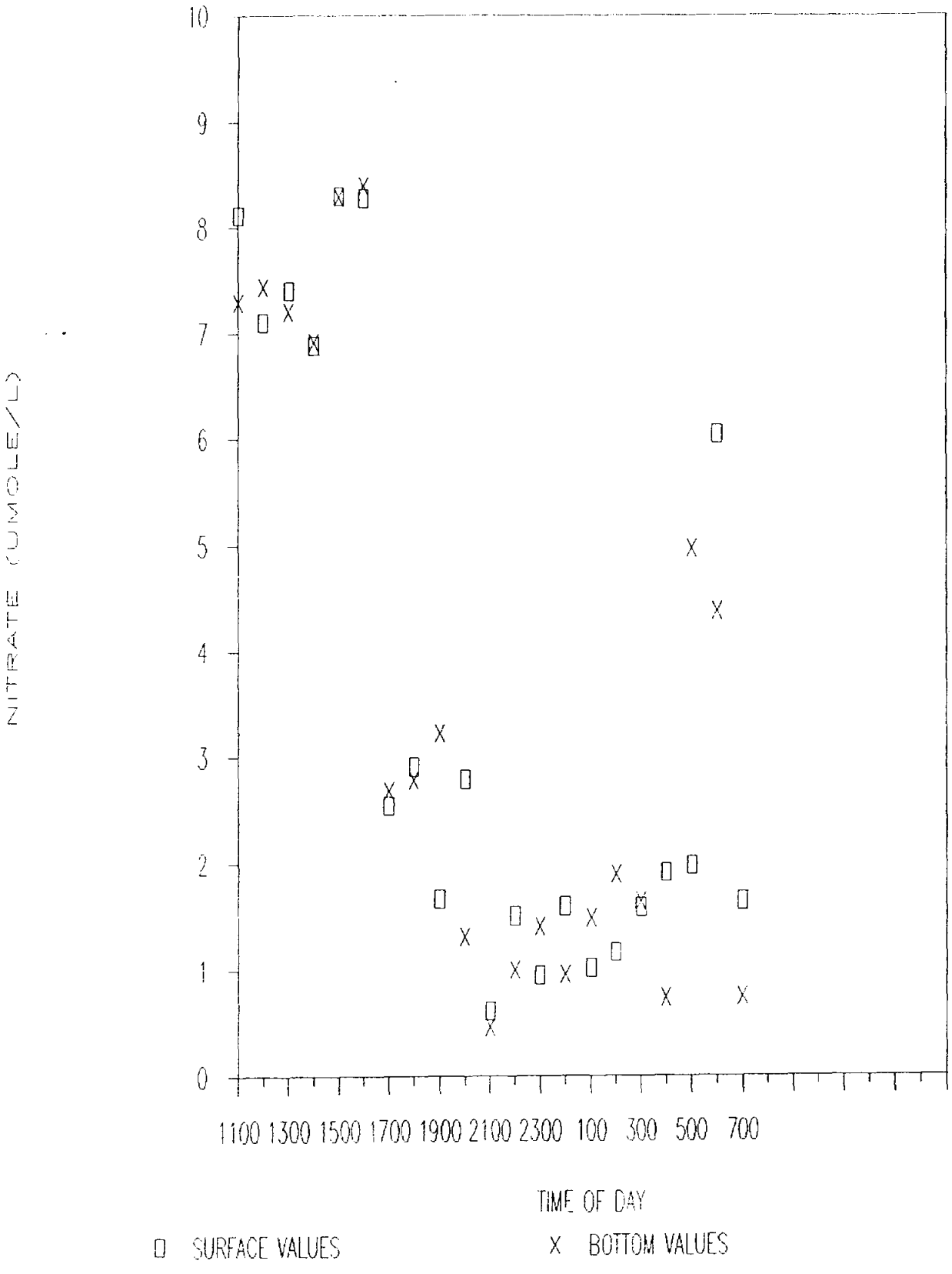

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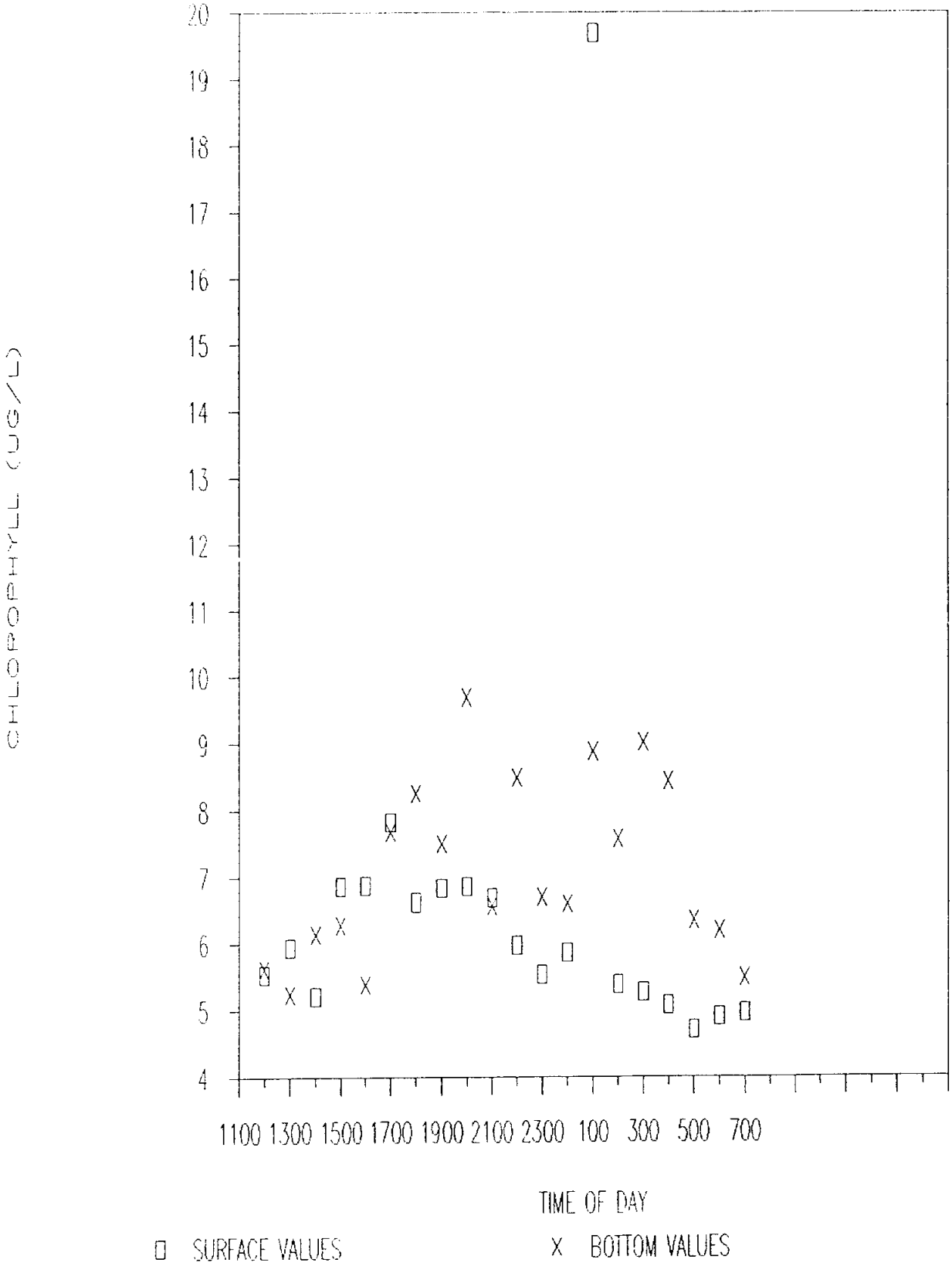

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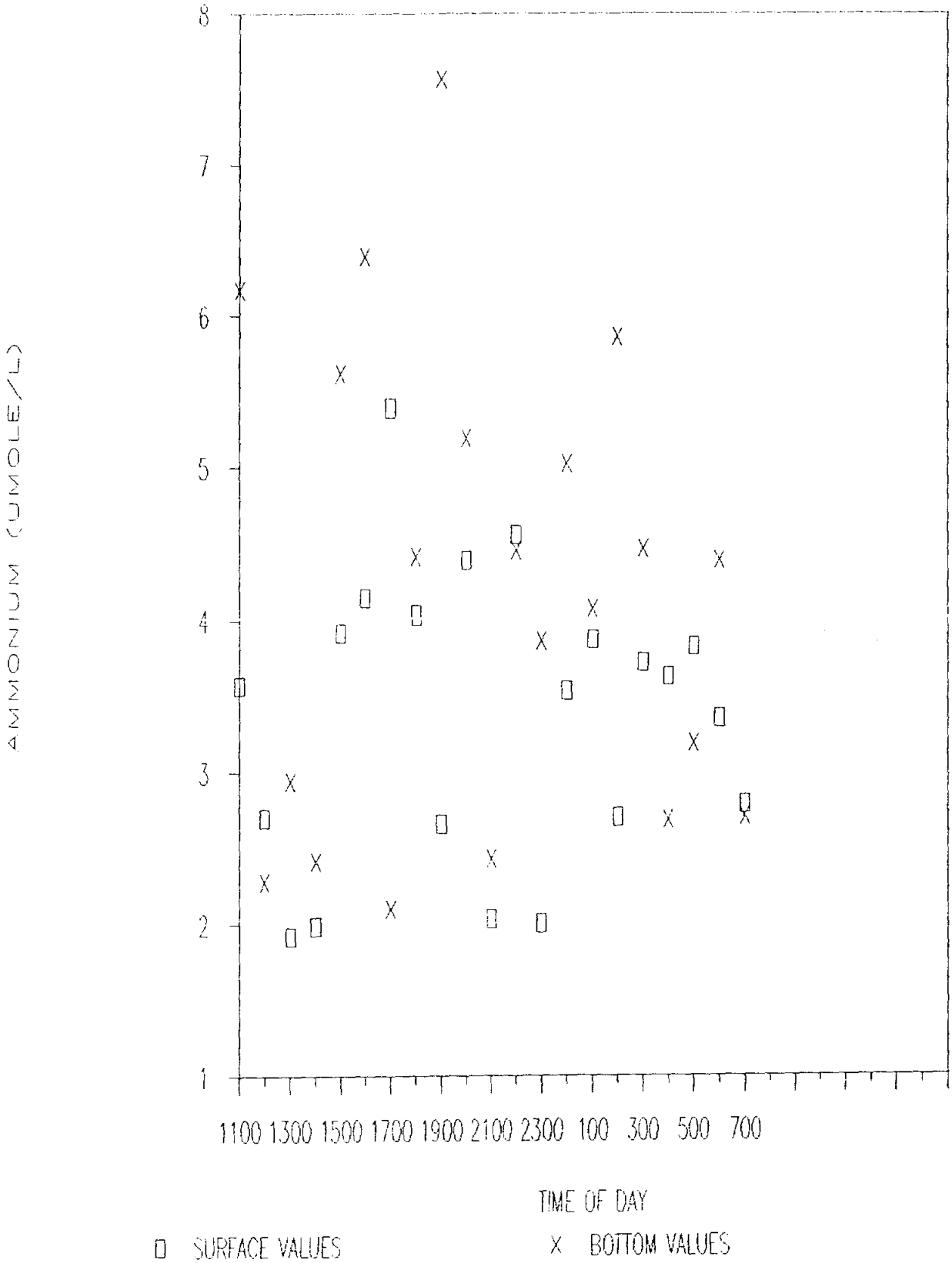

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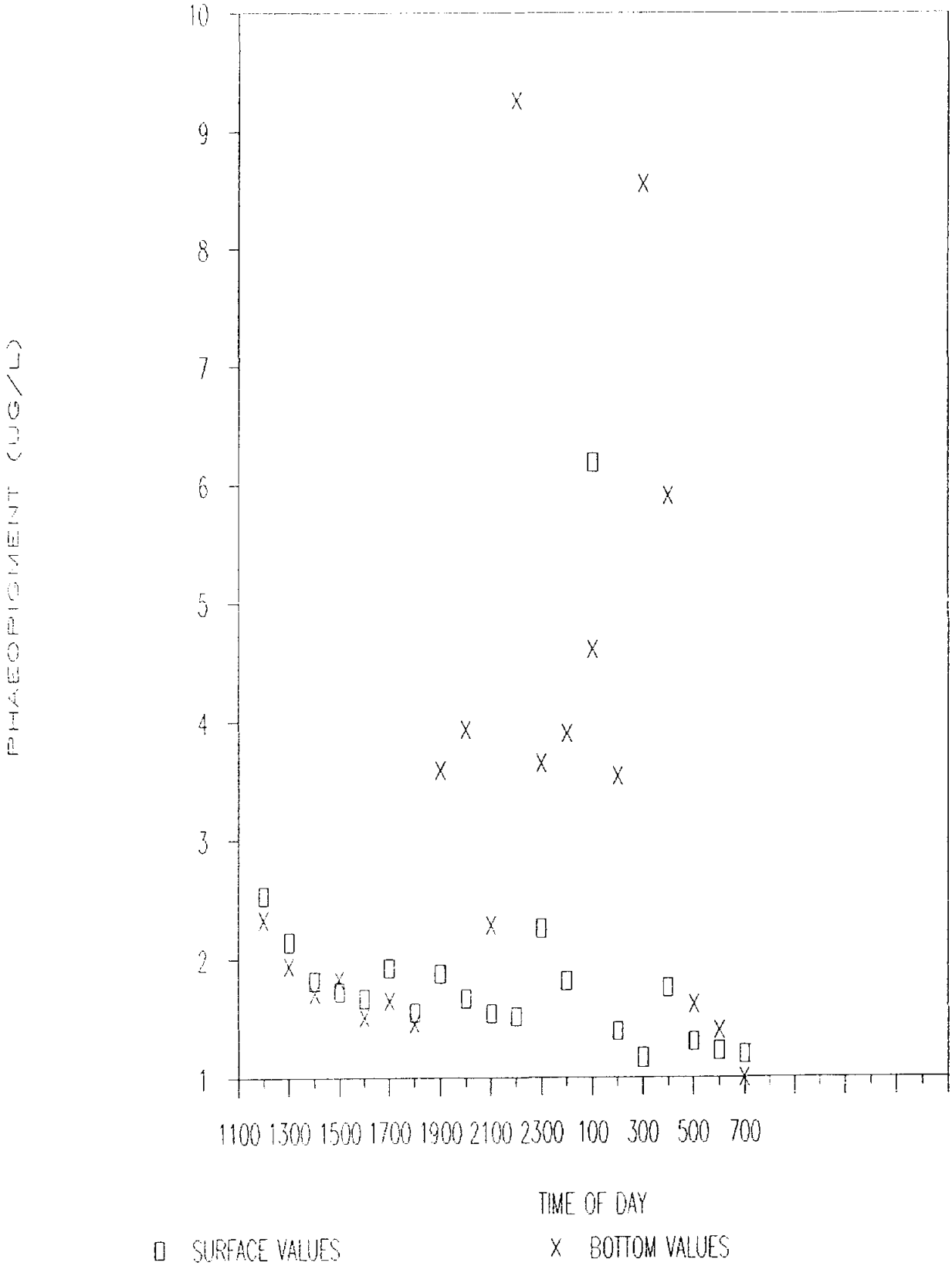

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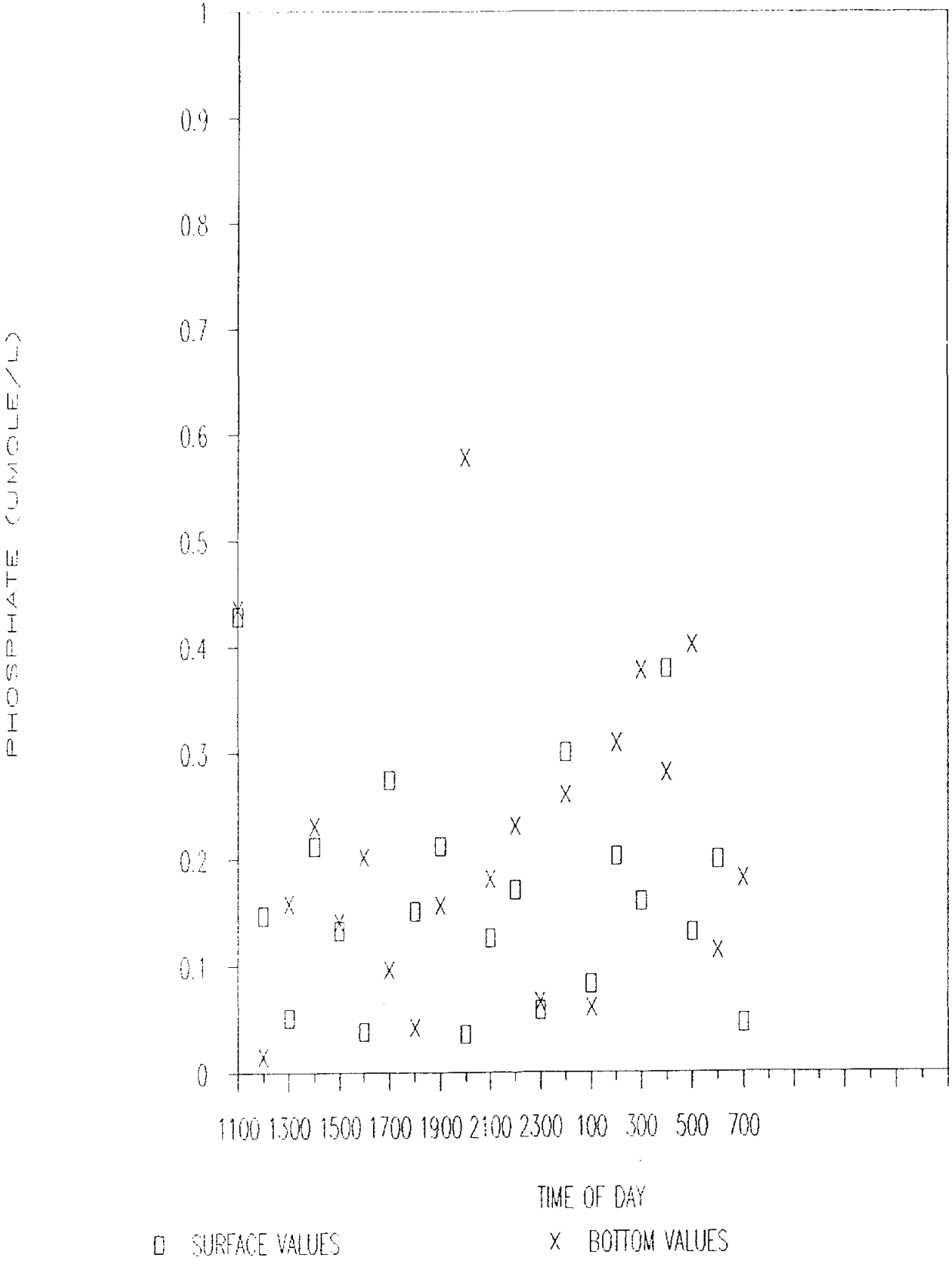

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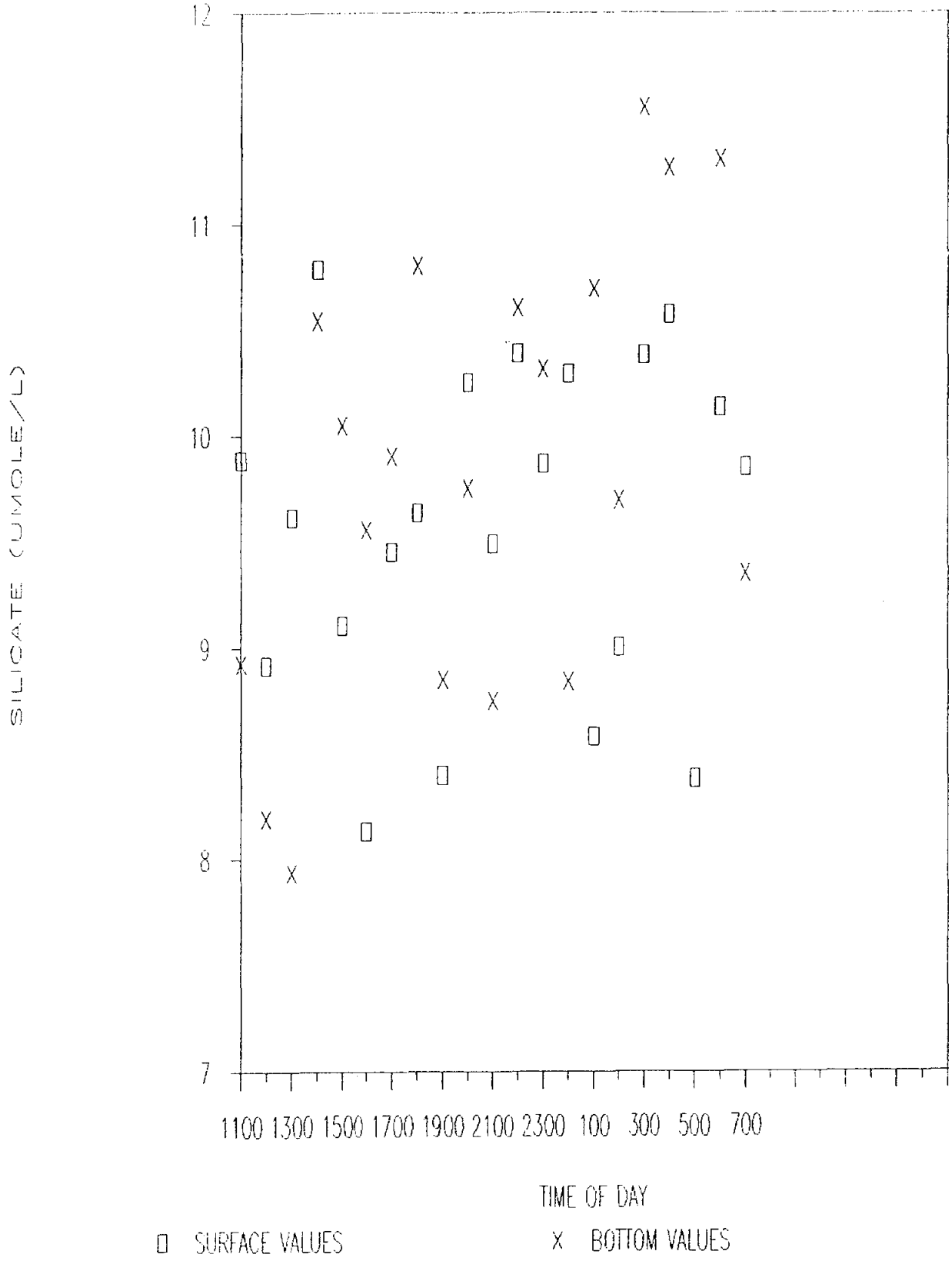

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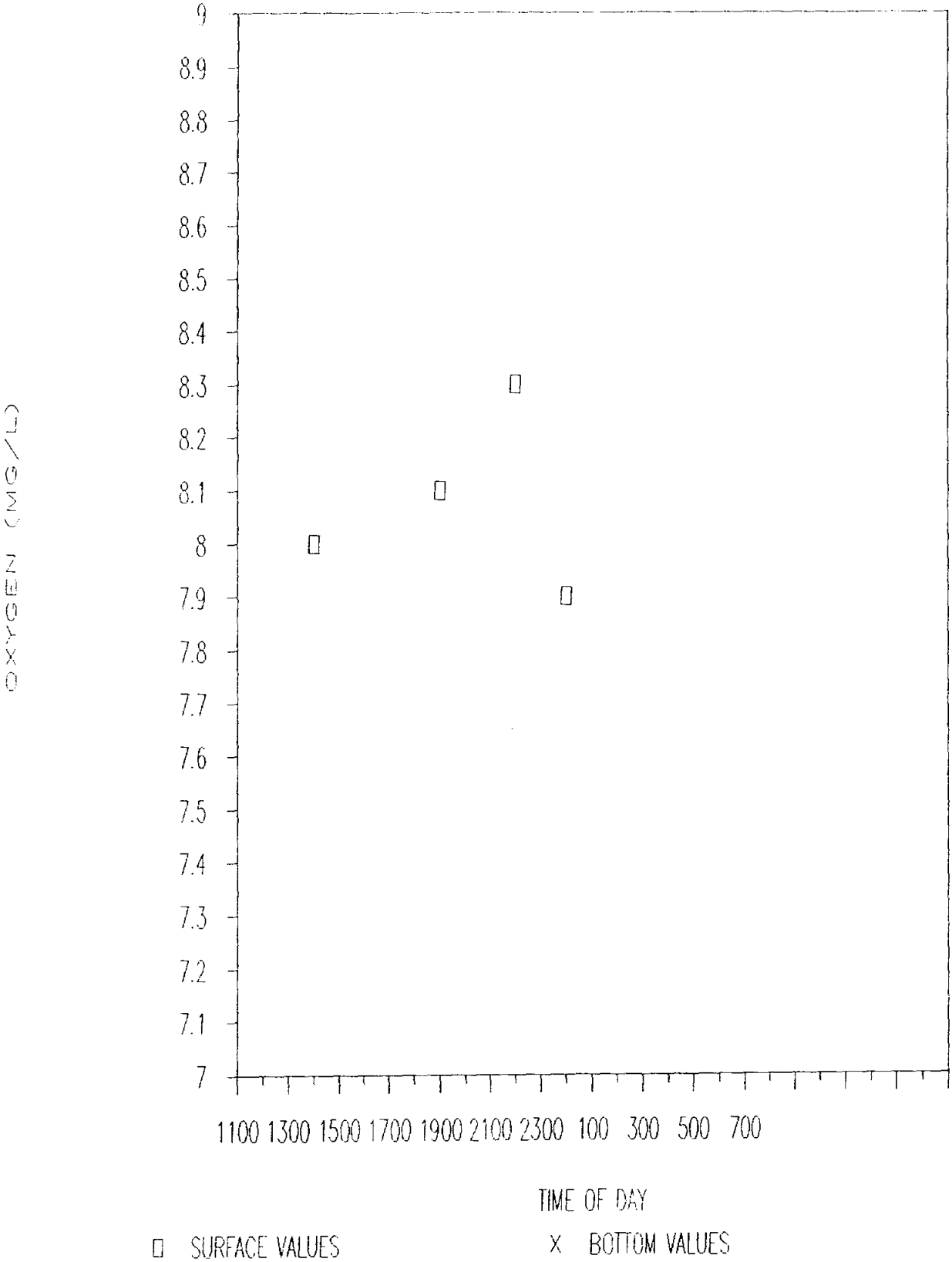

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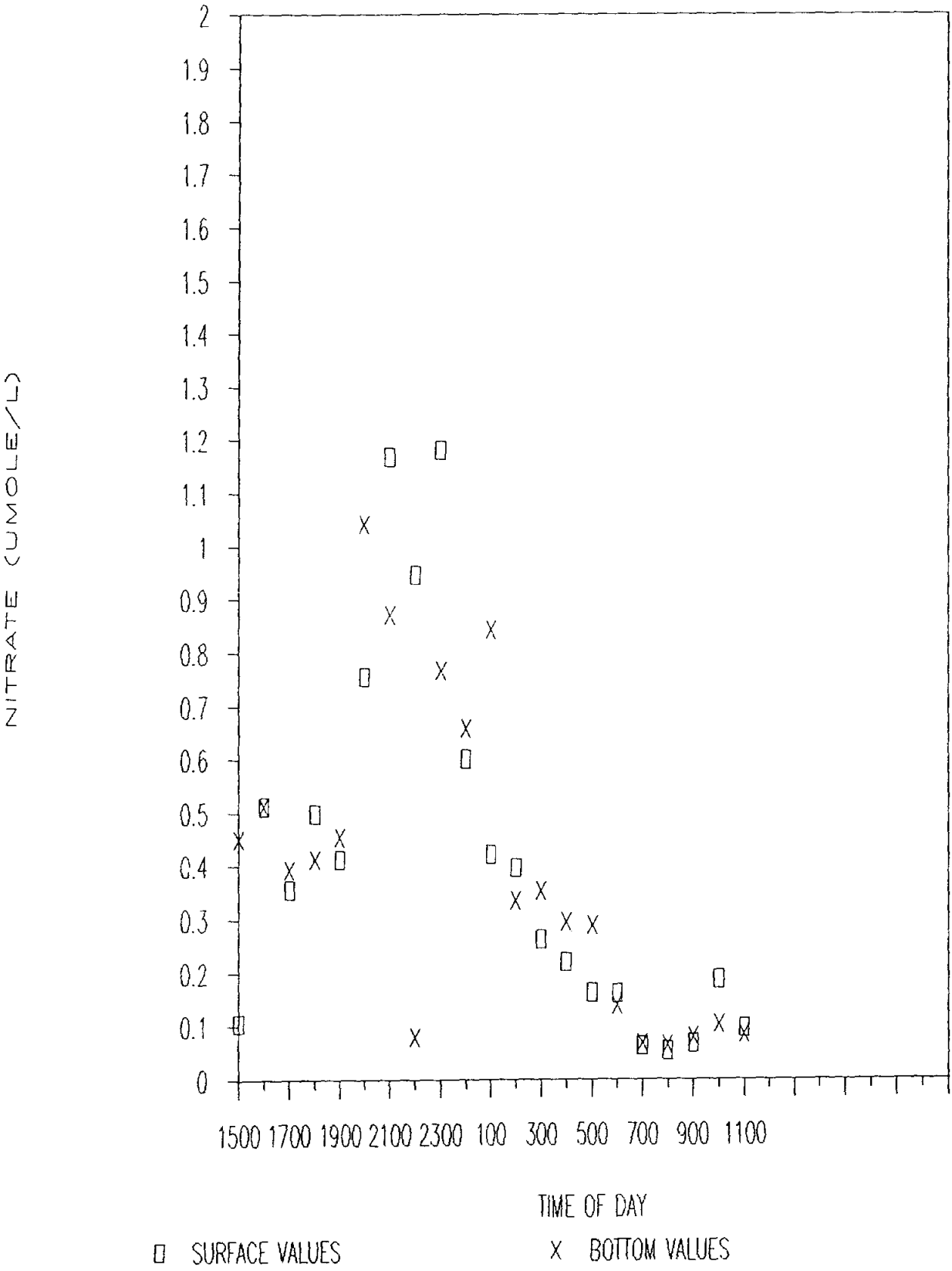

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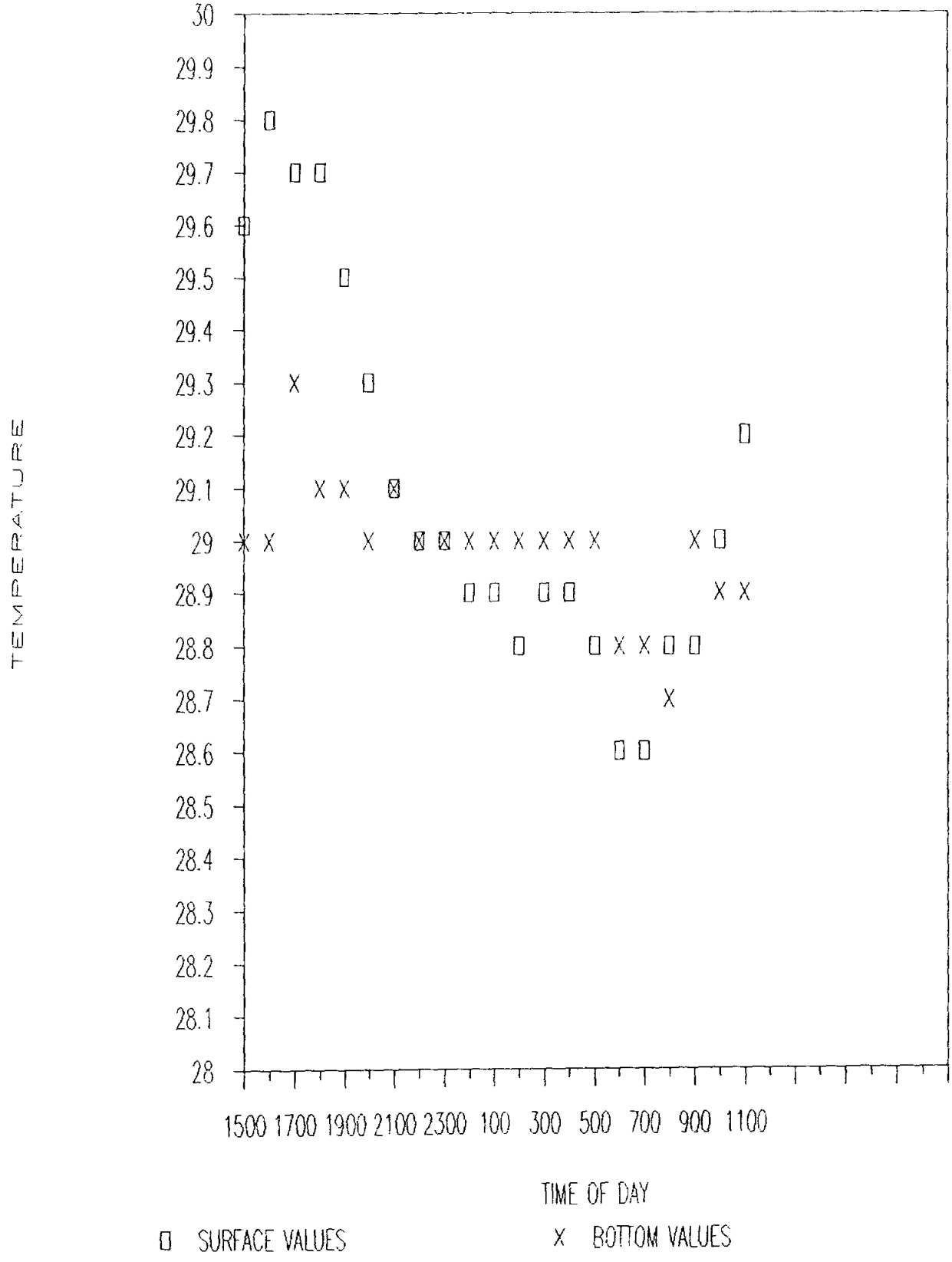

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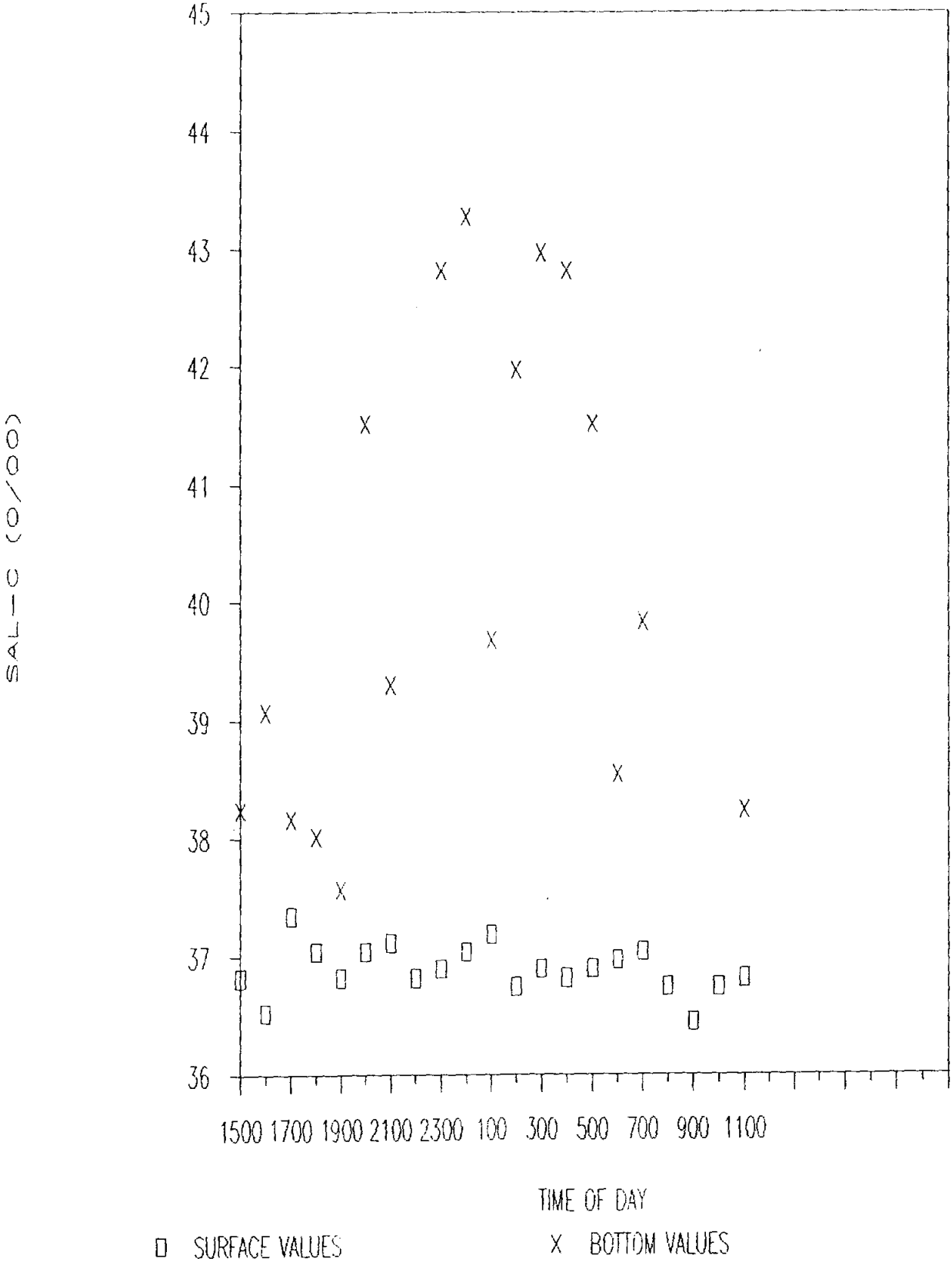

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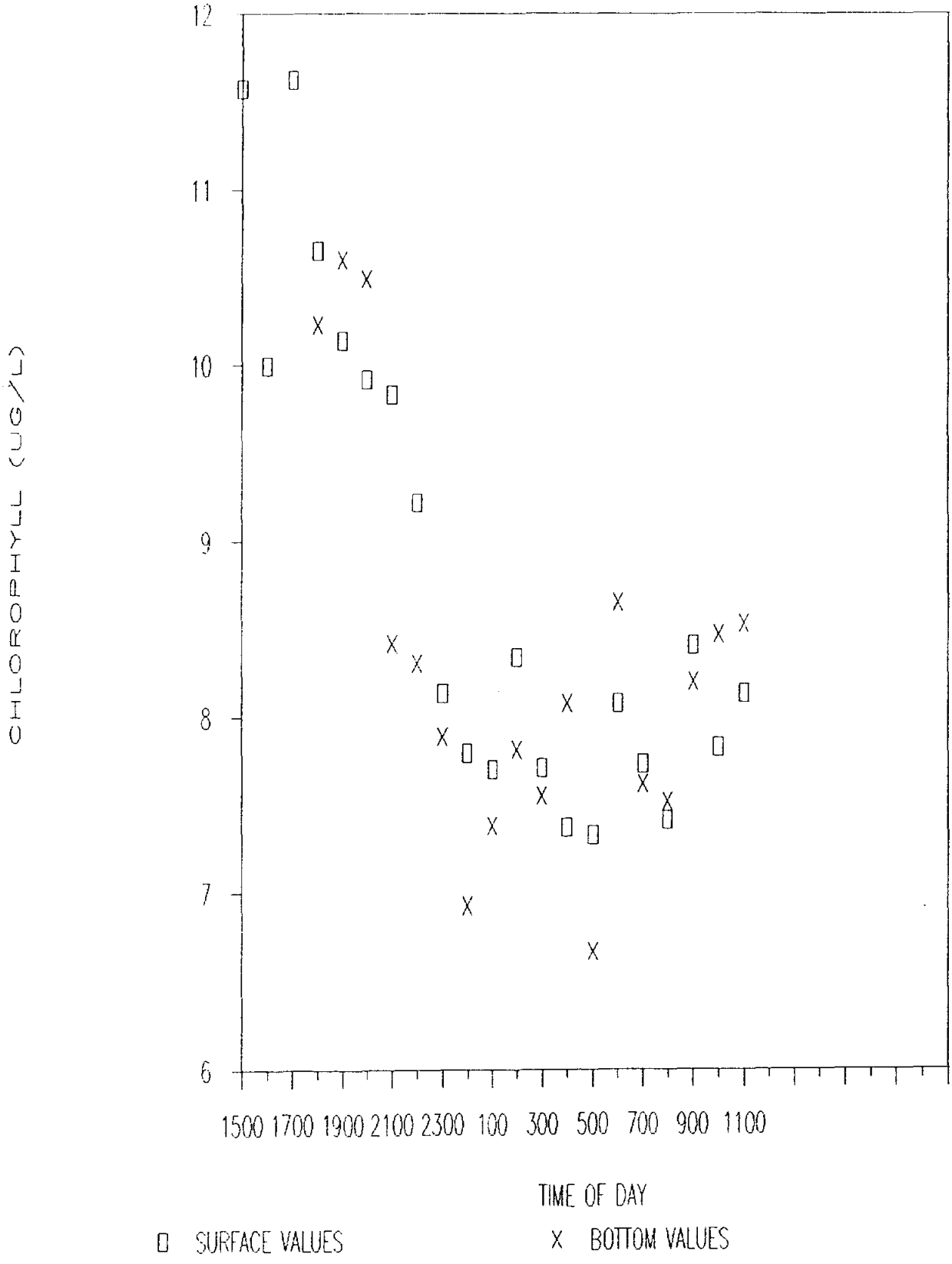

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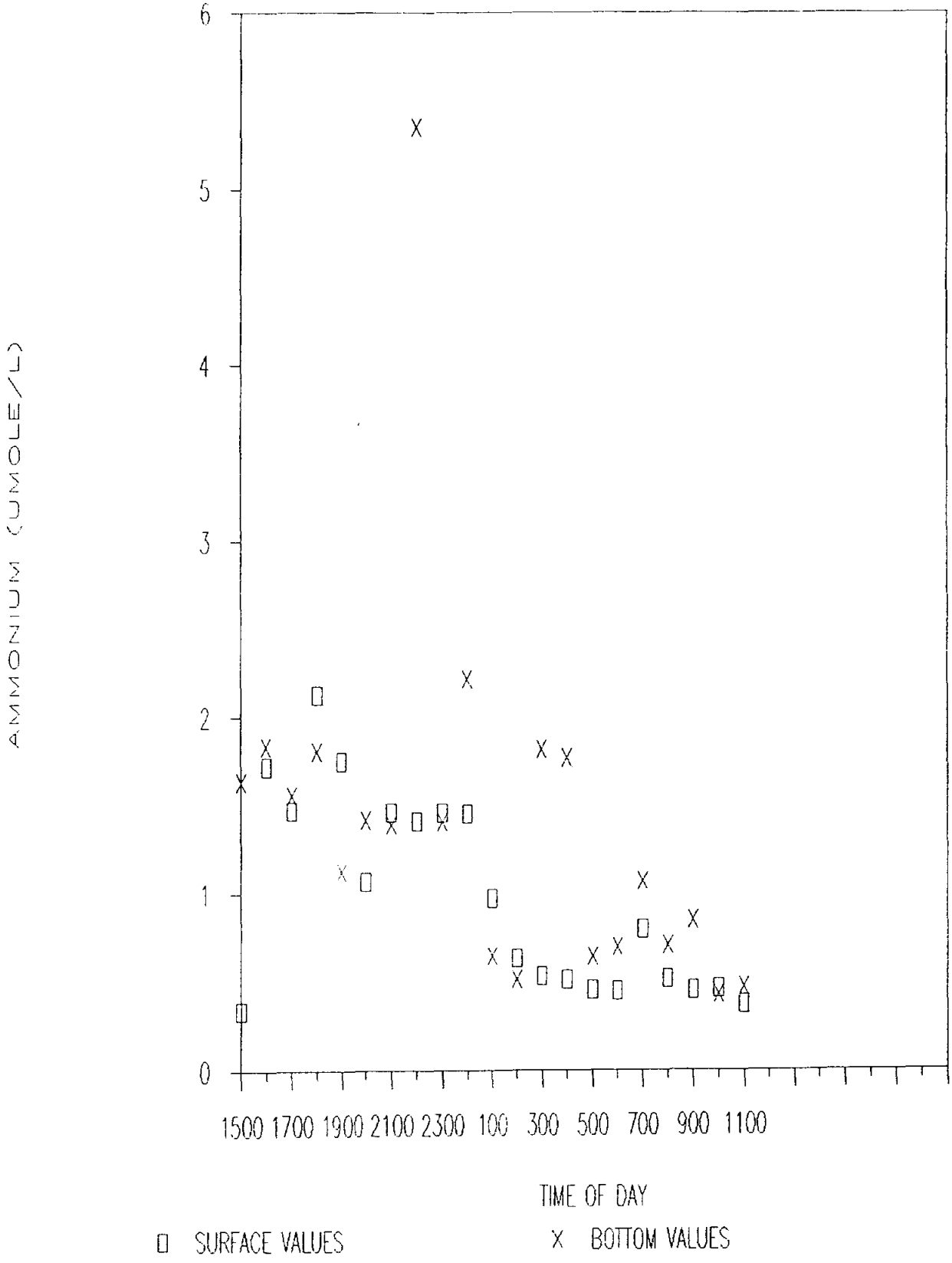

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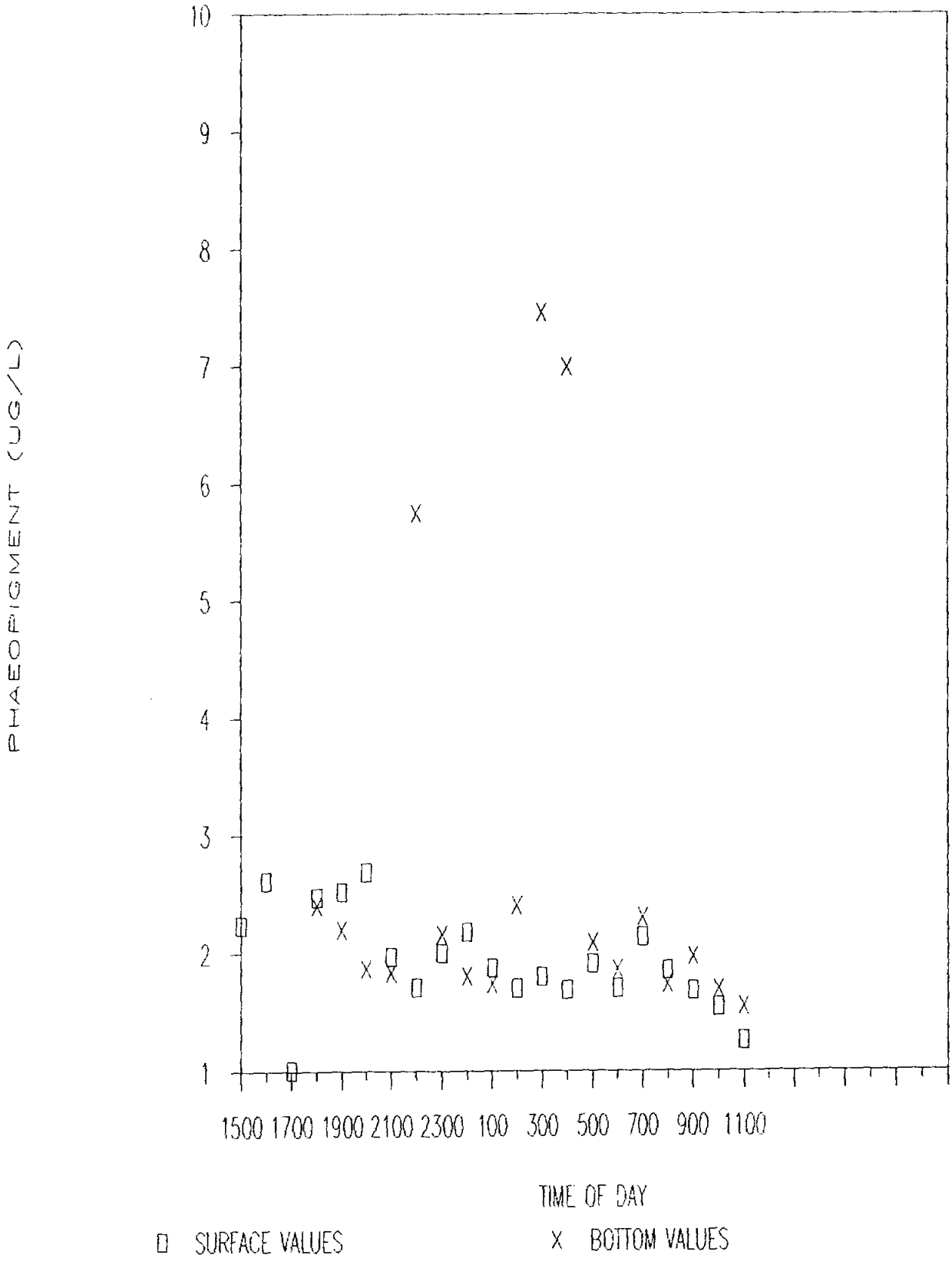

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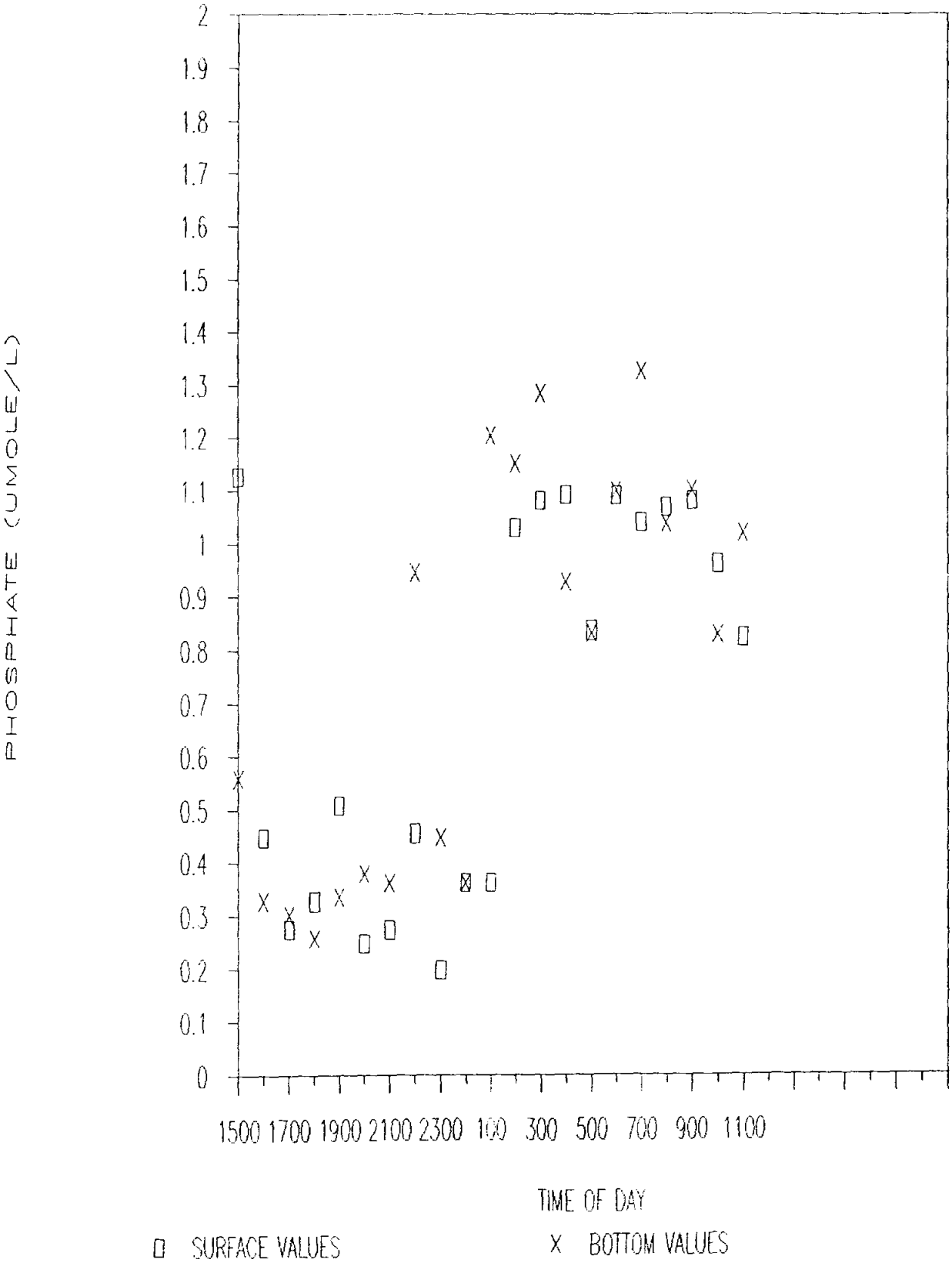

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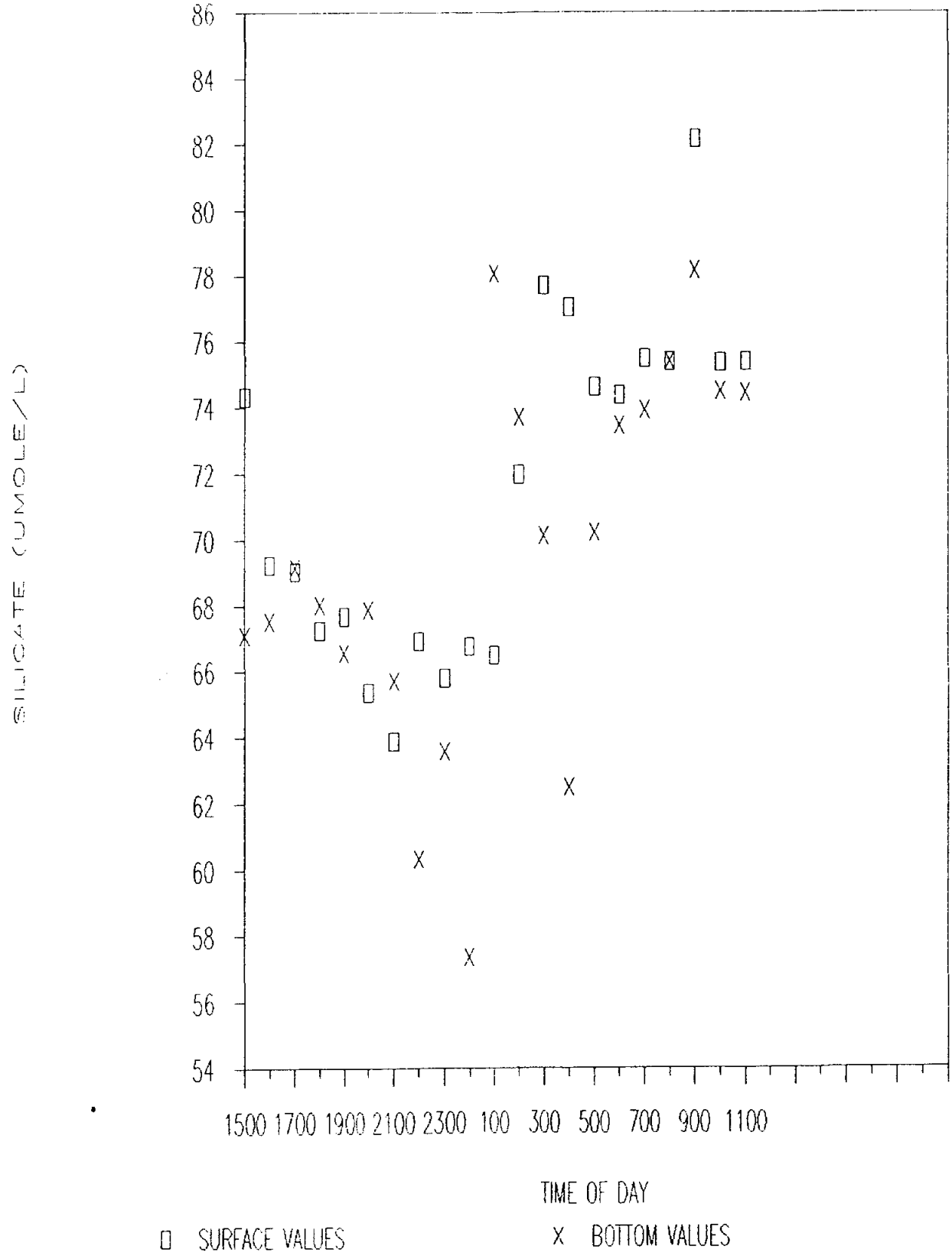

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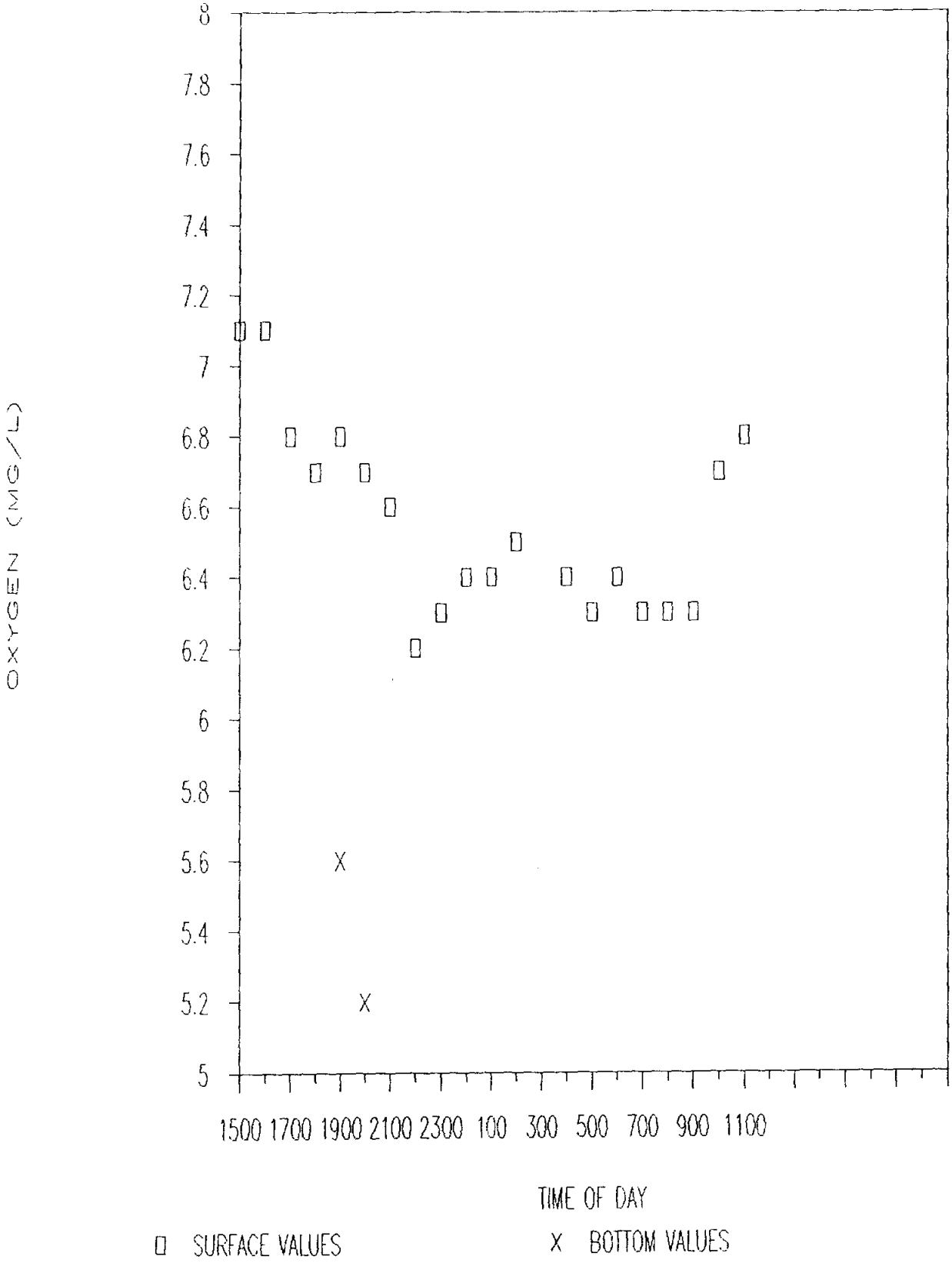
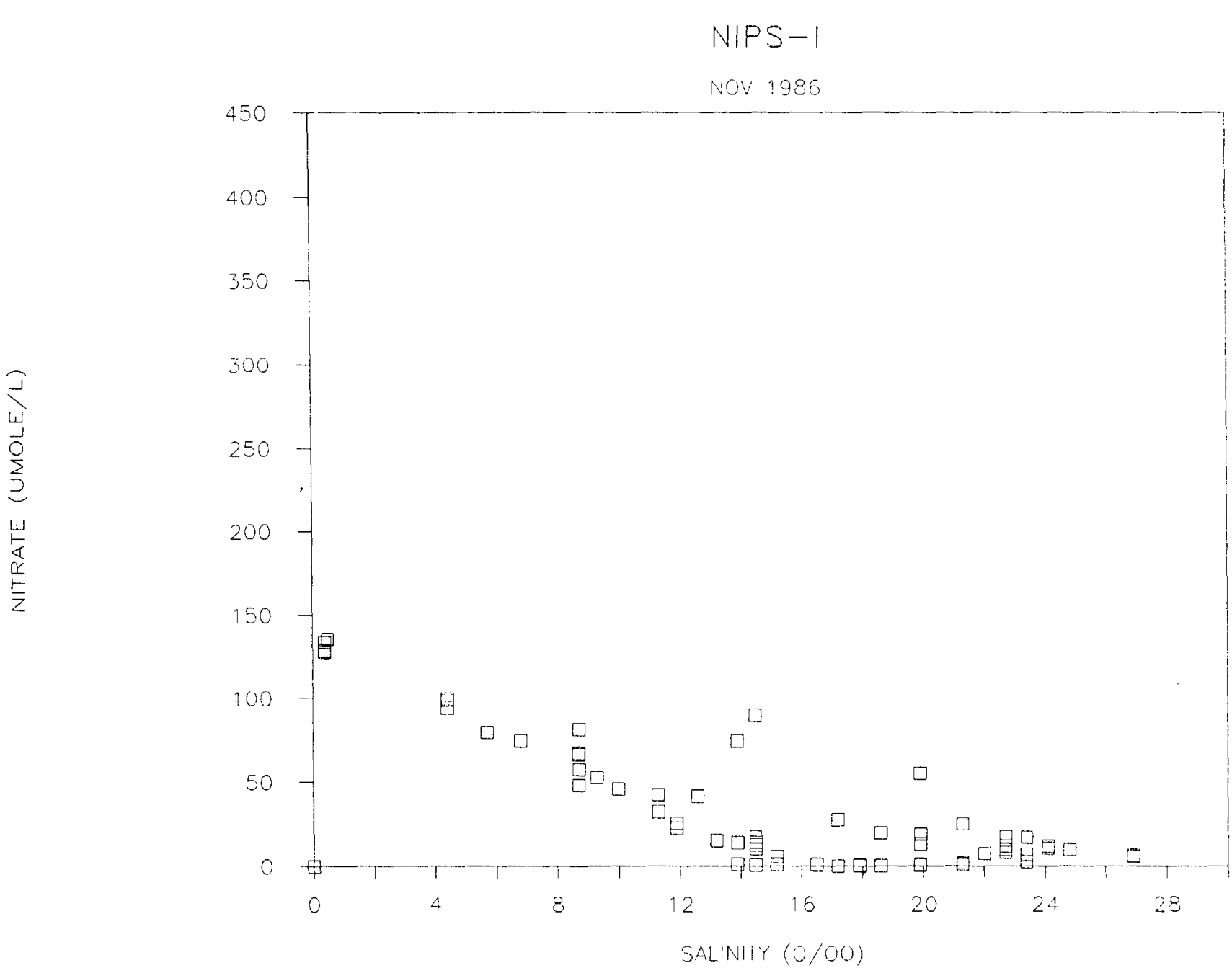
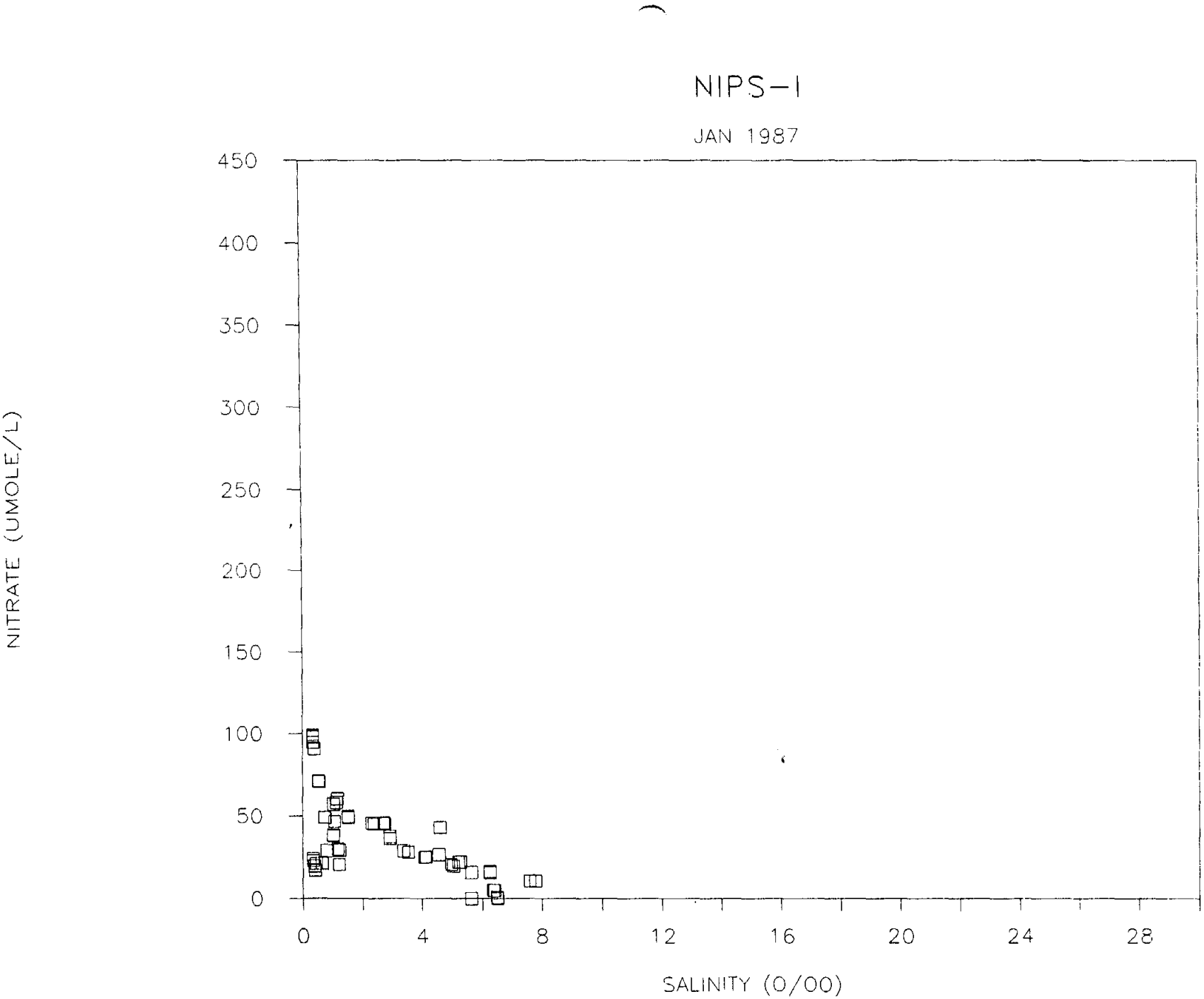



NIPS-I
NOV 1986
NITRATE (UMOLE/L)
450
400
350
300
250
200
150
100
50
0
0
4
8
12
16
20
24
28
SALINITY (O/OO)


NIPS-I
JAN 1987
NITRATE (UMOLE/L)
450
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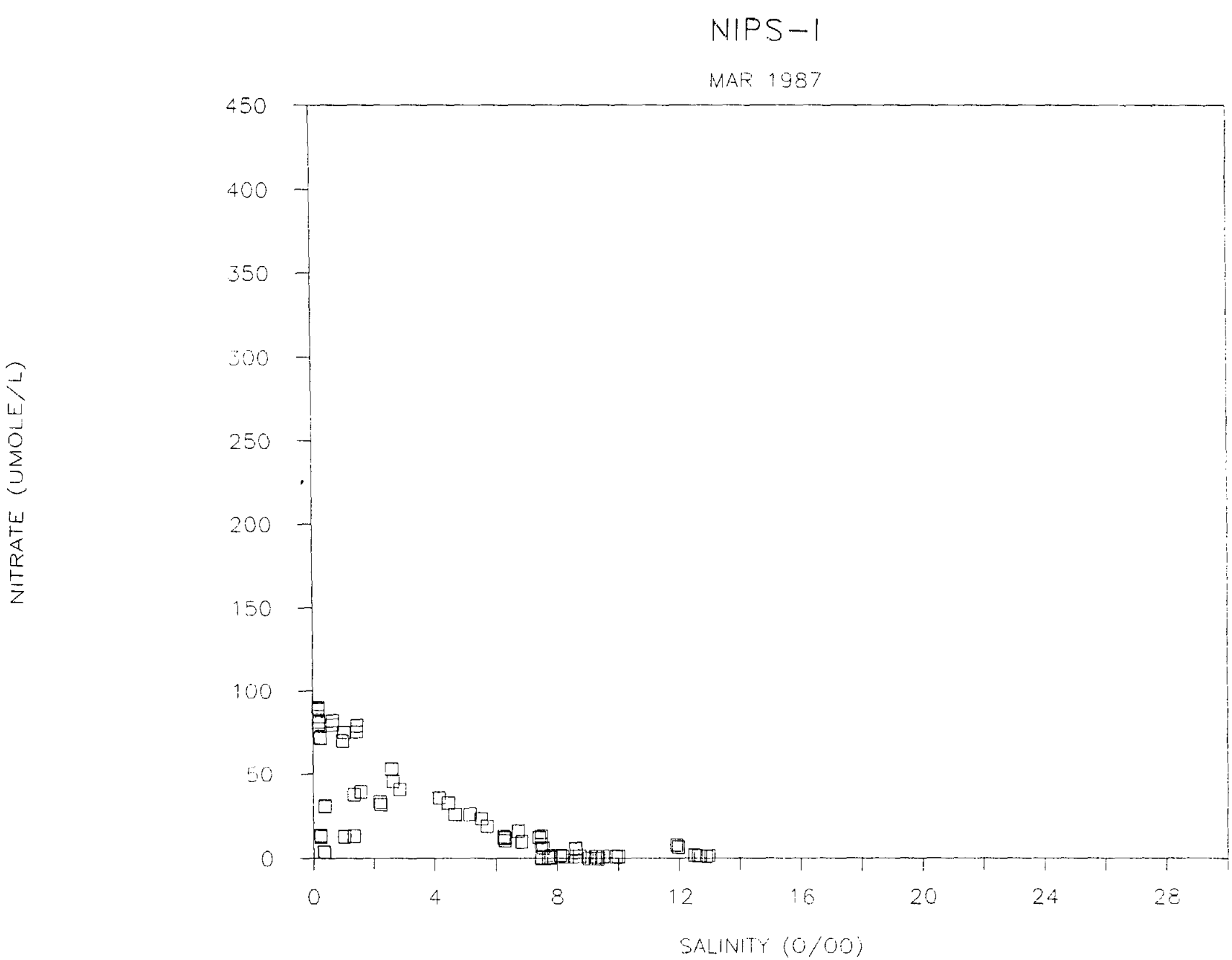
12
16
20
24
28
SALINITY (0/00)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MAR 1987
NITRATE (UMOLE/L)
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200
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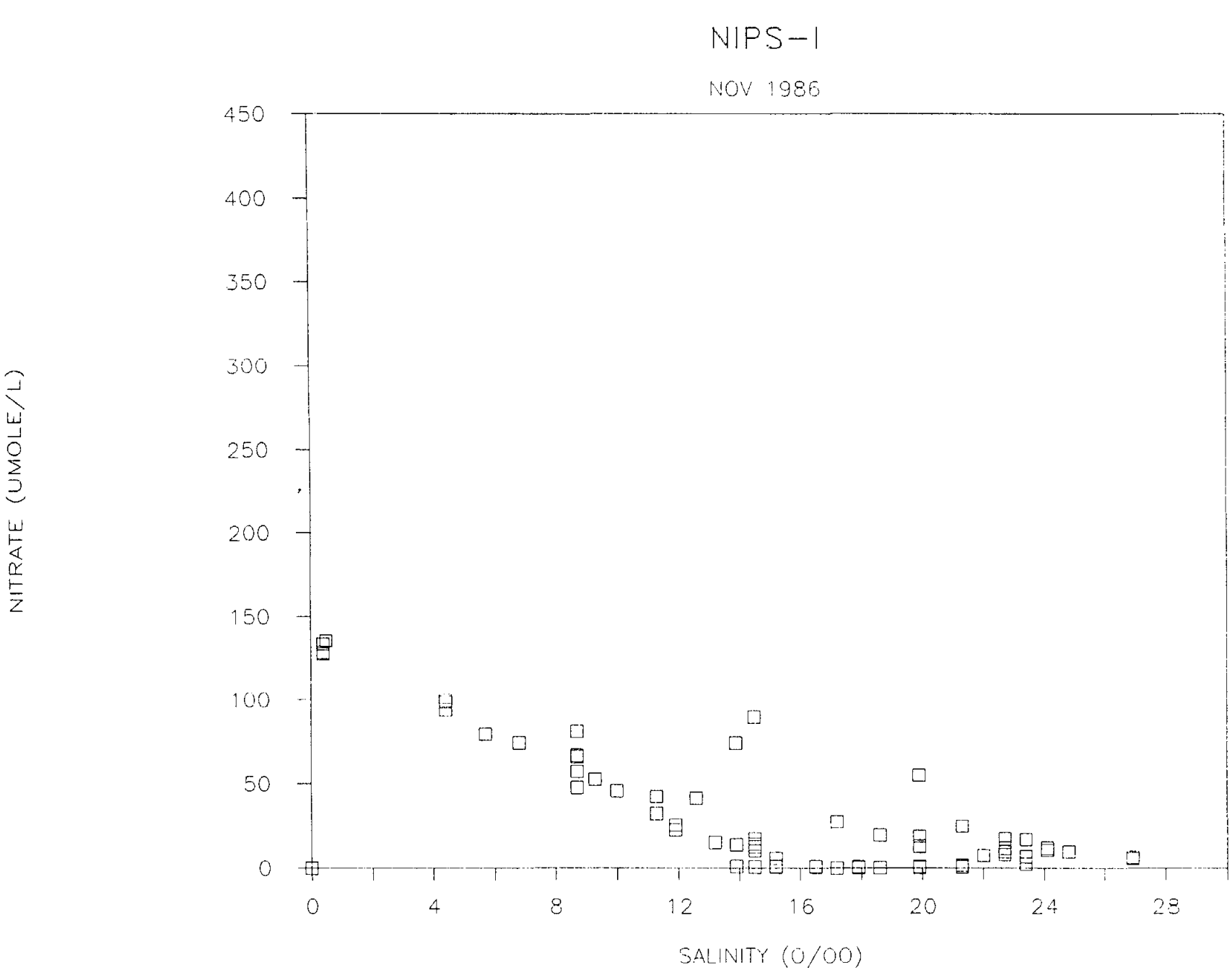
12
16
20
24
28
SALINITY (0/00)


NIPS-I
NOV 1986
NITRATE (UMOLE/L)
450
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4
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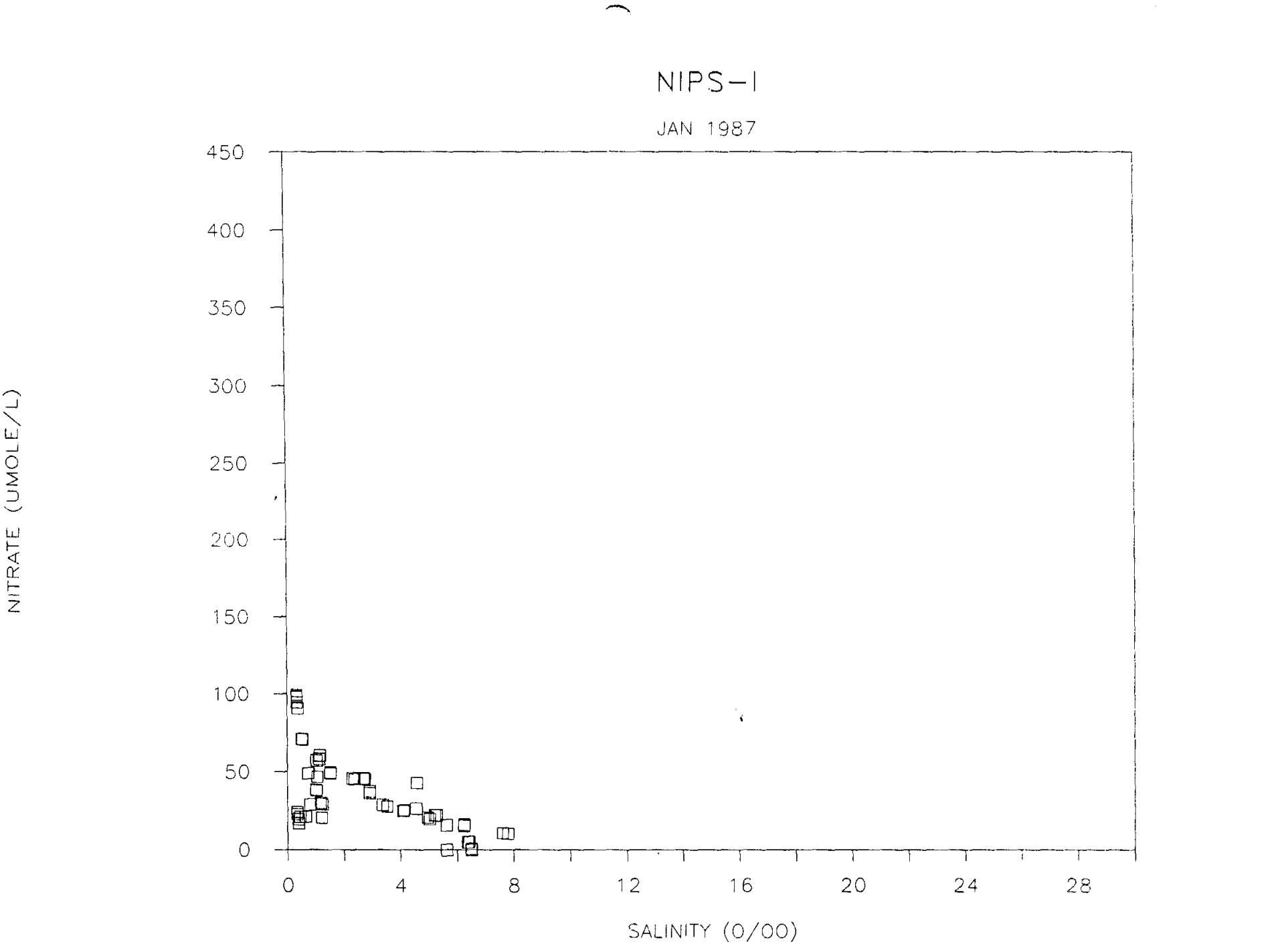
24
28
SALINITY (0/00)


NIPS-I
JAN 1987
NITRATE (UMOLE/L)
450
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200
150
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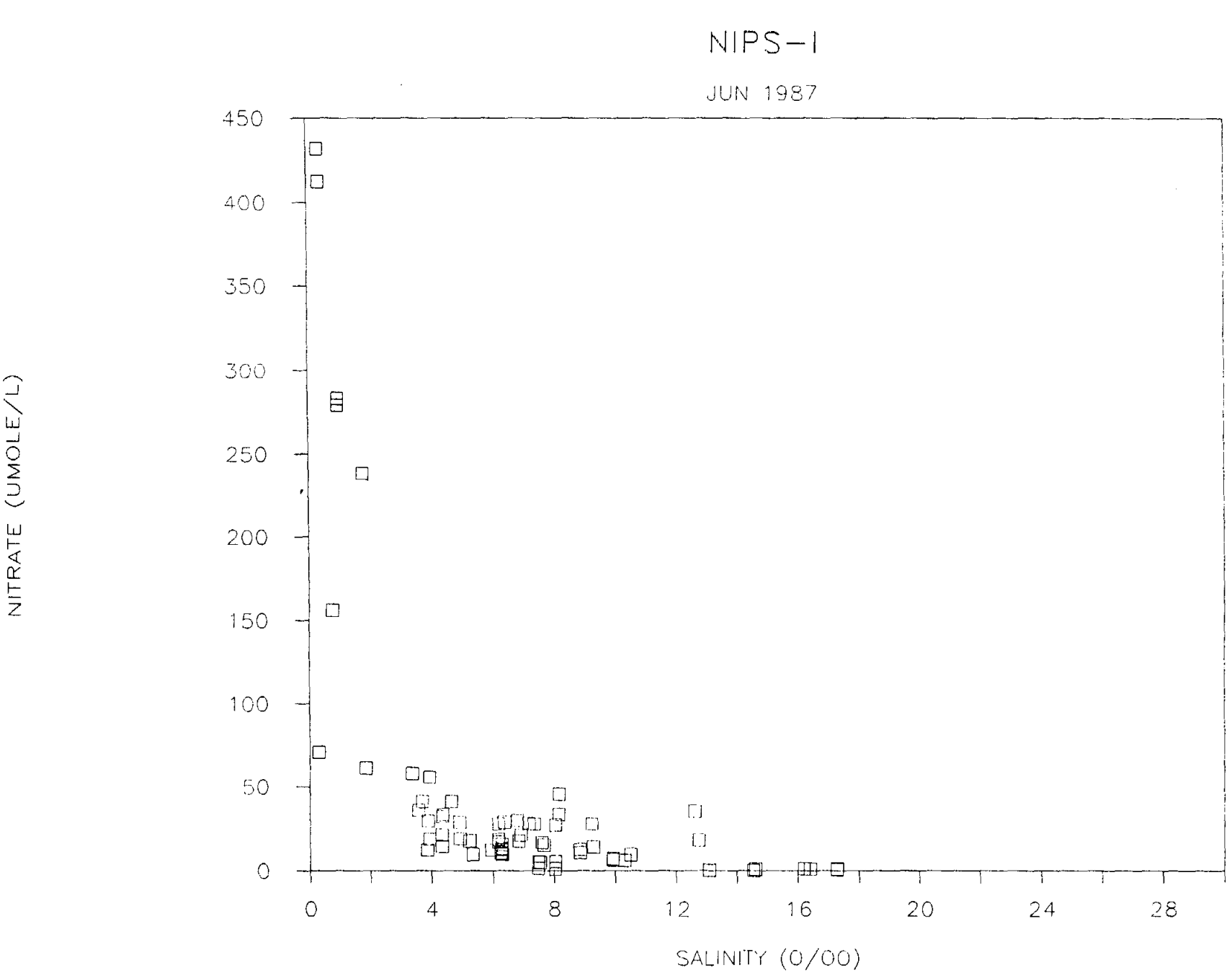
20
24
28
SALINITY (0/00)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JUN 1987
NITRATE (UMOLE/L)
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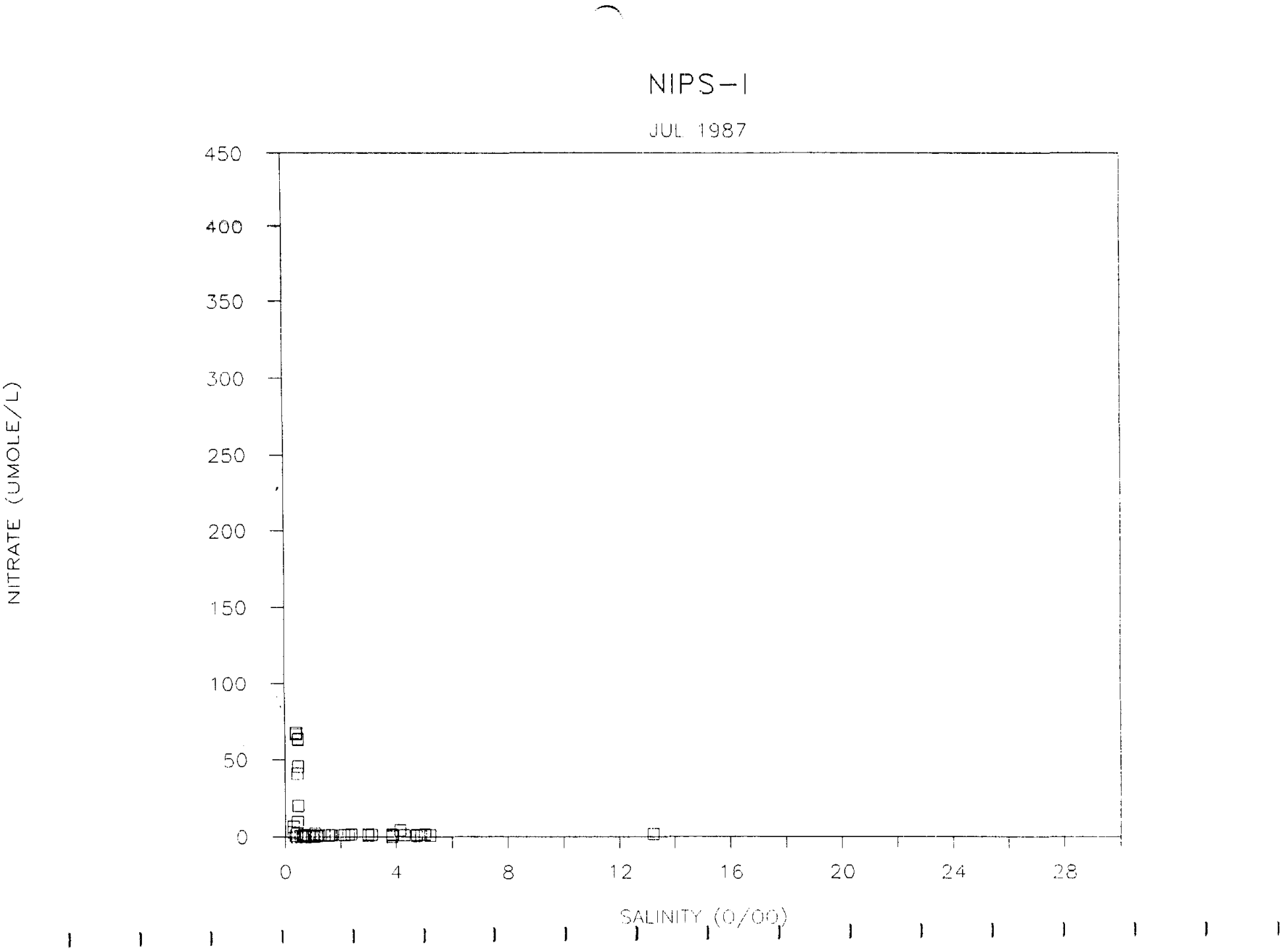
SALINITY (0/00)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JUL 1987
NITRATE (UMOLE/L)
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4
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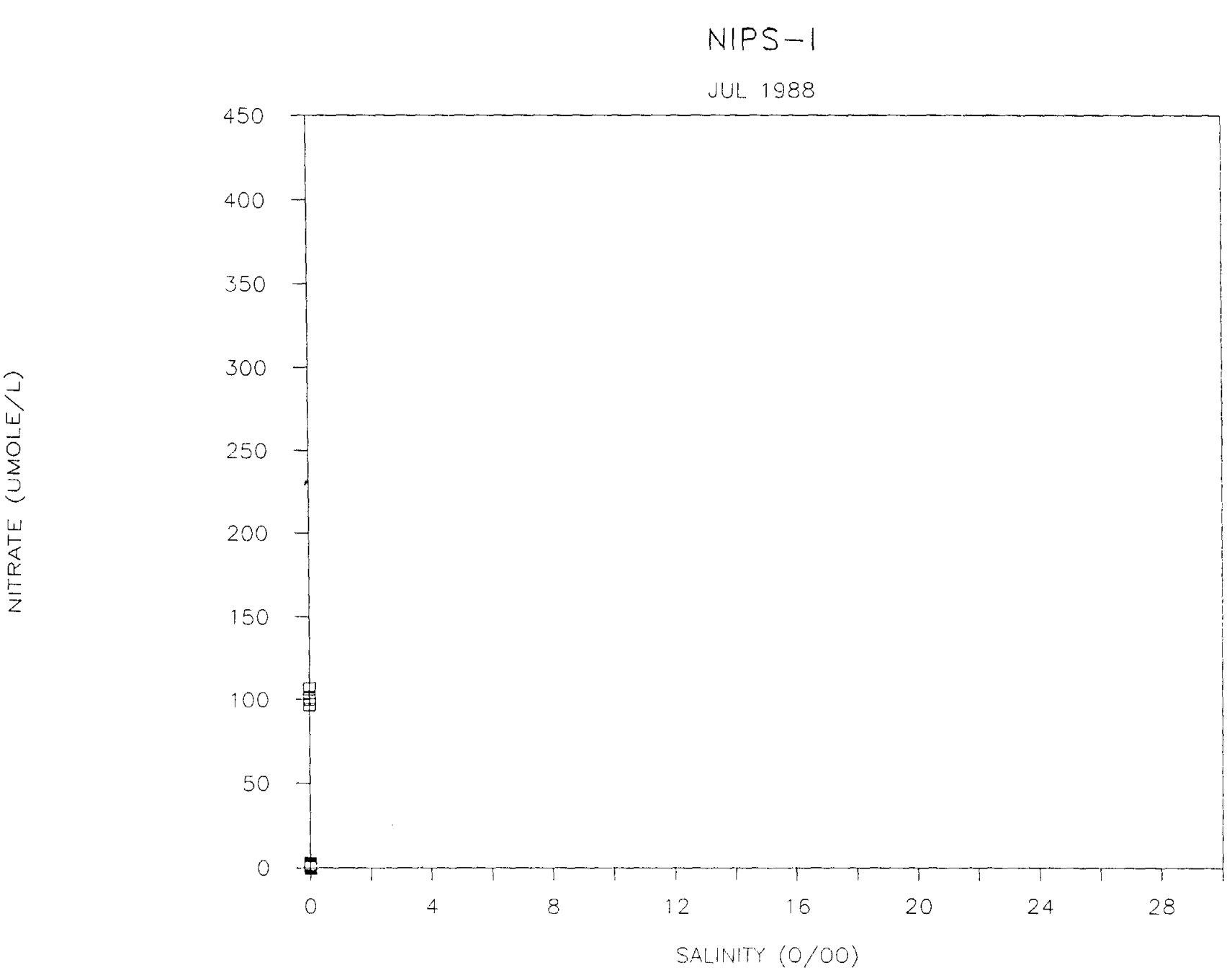
12
16
20
24
28
SALINITY (O/OO)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JUL 1988
NITRATE (UMOLE/L)
450
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200
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100
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0
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4
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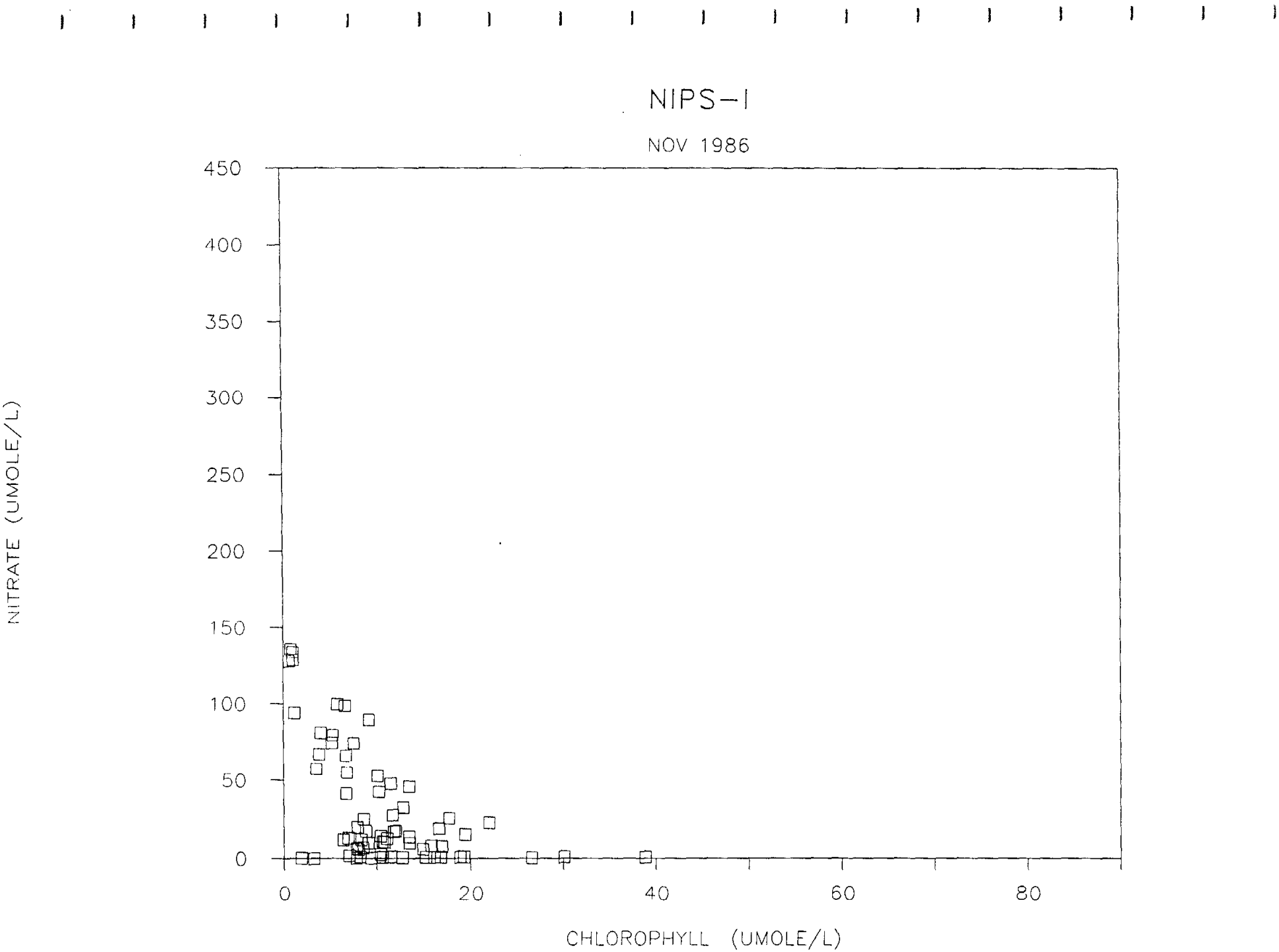
12
16
20
24
28
SALINITY (O/OO)


NIPS-I
NOV 1986
NITRATE (UMOLE/L)
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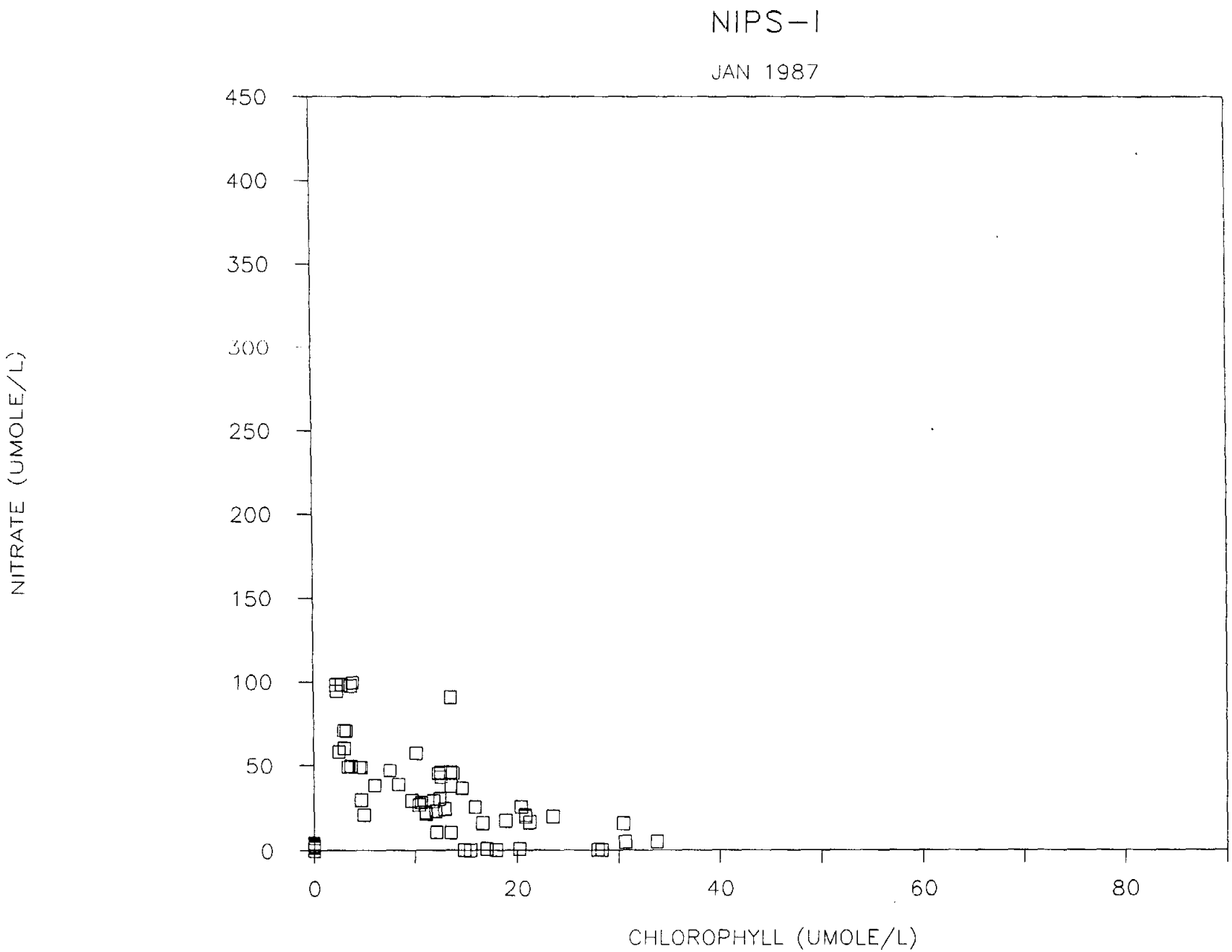
40
60
80
CHLOROPHYLL (UMOLE/L)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JAN 1987
NITRATE (UMOLE/L)
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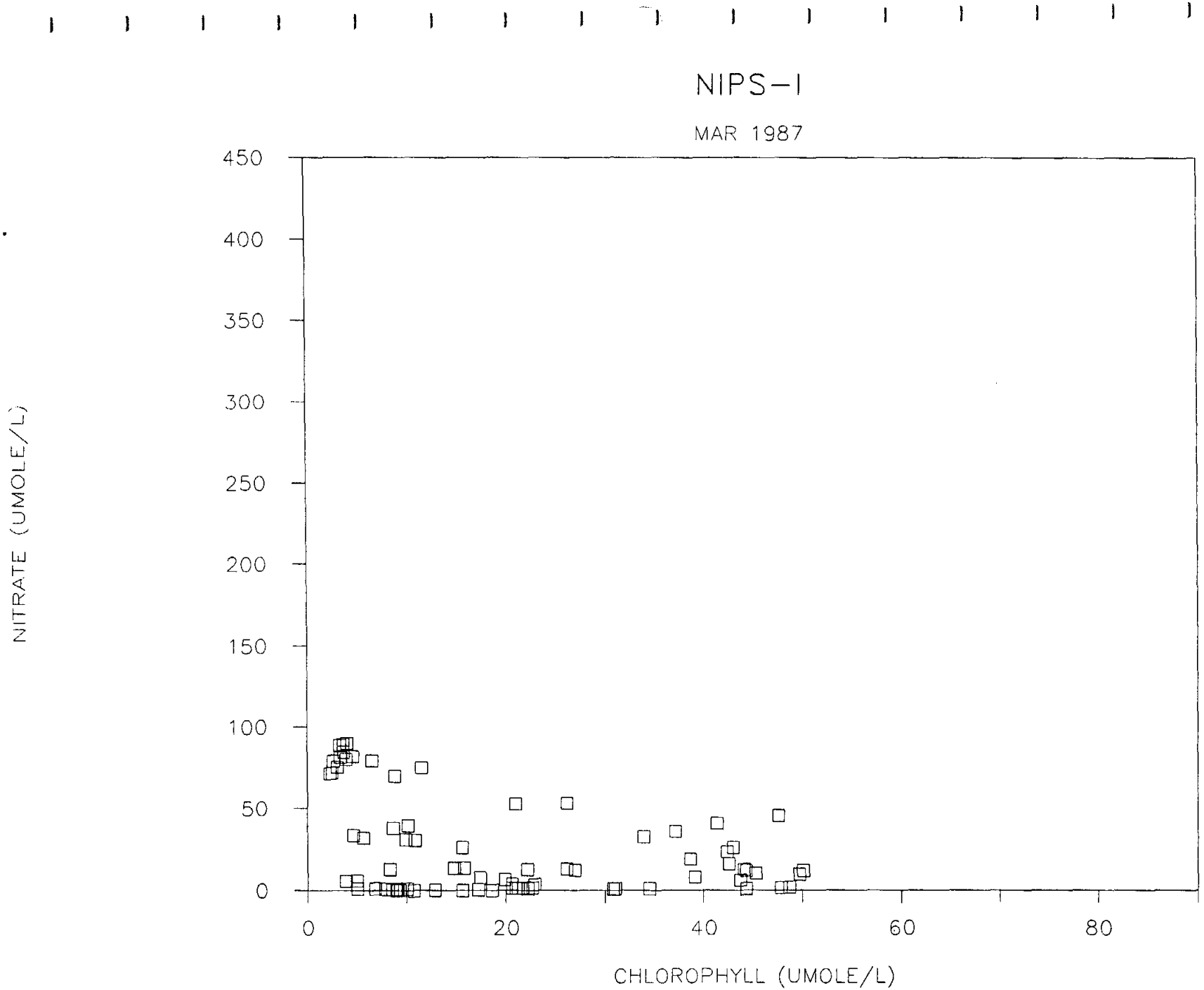
40
60
80
CHLOROPHYLL (UMOLE/L)


NIPS-I
MAR 1987
NITRATE (UMOLE/L)
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200
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50
0
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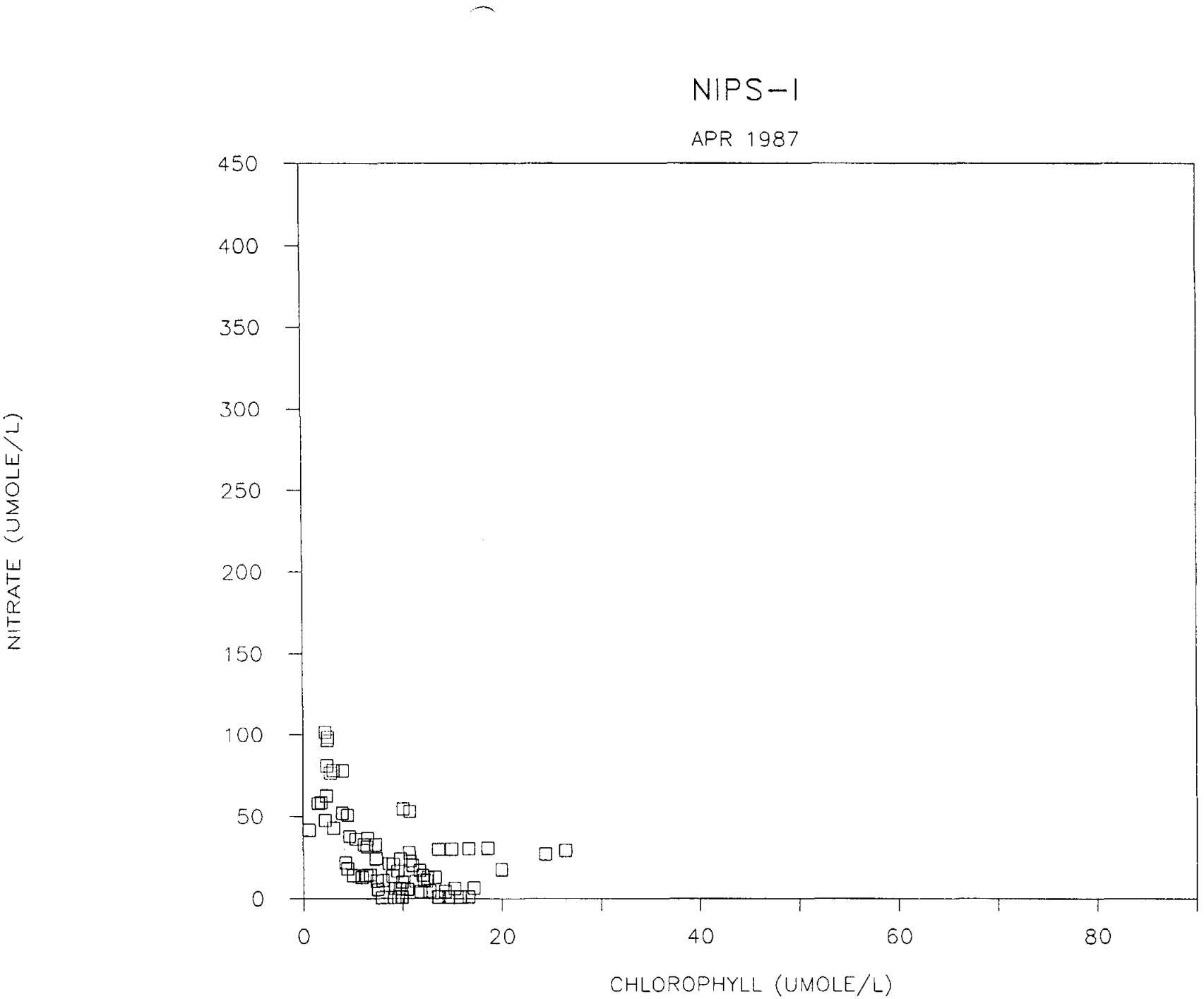
20
40
60
80
CHLOROPHYLL (UMOLE/L)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APR 1987
NITRATE (UMOLE/L)
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40
60
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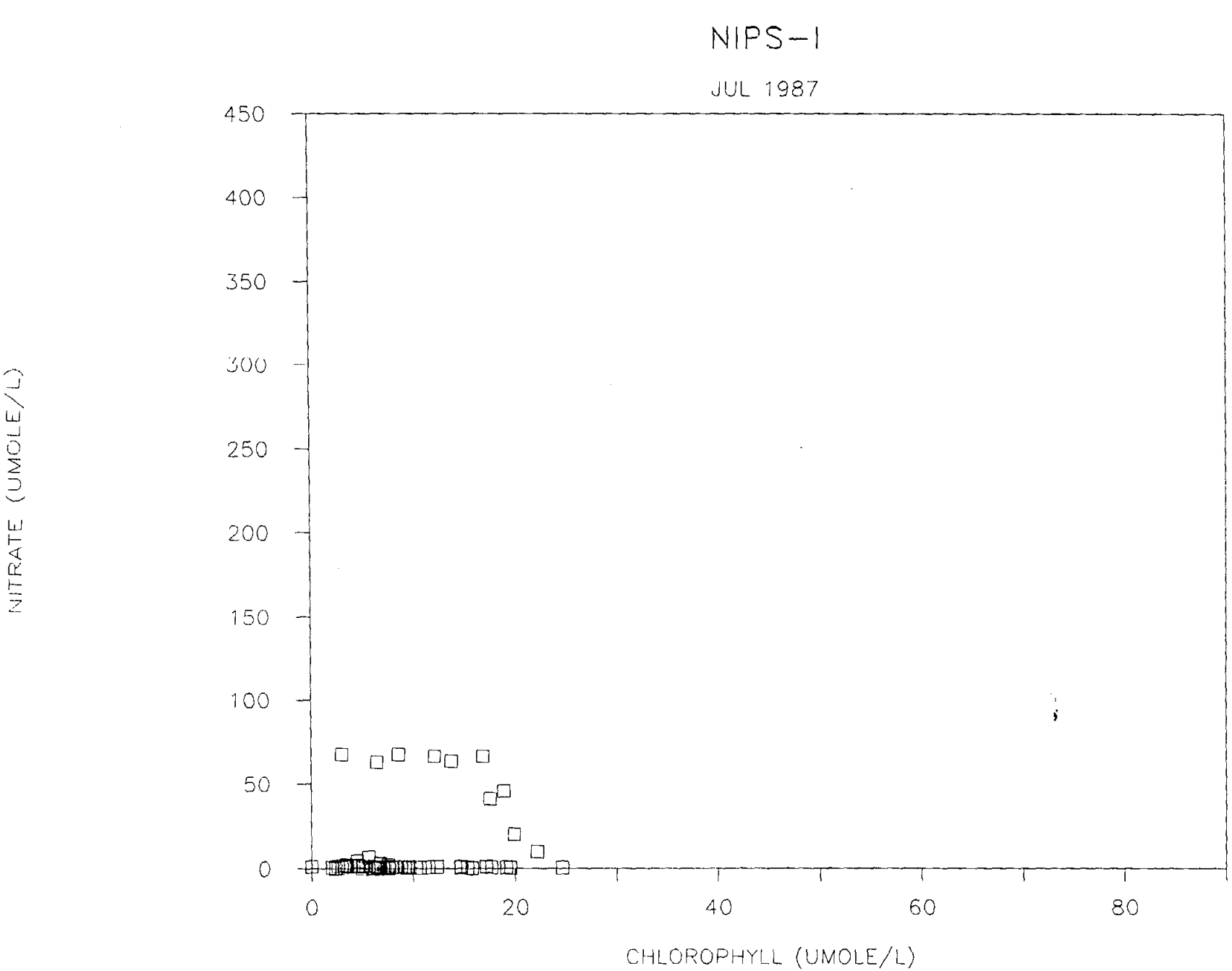
CHLOROPHYLL (UMOLE/L)


NIPS-I
JUL 1987
NITRATE (UMOLE/L)
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400
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250
200
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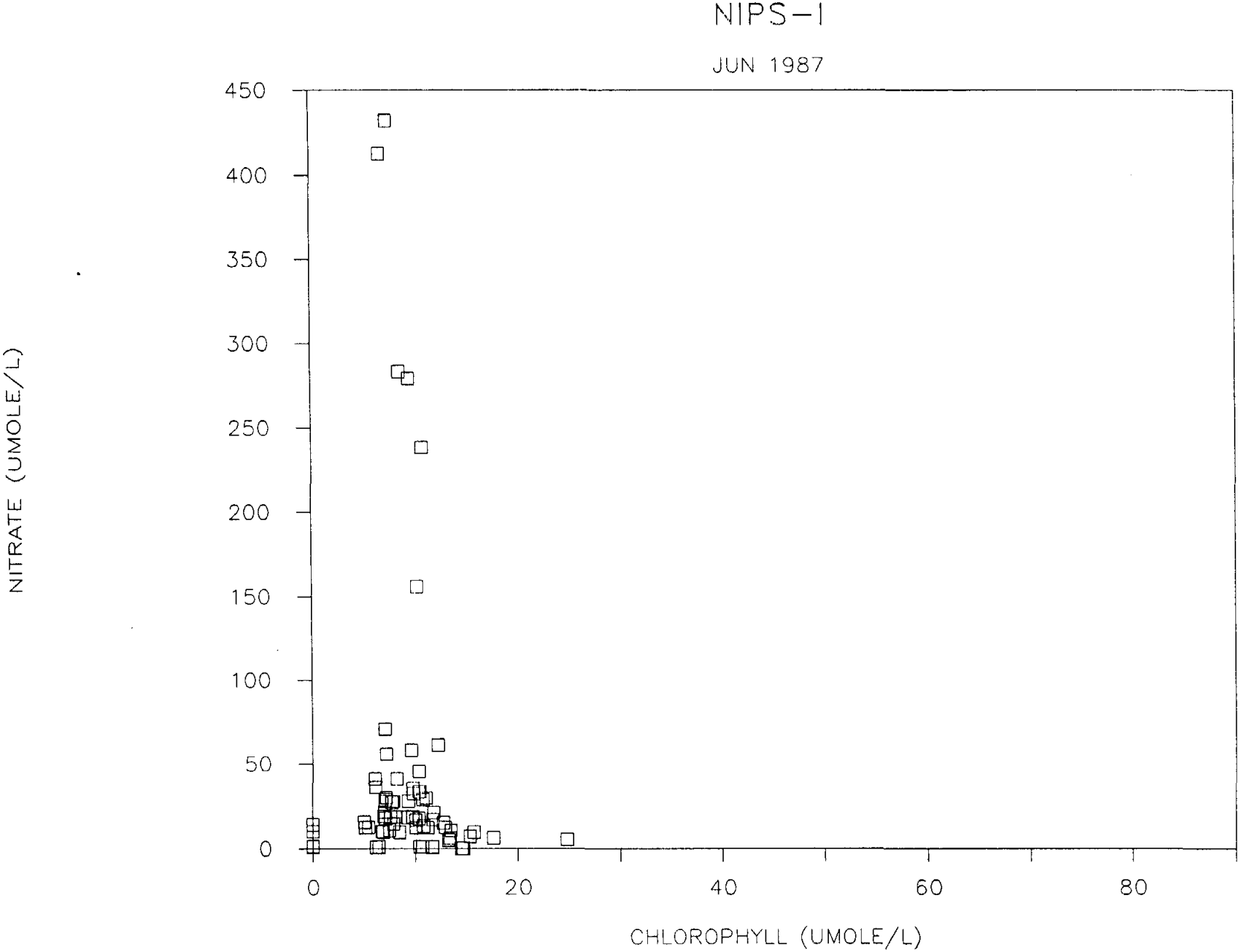
40
60
80
CHLOROPHYLL (UMOLE/L)


NIPS-I
JUN 1987
NITRATE (UMOLE/L)
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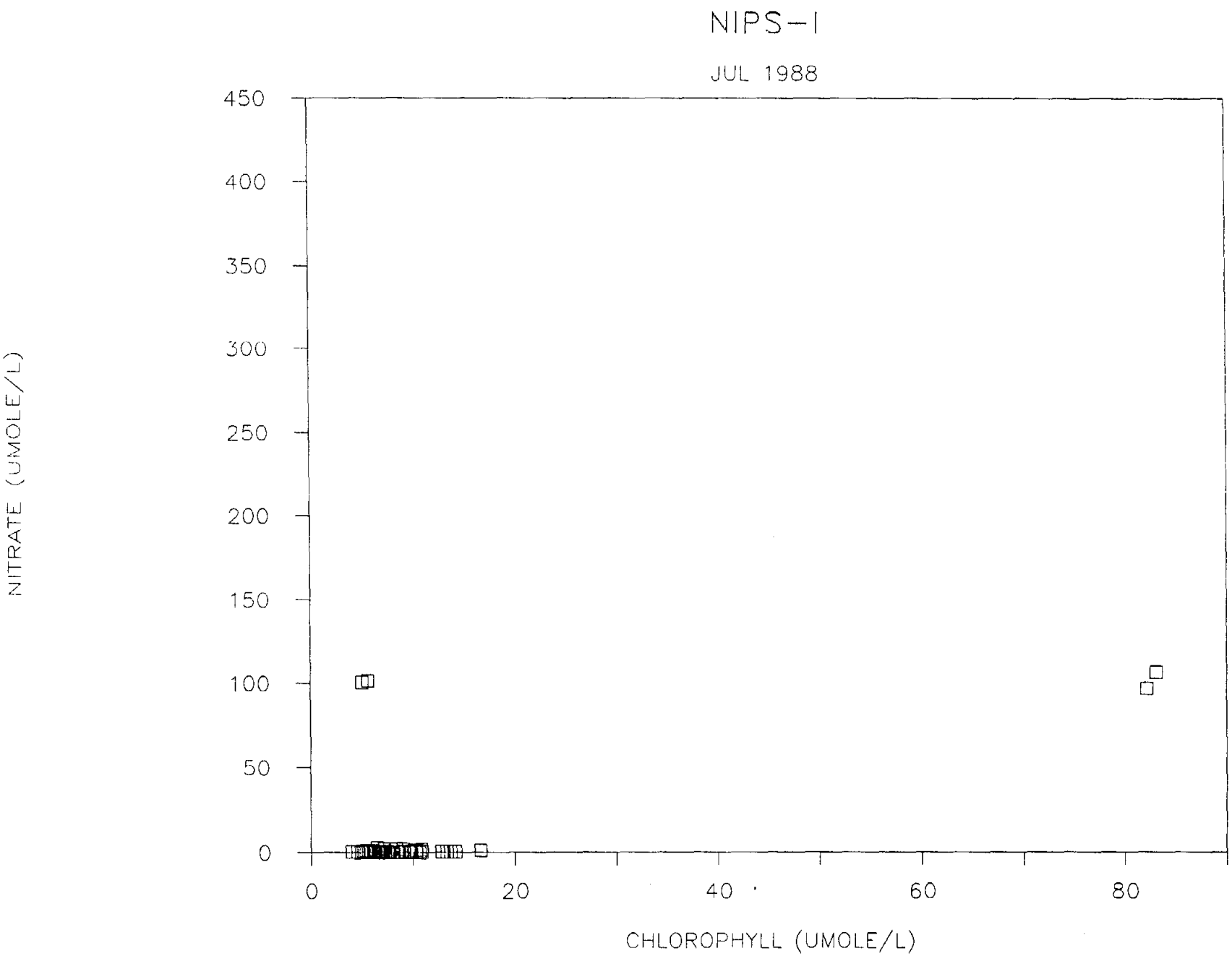
CHLOROPHYLL (UMOLE/L)


NIPS-I
JUL 1988
NITRATE (UMOLE/L)
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60
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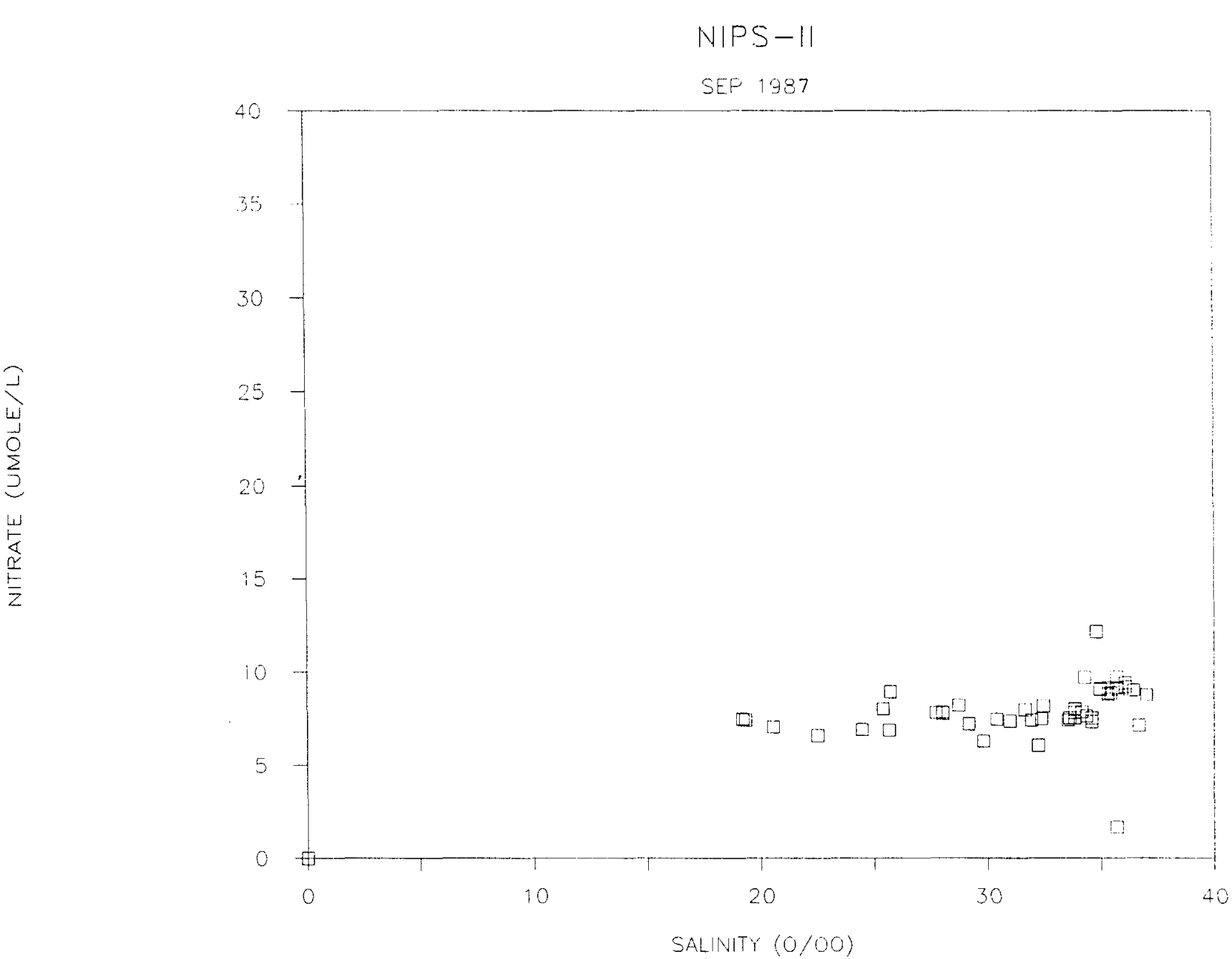
CHLOROPHYLL (UMOLE/L)


NIPS-II
SEP 1987
NITRATE (UMOLE/L)
SALINITY (O/OO)
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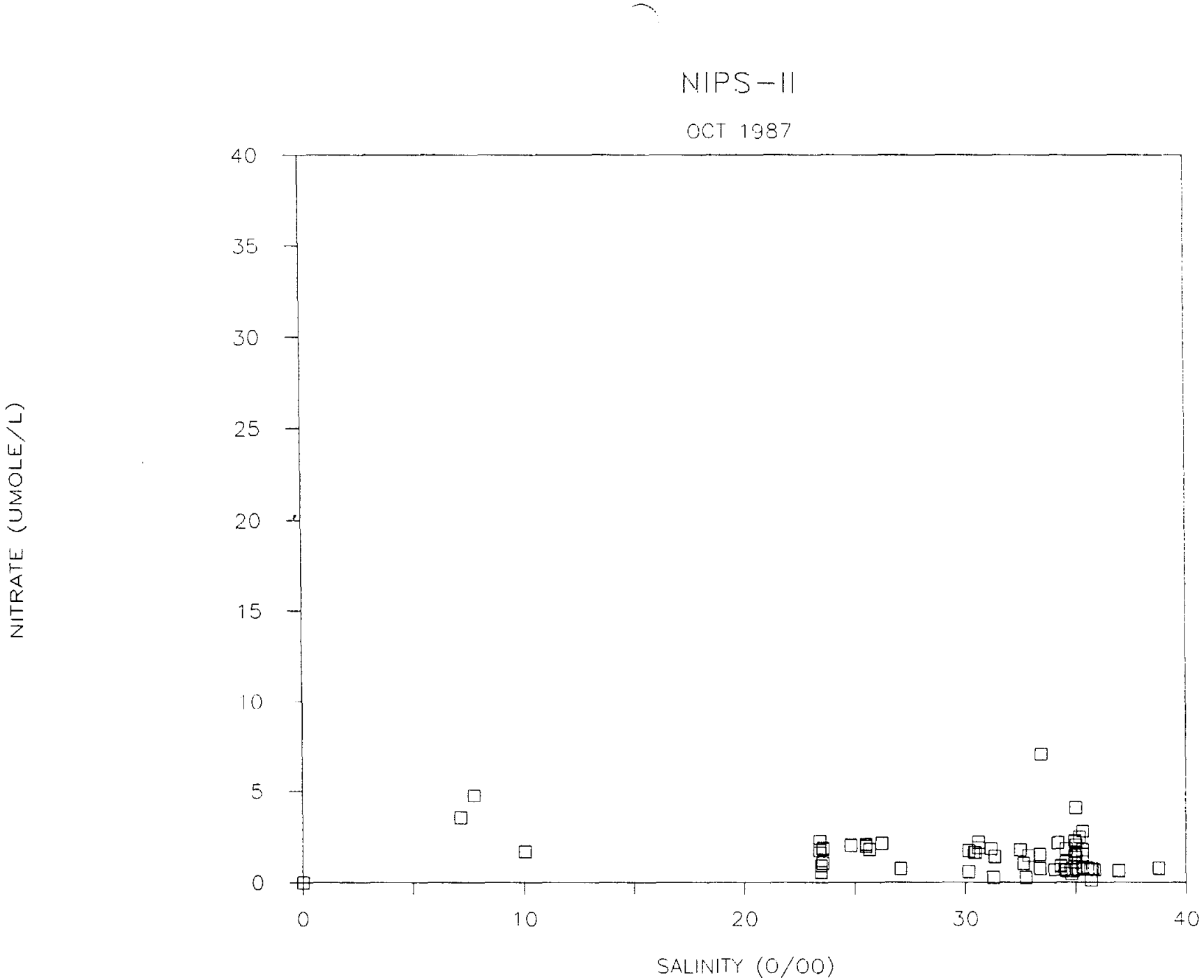
NIPS-II
OCT 1987
NITRATE (UMOLE/L)
SALINITY (O/OO)
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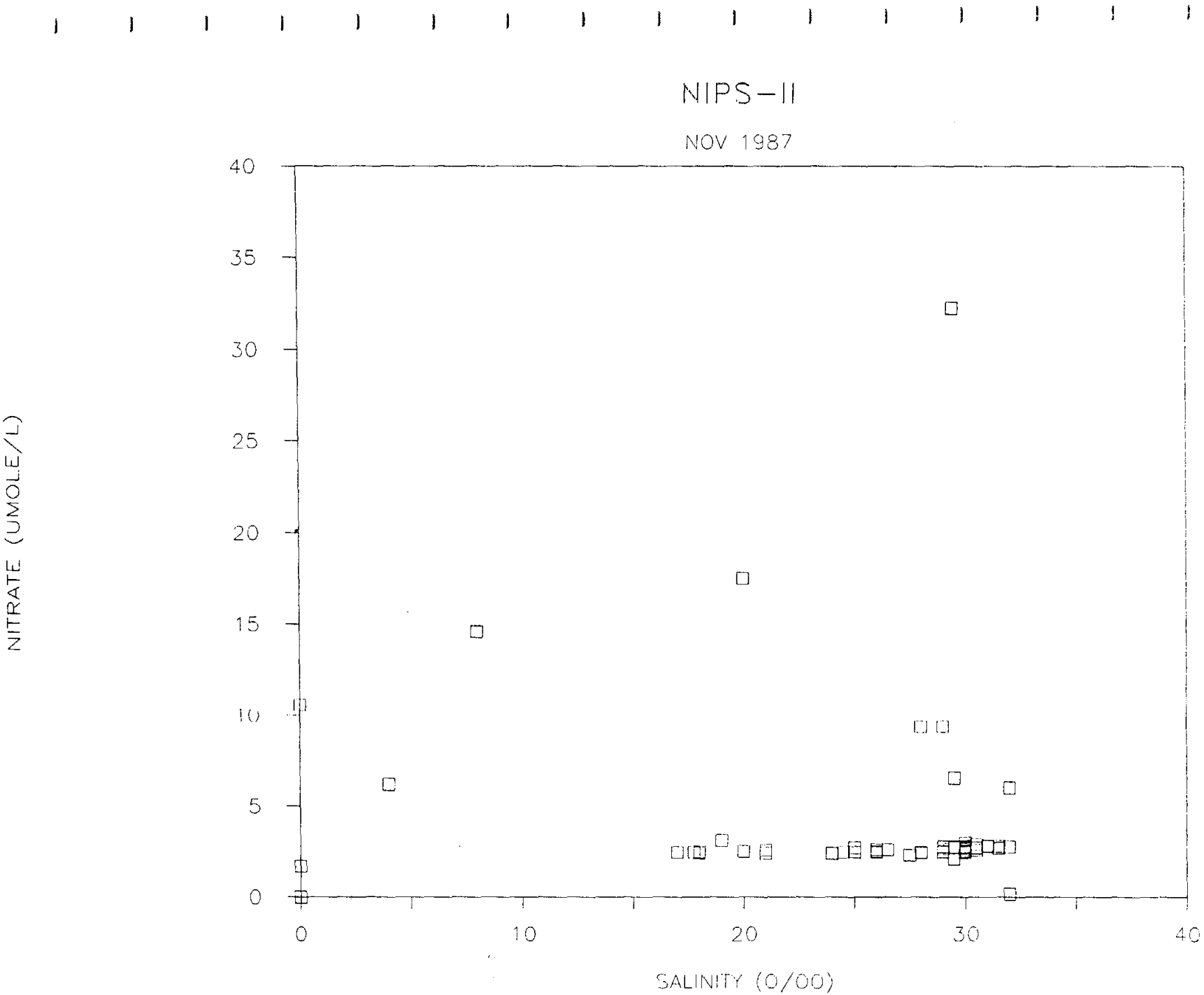
NIPS-II
NOV 1987
NITRATE (UMOLE/L)
SALINITY (0/00)
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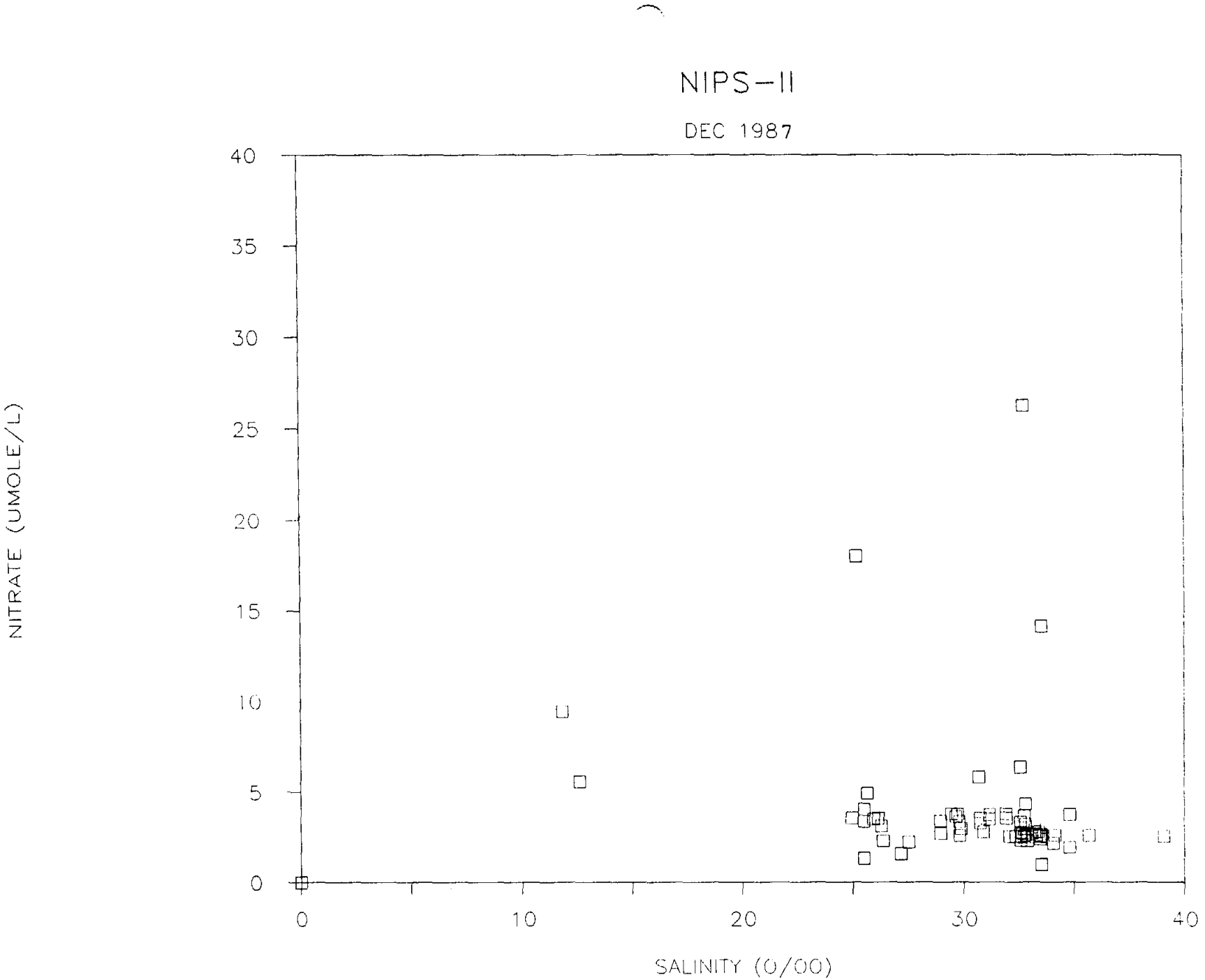
NIPS-II
DEC 1987
NITRATE (UMOLE/L)
SALINITY (0/00)
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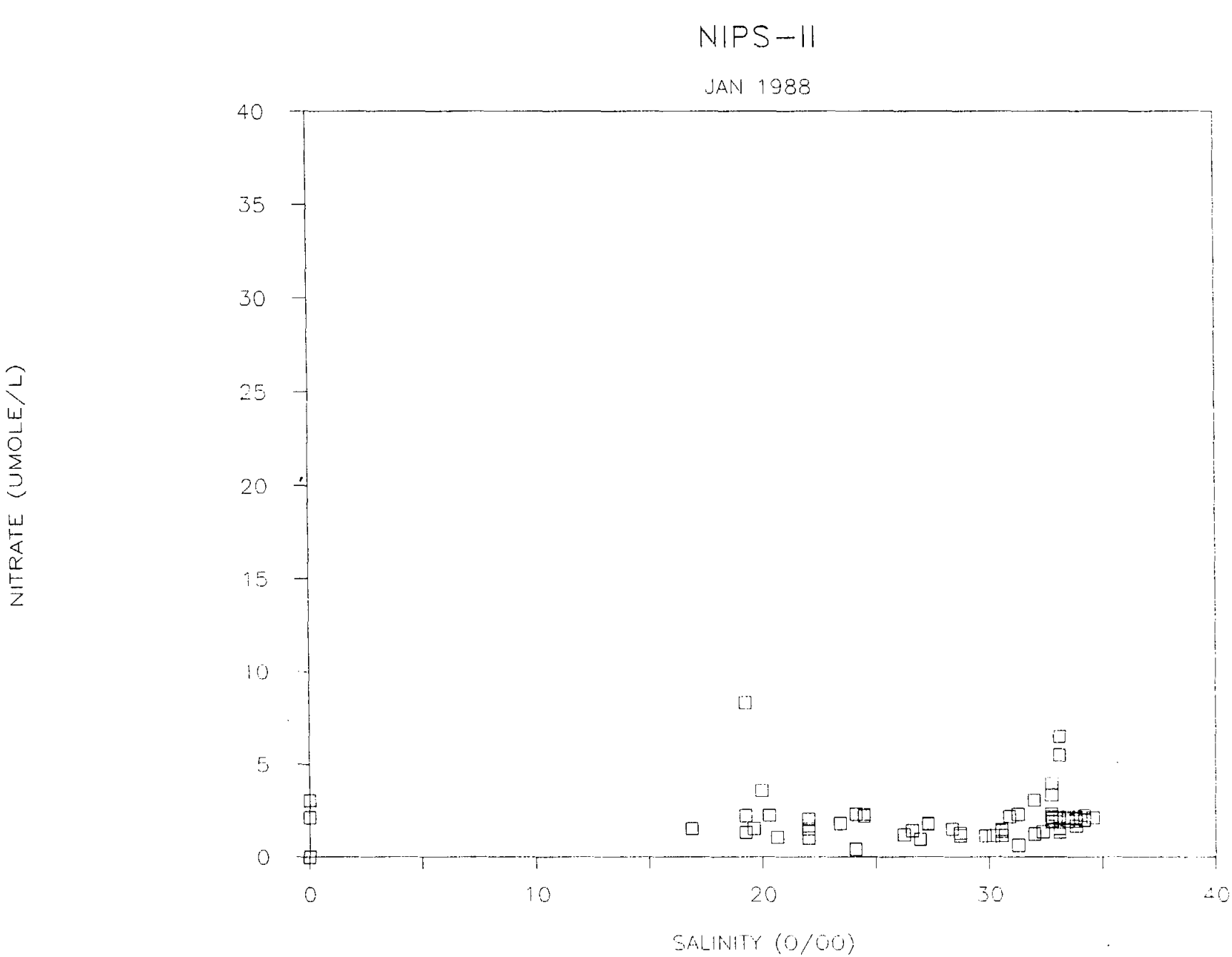
NIPS-II
JAN 1988
NITRATE (UMOLE/L)
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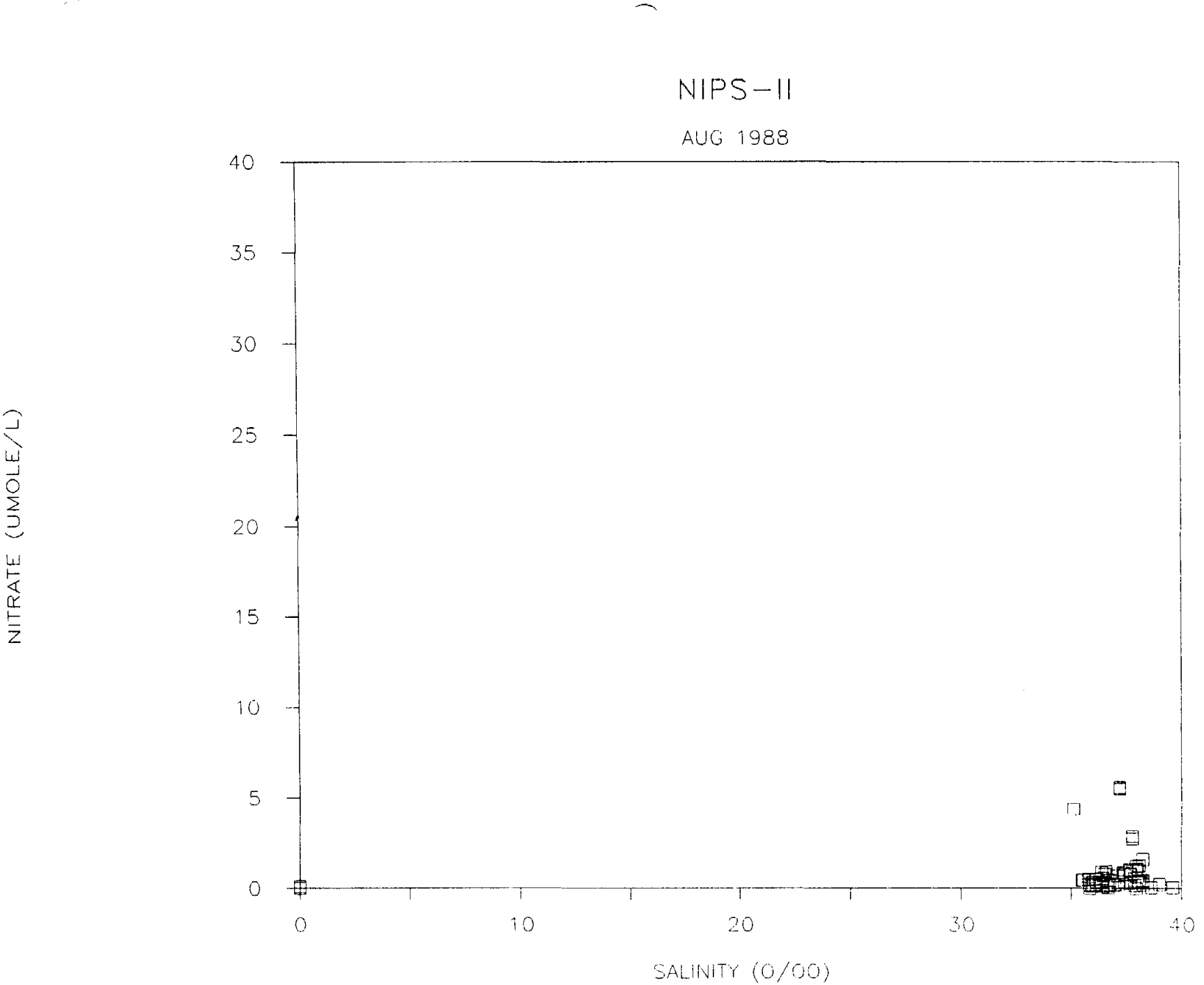
30
40
SALINITY (0/00)


NIPS-II
AUG 1988
NITRATE (UMOLE/L)
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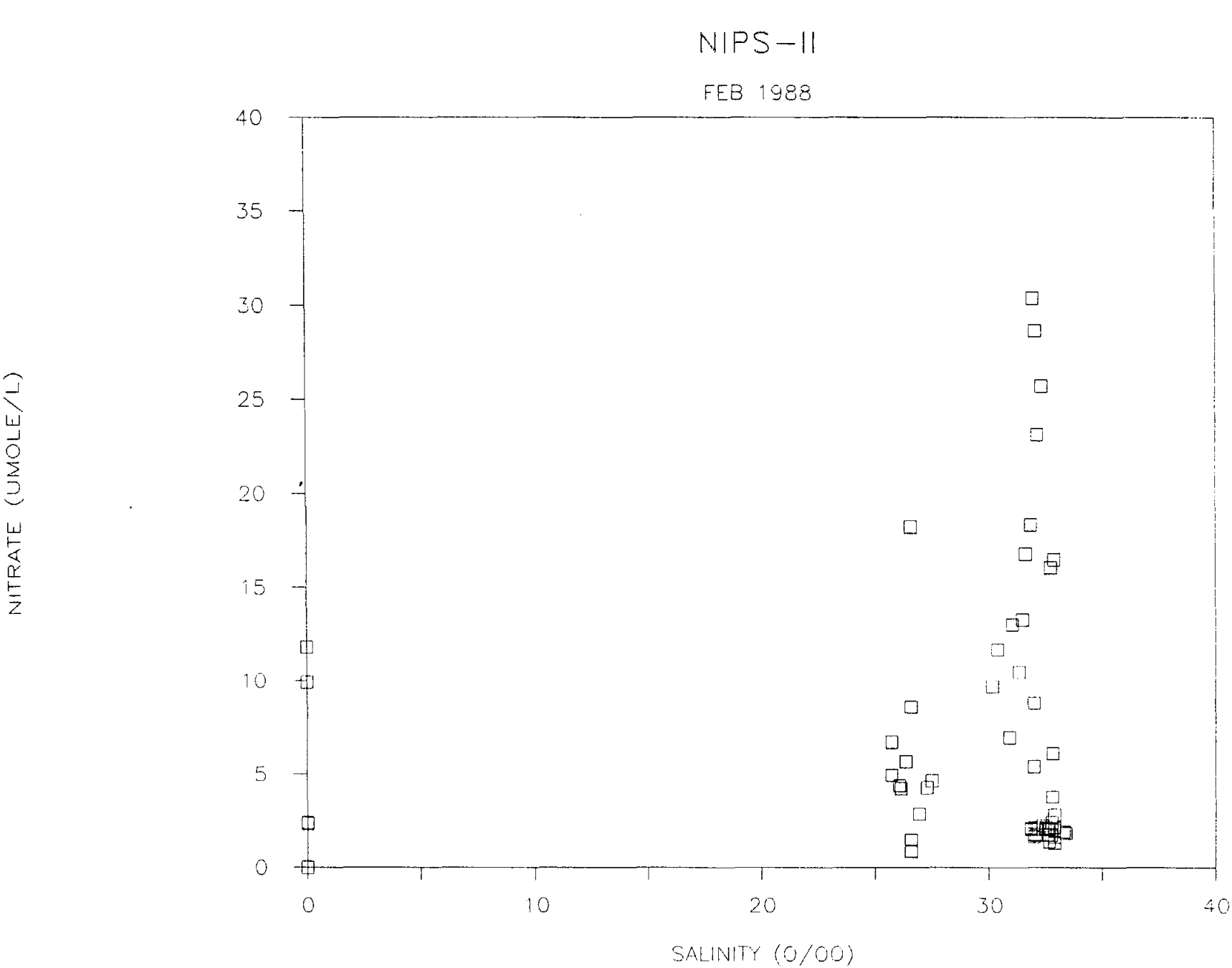
40
SALINITY (0/00)


NIPS-II
FEB 1988
NITRATE (UMOLE/L)
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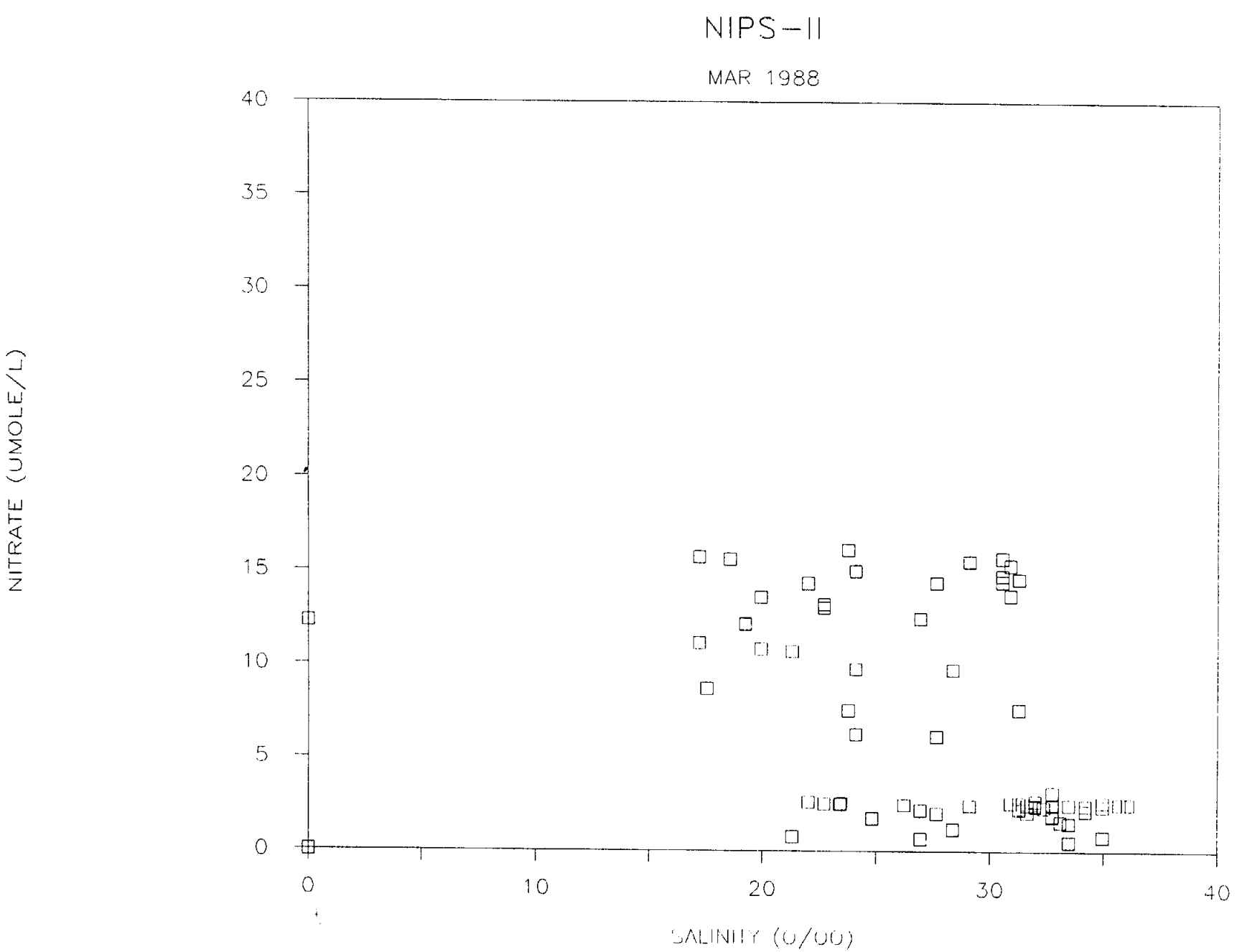
35
40
0
10
20
30
40
SALINITY (0/00)


NIPS-II
MAR 1988
NITRATE (UMOLE/L)
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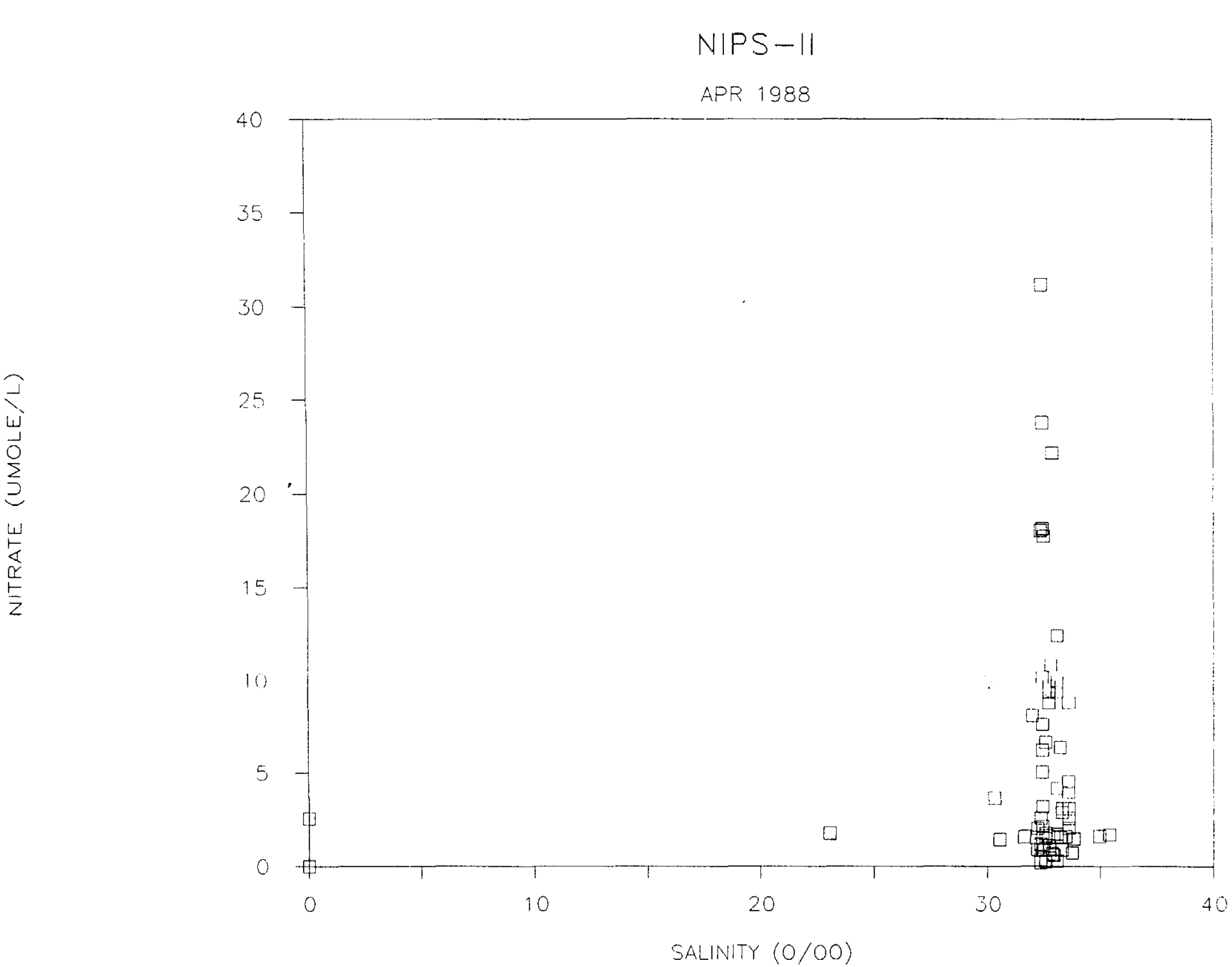
40
SALINITY (O/OO)


NIPS–II
APR 1988
NITRATE (UMOLE/L)
SALINITY (0/00)
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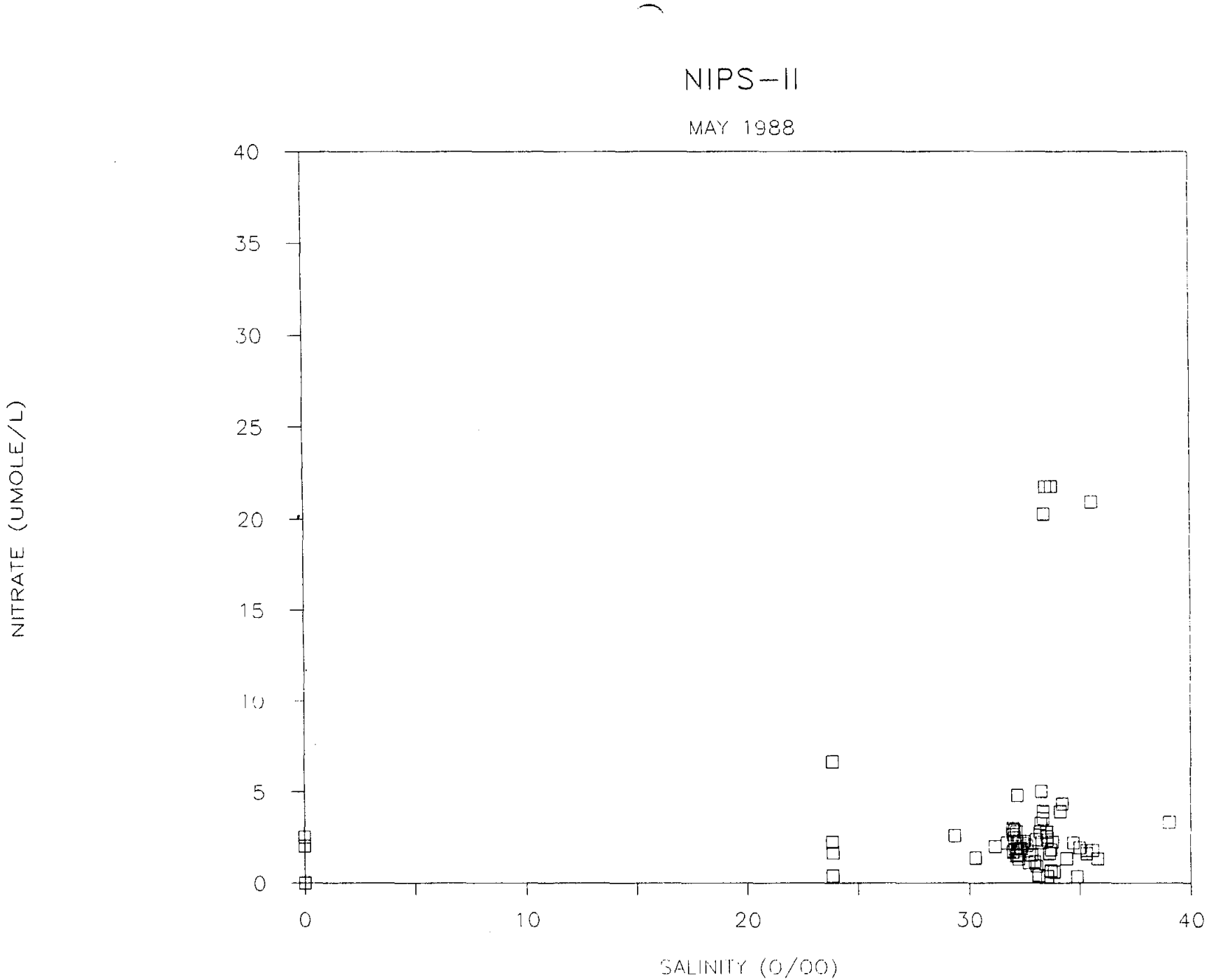
NIPS-II
MAY 1988
NITRATE (UMOLE/L)
SALINITY (O/OO)
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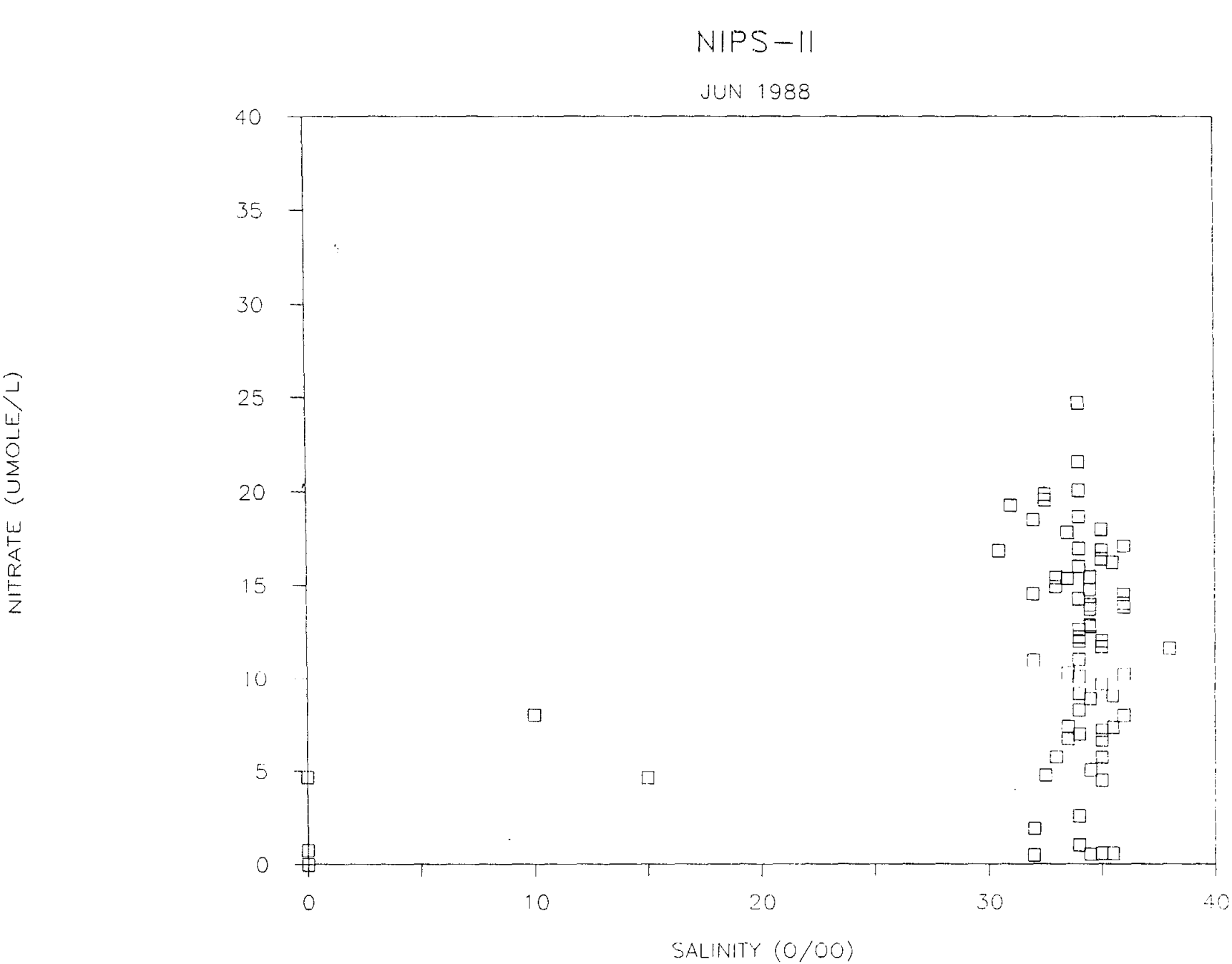
NIPS-II
JUN 1988
NITRATE (UMOLE/L)
SALINITY (0/00)
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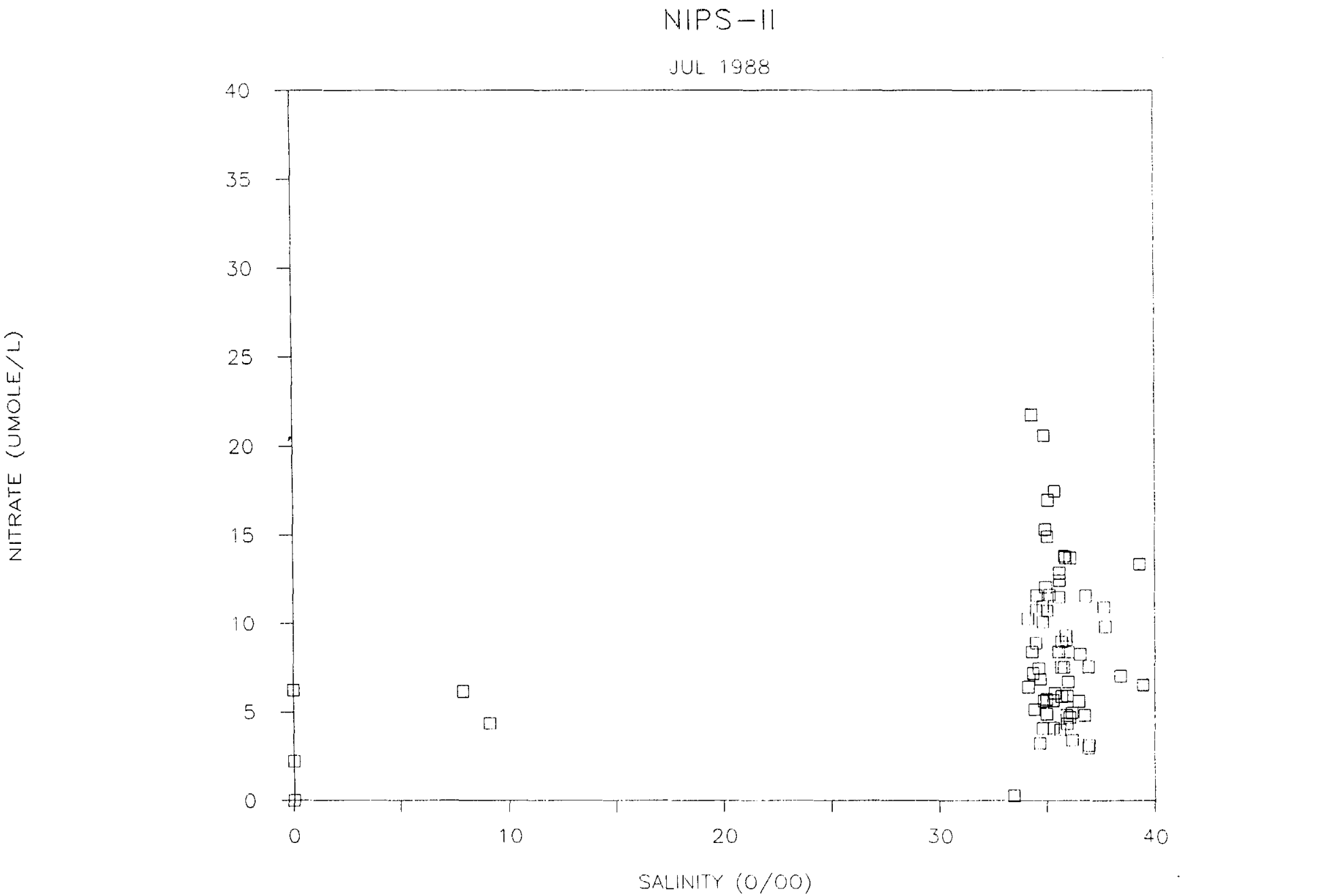
NIPS-II
JUL 1988
NITRATE (UMOLE/L)
SALINITY (0/00)
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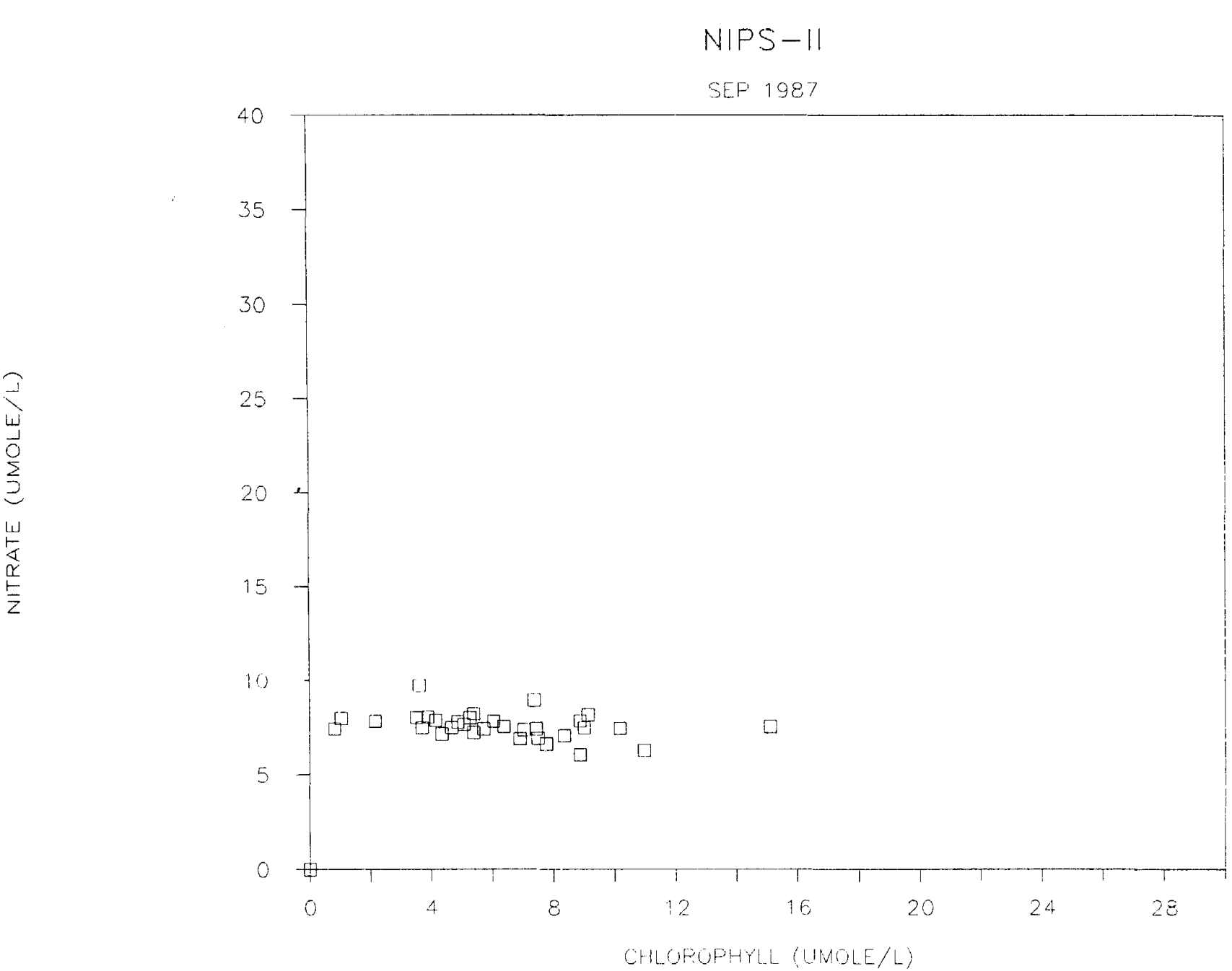
NIPS-II
SEP 1987
NITRATE (UMOLE/L)
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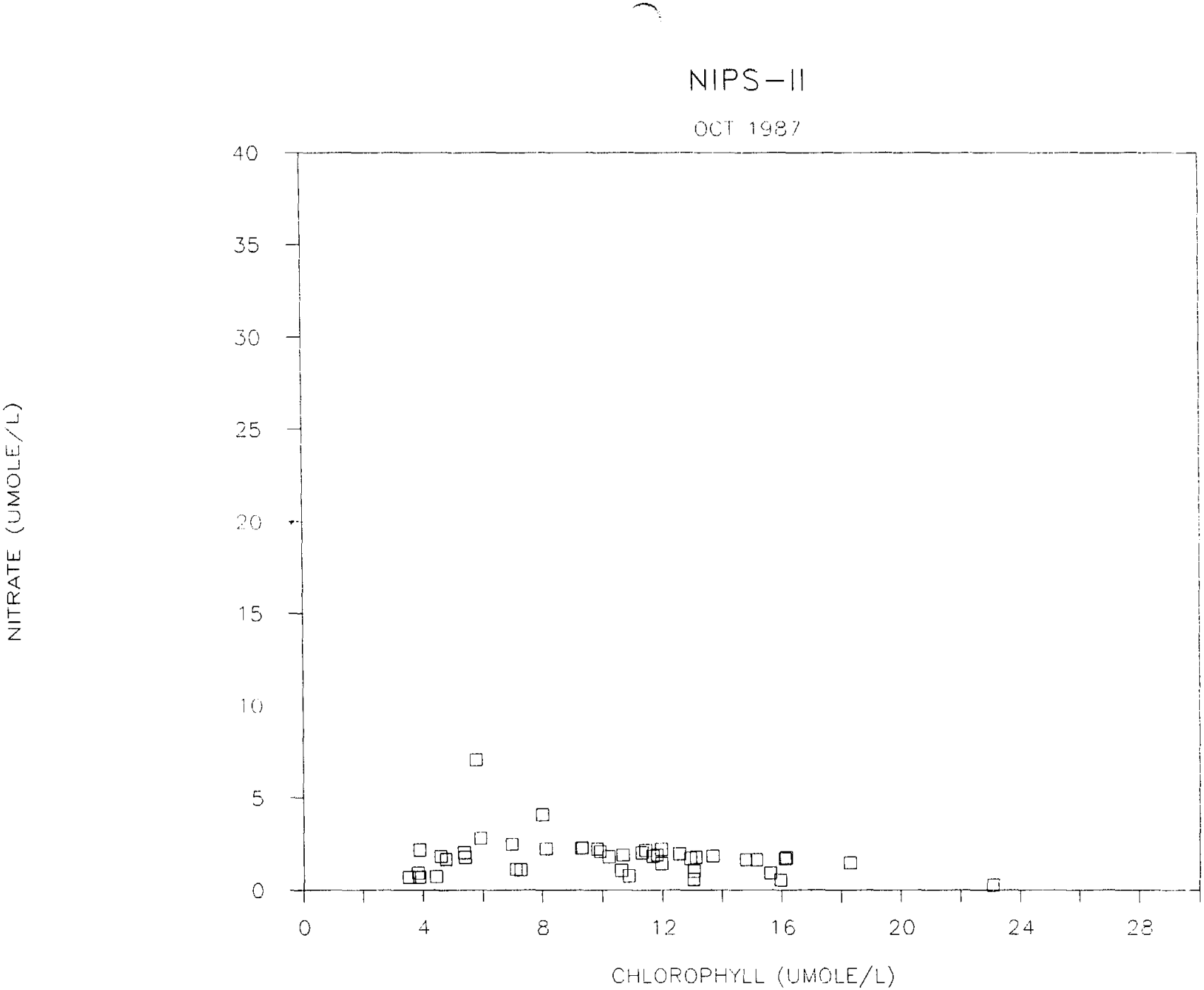
CHLOROPHYLL (UMOLE/L)


NIPS-II
OCT 1987
NITRATE (UMOLE/L)
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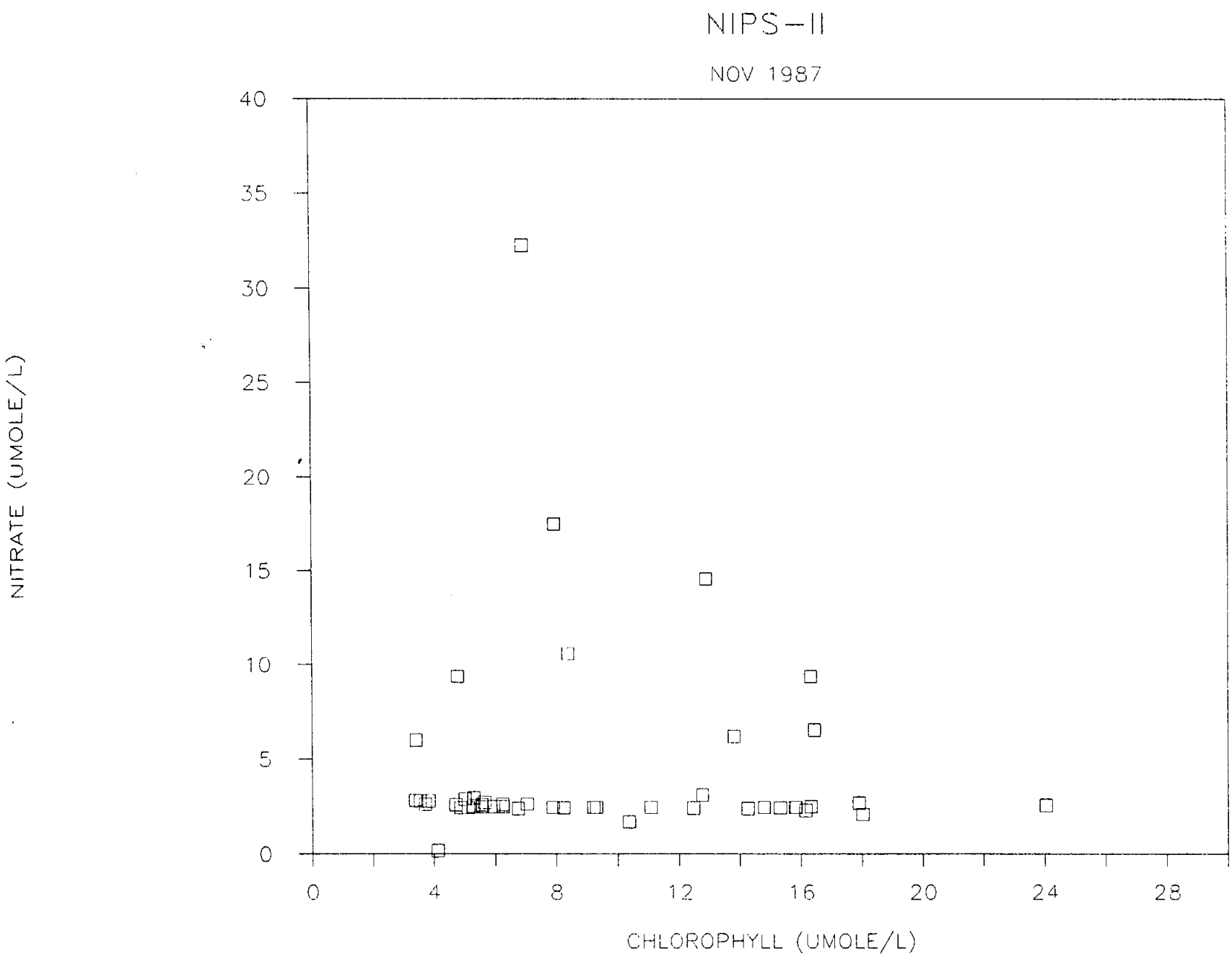
CHLOROPHYLL (UMOLE/L)


NIPS-II
NOV 1987
NITRATE (UMOLE/L)
CHLOROPHYLL (UMOLE/L)
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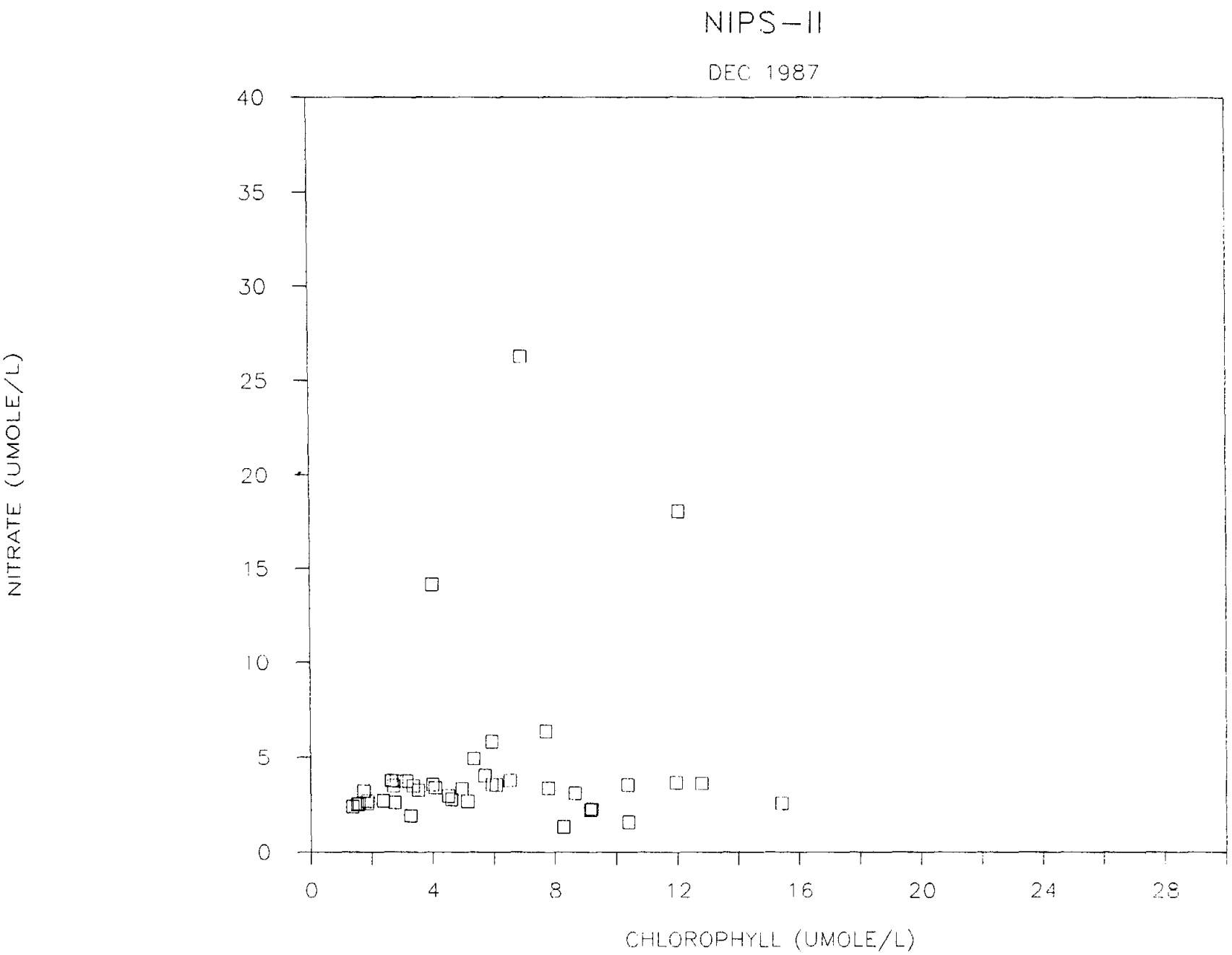
NIPS–II
DEC 1987
NITRATE (UMOLE/L)
CHLOROPHYLL (UMOLE/L)
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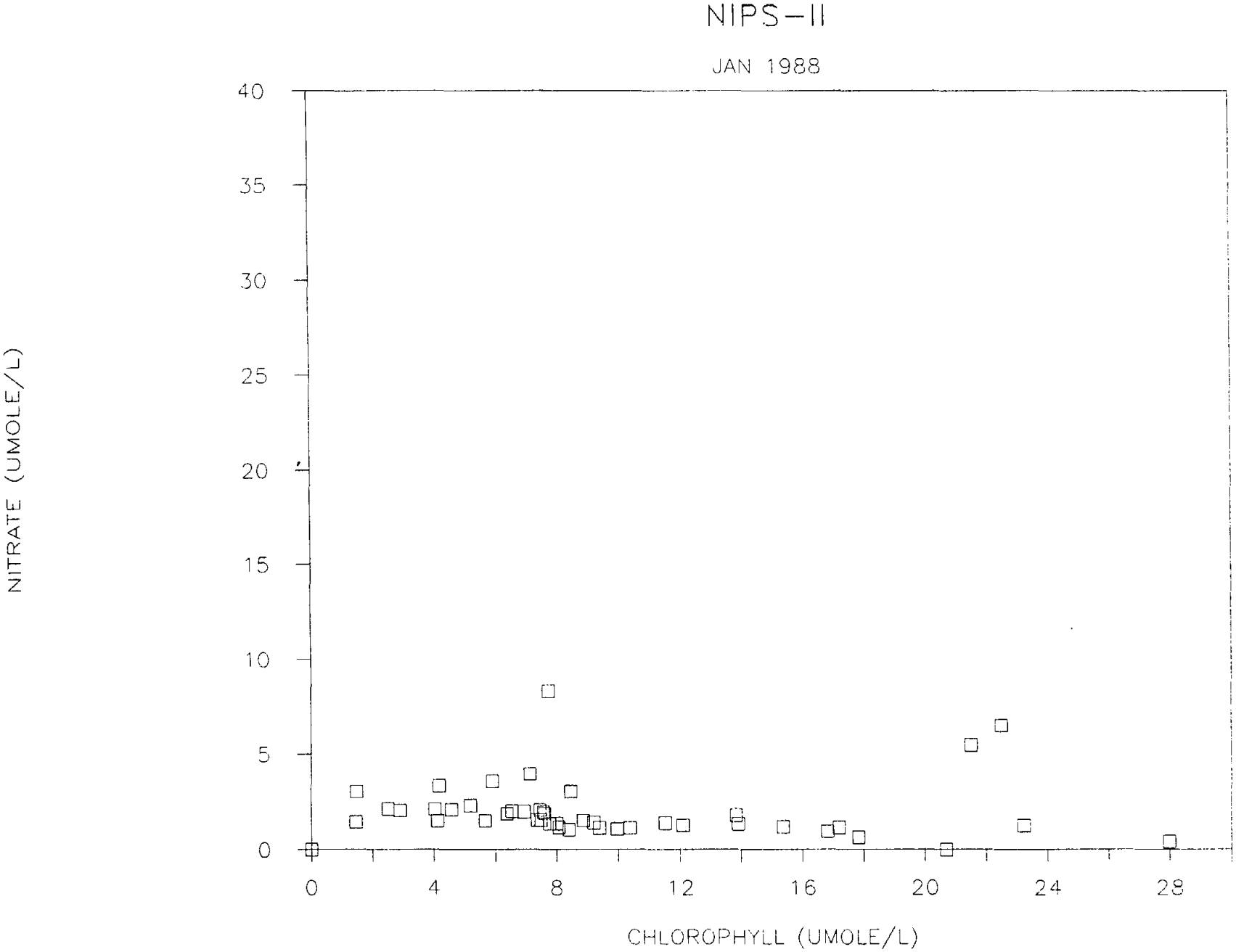
NIPS-II
JAN 1988
NITRATE (UMOLE/L)
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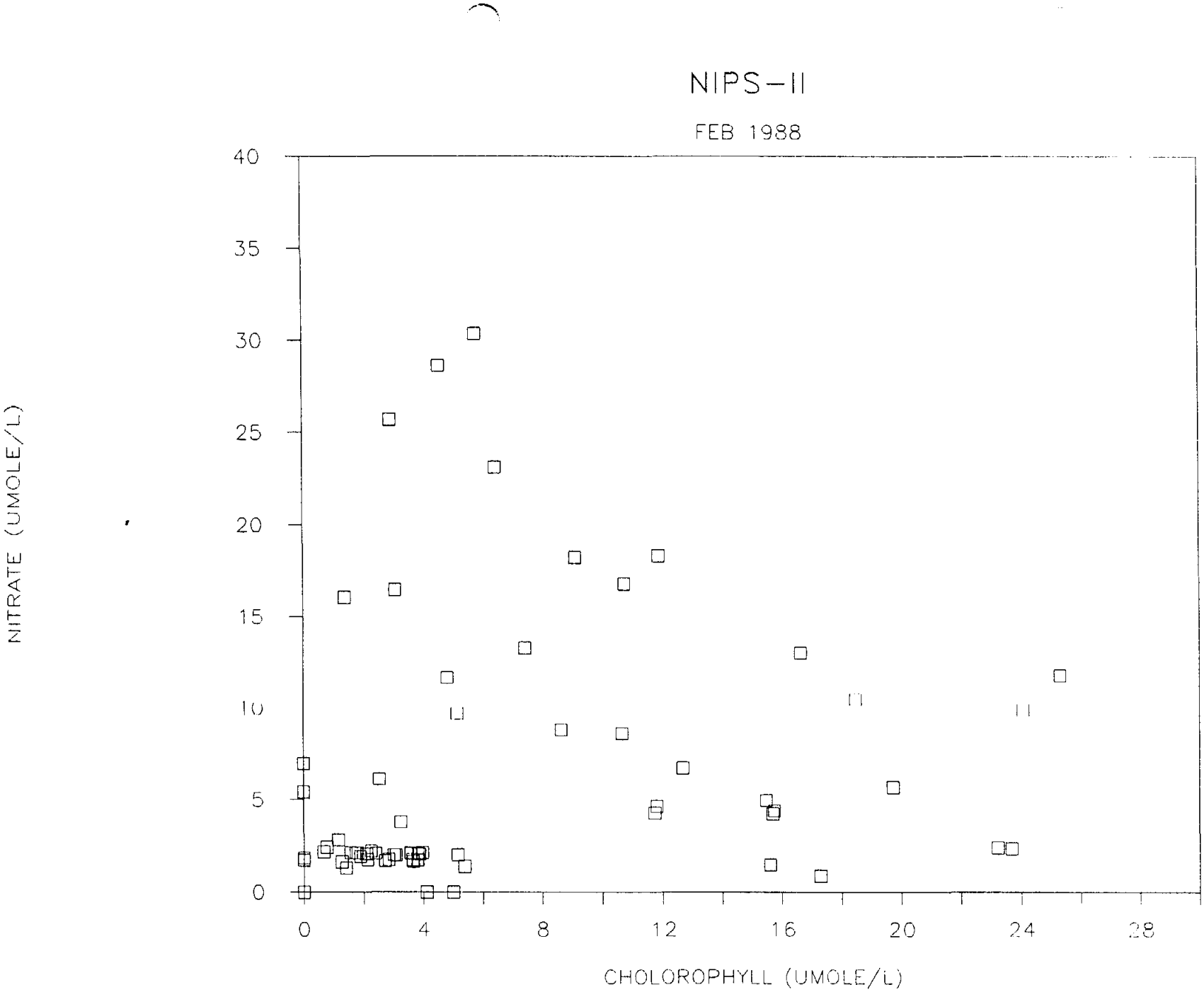
CHLOROPHYLL (UMOLE/L)


NIPS-II
FEB 1988
NITRATE (UMOLE/L)
CHOLOROPHYLL (UMOLE/L)
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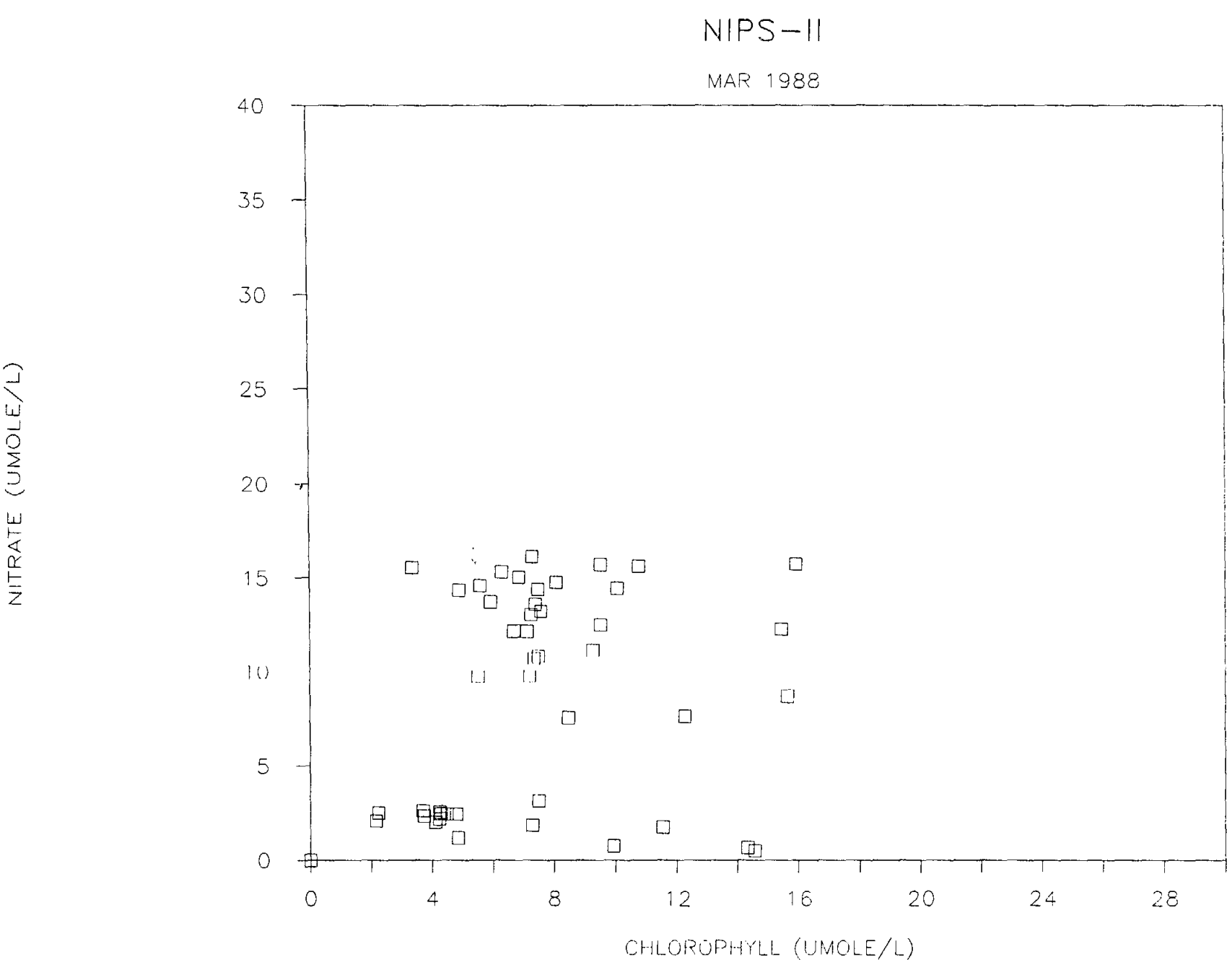
NIPS-II
MAR 1988
NITRATE (UMOLE/L)
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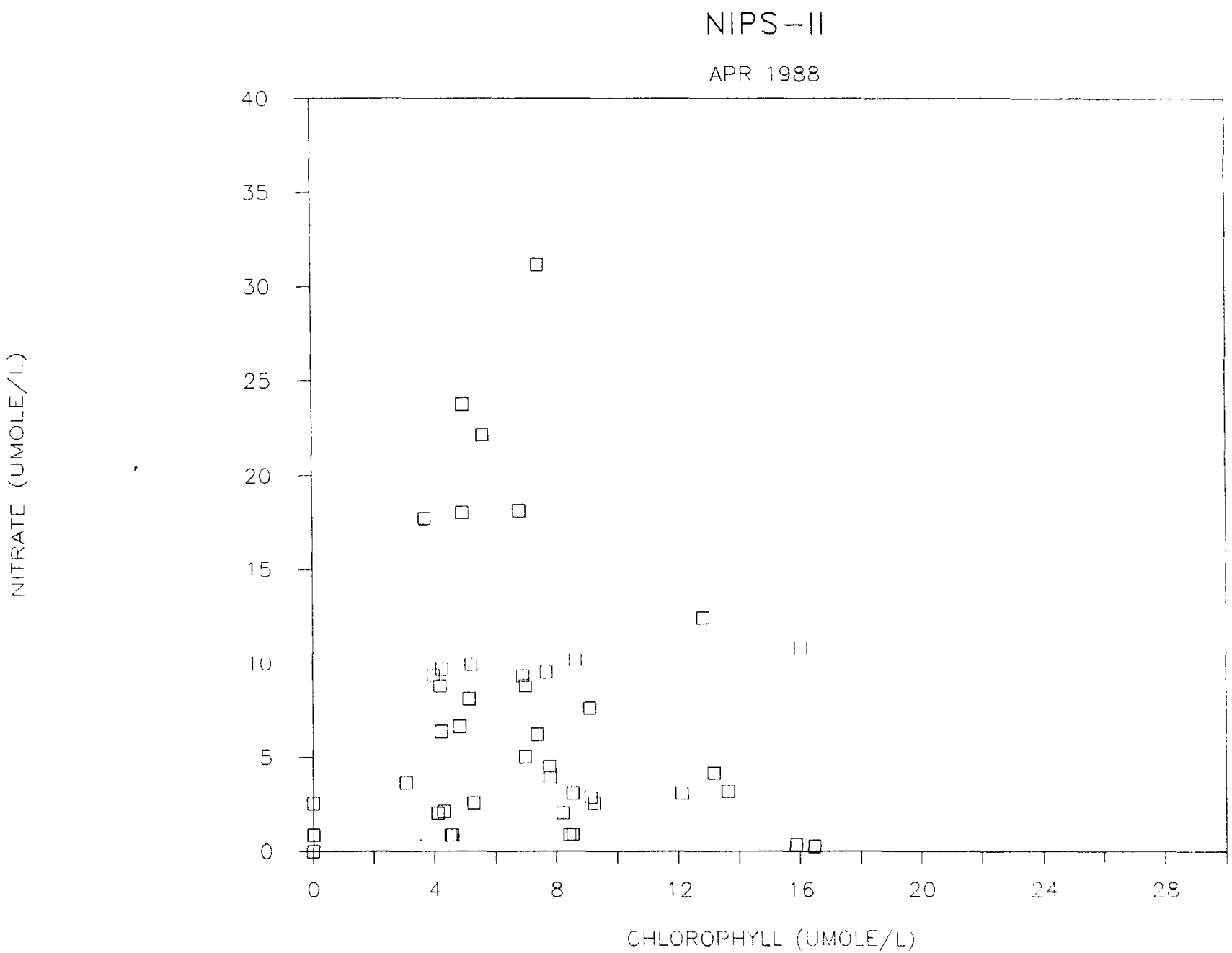
CHLOROPHYLL (UMOLE/L)


NIPS-II
APR 1988
NITRATE (UMOLE/L)
CHLOROPHYLL (UMOLE/L)
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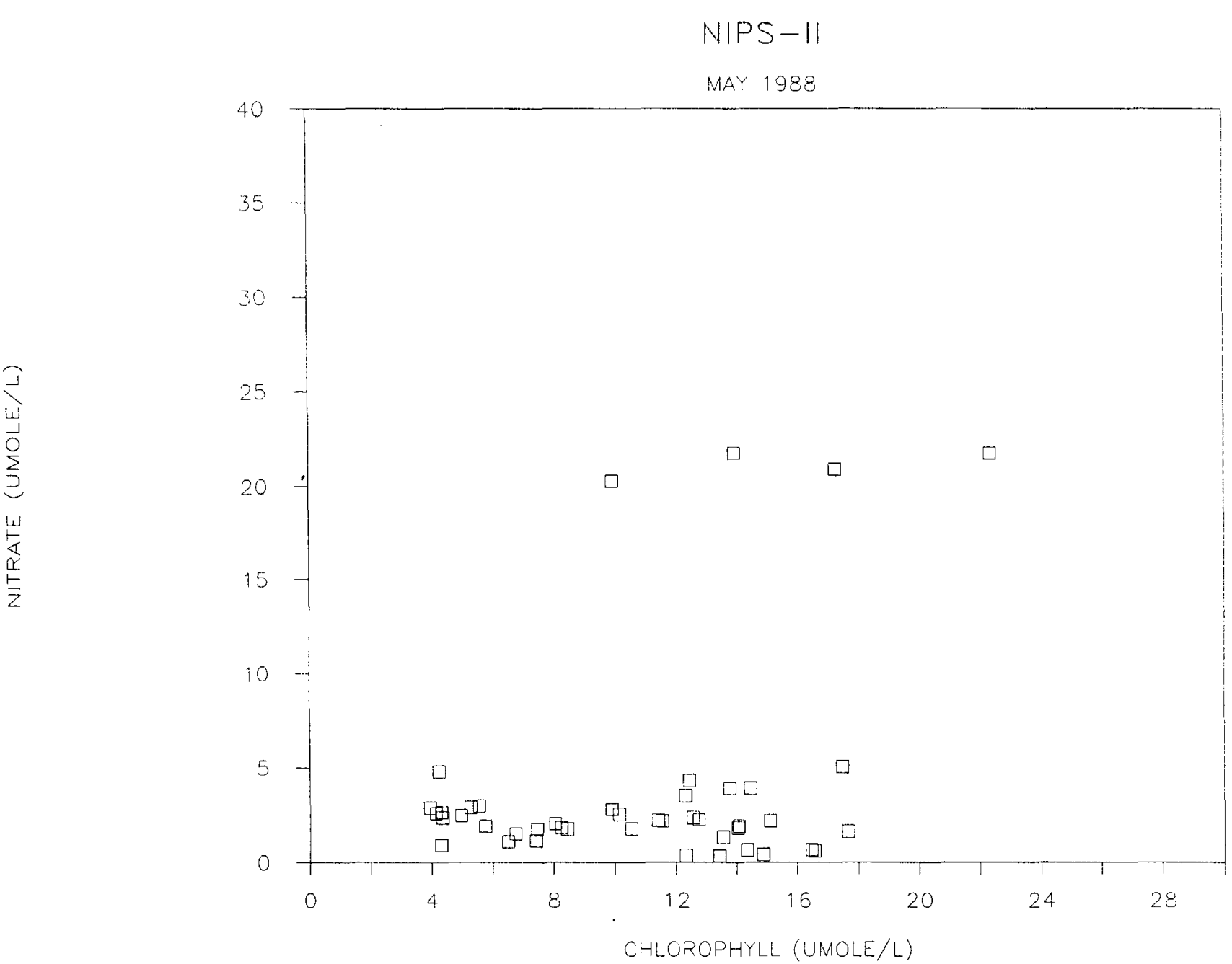
NIPS-II
MAY 1988
NITRATE (UMOLE/L)
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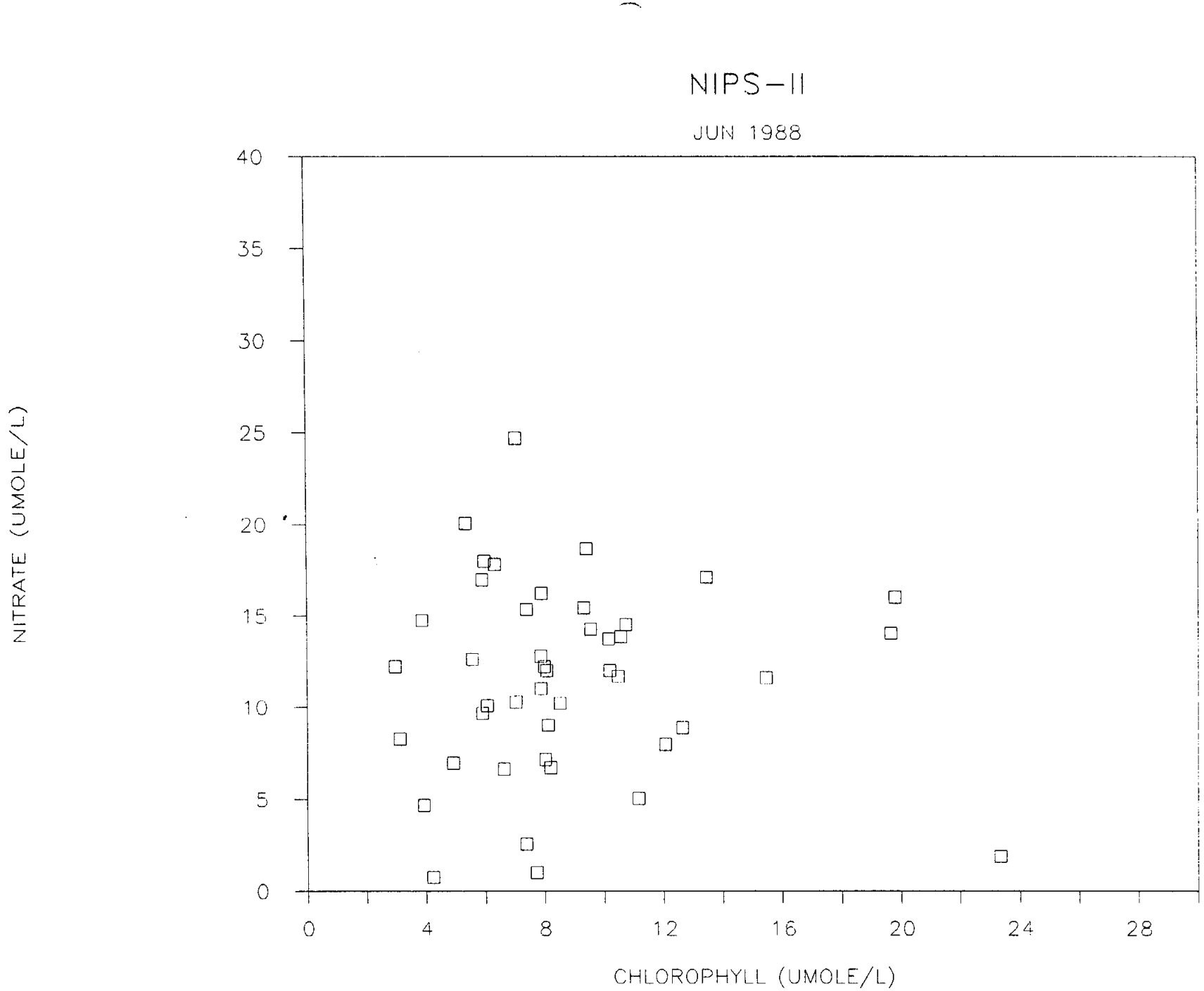
CHLOROPHYLL (UMOLE/L)


NIPS-II
JUN 1988
NITRATE (UMOLE/L)
CHLOROPHYLL (UMOLE/L)
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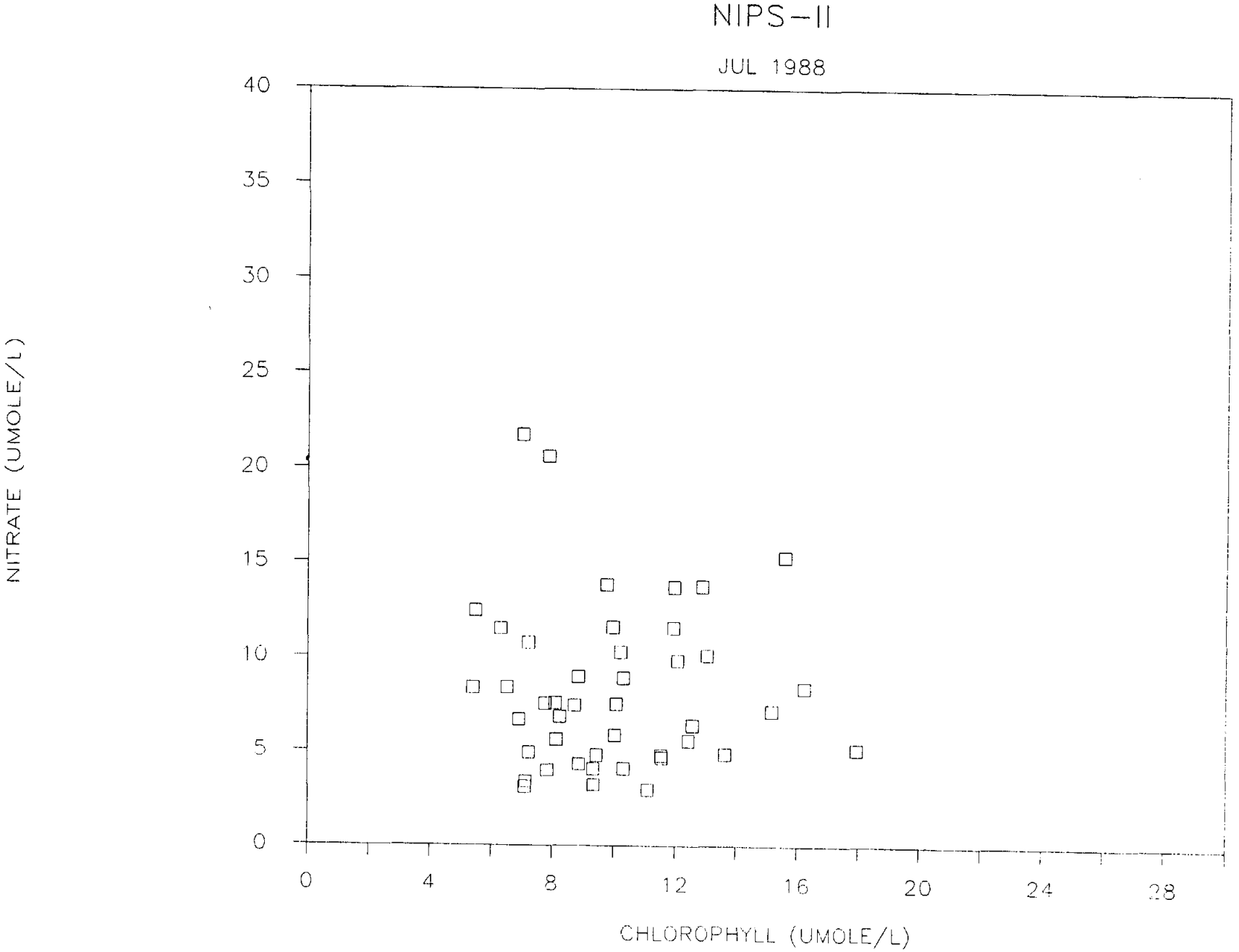
NIPS-II
JUL 1988
NITRATE (UMOLE/L)
CHLOROPHYLL (UMOLE/L)
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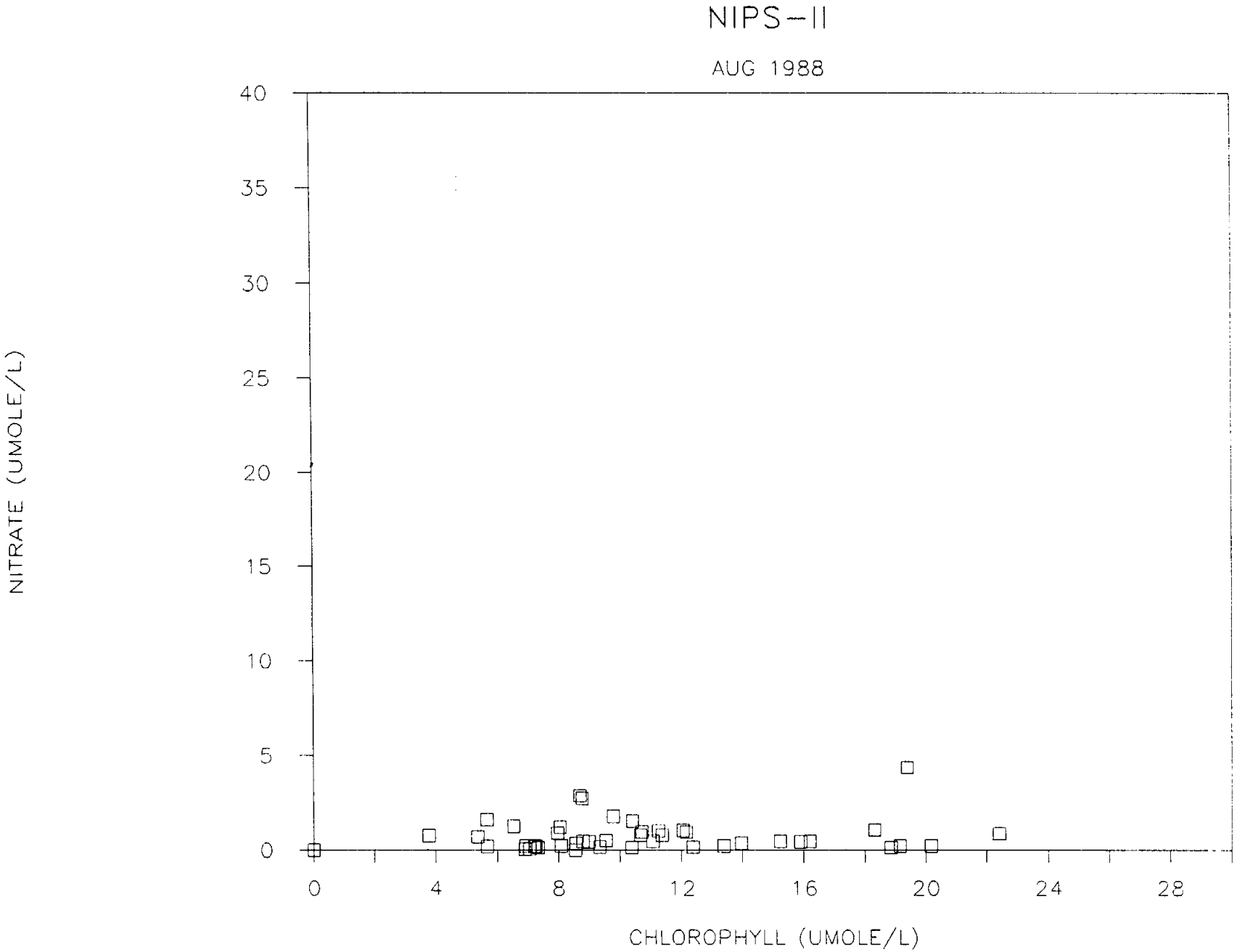
NIPS-II
AUG 1988
NITRATE (UMOLE/L)
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CHLOROPHYLL (UMOLE/L)