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STATISTICALLY-BASED DECOMPRESSION TABLES VI: REPEAT DIVES ON OXYGEN/NITROGEN MIXES

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The experiments reported herein were conducted according to the principles set forth in the current edition of the "Guide for the Care and Use of Laboratory Animals," Institute of Laboratory Animal Resources, National Research Council.

This technical report has been reviewed by the NMRI scientific and public affairs staff and is approved for publication. It is releasable to the National Technical Information Service where it will be available to the general public, including foreign nations.

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The risk of decompression sickness (DCS) during dives on various nitrogen/oxygen breathing mixes is analyzed using likelihood maximization. Risk is treated as cumulative, resulting from periods during which the partial pressure of dissolved N_2 exceeds the hydrostatic pressure in one or more hypothetical separate "tissues". Gas uptake and release are assumed to follow either mono- or bi-exponential kinetics. The database consists of 2006 well-documented wet man-dives. No statistical evidence is found to justify the use of different models or different parameter values for single dives versus repeat dives or for dives on different N_2/O_2 mixes. Under these models, then, the single and repeat dives in our database should be considered as belonging to the same population. However, the models *do not* adequately predict the probability of DCS associated with a series of 128 multilevel dives (which feature ascents to 20-30 fsw interspersed with deeper excursions) while simultaneously making a plausible prediction of the risk of any other type of dive in the database.

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I. BACKGROUND

The work detailed in this report is part of an ongoing effort to develop models predicting the incidence of decompression sickness (DCS) (1-5). Report I of the series postulated DCS as being a random event subject to the laws of probability, in contrast to the traditional view of DCS as a deterministic event. Semi-theoretical models (describing the exchange of inert gas between blood and tissue) were introduced to predict the probability of decompression sickness [P(DCS)] for any given dive profile, with the histories of depth and breathing gas composition considered the sole independent variables. A further important innovation of Report I was the use of cumulative risk integrals as determinants of total P(DCS) in the models. In other words, P(DCS) was considered to increase over the course of the dive as risk accumulated according to the model's "rules". These models were fitted to over 1700 well-documented air dives.

In Report II the most successful of the models from Report I was used as a predictor of P(DCS) to generate recommended air diving tables. In Report III, this same model was used to compare the P(DCS) of dives in the current U.S. Navy, British Royal Navy, and Canadian Forces air tables. In Report IV, the data-fitting and analysis were extended to "saturation" dives, and it was demonstrated that the modelling approach outlined in Report I could satisfactorily predict the risks of dives ranging from less than a minute to more than a day in duration. Accordingly, recommended tables for saturation dives were included with this report. Report V is an examination of an alternative set of risk models, in which risk is viewed as something that depends on a single incident of excess dissolved gas at some instant during the dive. These models were found to be less adept than ours at fitting heterogeneous data sets such as those assembled for Report IV.

In this report we compare repeat and multilevel dives with single dives, asking whether a single model can adequately describe the various sorts of dives. A repeat dive is defined here as a series of two or more descents separated by an interval of less than 12 h on the surface. We define a multilevel dive as a series of two or more descents separated by an interval of less than 12 h at a shallow depth. All of the data assembled for this report consist of wet dives on oxygen/nitrogen performed in U.S. Navy, Canadian Forces, or British Royal Navy trials. Various nitrogen/oxygen breathing mixes were used, although most were air dives and most of the remainder were on 0.7 atm oxygen, the balance nitrogen (henceforth to be called simply "0.7"). Only data reported since 1978 were used, in accordance with our perception that possible DCS symptoms are judged by substantially different standards now than in the past. Therefore, we did not use the data from reports I or IV of this series because they all predated 1970.

Since this study includes dives on several gas mixes, it became necessary to test the validity of our conception of how P(DCS) is affected by the composition of the breathing gas mixture. This was done by comparing dives on different breathing gas mixes and asking whether data collected using various gas mixes can be described by a single predictive model.

The comparisons mentioned above were performed using objective statistical tests after each available data set, or combination of data sets, had been described by fitting the probabilistic models to it. The indicated results are that the models do not discriminate between single and repeat dives or between dives on different nitrogen/oxygen breathing mixes, that is, it does not seem necessary to use different values of the fitted parameters when moving from one category of dives to another. However, none of the models used in this report can adequately describe our only set of multilevel dives while simultaneously providing an adequate description of any of the other data sets. Therefore, we cannot say with confidence that the present models are suitable for predicting the outcomes of multilevel dives.

II. MATHEMATICAL MODELS

The models have been described in previous reports; only a short review will be presented here. In the simplest conceivable model, every dive in a data set has the same P(DCS), and the reasonable course is to set this value of P(DCS) equal to the observed average P(DCS) for the data set. We call this one-parameter model the "null model" and use it as a minimum standard that any creditable semi-theoretical model must out-perform.

The models of real interest are those that include descriptions of gas exchange kinetics. In such a model, evaluation of the safety of a dive is accomplished by relating the entire dive profile to the probability of DCS by a "risk function":

$$DCS = 1.0 - \exp\left(- \int_0^{\infty} r \, dt \right) \qquad [1]$$

Here r is a measure of instantaneous risk that is integrated over the course of a dive and post-dive period. When more than one hypothetical "tissue" is assumed to exist, we obtain the total instantaneous r by summing the contributions from the individual tissues:

$$r = \sum_i r_i \qquad [2]$$

where r_i = instantaneous risk due to tissue i. The form we give to r_i for tissue i is as follows:

$$r_i = A_i [P_{tis,i} - P_{amb} - P_{thr} + k_{O2}(P_{O2})] / Pamb , \quad r_i > 0 \qquad [3]$$

where $P_{tis,i}$ = partial pressure of inert gases in tissue i (fsw);
P_{amb} = ambient hydrostatic pressure (fsw);
P_{O2} = partial pressure of oxygen in breathing gas (fsw);
A_i = gain factor for tissue i (min^{-1});
P_{thr} = threshold pressure difference (fsw);
k_{O2} = a risk coefficient for P_{O2} (dimensionless).

Thus, when two or more "tissues" are postulated, the models predict that the probability that DCS will occur is the joint probability of DCS in all of the tissues. The metabolic gases CO_2 and H_2O are ignored in this calculation. Whenever the numerator on the right side of [3] is less than zero, r_i is set equal to zero, so that the integrated risk cannot diminish with time. In other words, risk can accumulate but it cannot be depleted. P_{thr} is an absolutely safe excess partial pressure of inert gas that can be sustained indefinitely with no risk of DCS. A non-zero value of k_{O2} indicates that the risk of DCS depends on the partial pressure of O_2 as well as the partial pressure of the inert gas: $k_{O2} > 0$ suggests that breathing a high P_{O2} increases the risk of DCS independently of the effect of the inert gas, and $k_{O2} < 0$ suggests that a high P_{O2} is beneficial from the standpoint of DCS prevention, aside from the decreased partial pressure of inert gas that it implies. The risk model contains three adjustable parameters besides those used in computing Ptis: A, k_{O2}, and P_{thr}. These last two parameters can easily have values of zero and can be fixed at zero in order to simplify the fitting routine. The parameter A would be zero only if there was no risk of DCS, regardless of the dive profile. $P_{tis,i}$ in equation [3] is calculated by assuming that gas exchange kinetics in the hypothetical tissue are either mono-exponential or bi-exponential. The various models consist of combinations of various numbers of "tissues" governed by one or the other of these kinetic models. The following is a summary of the models; they are presented in increasing order of complexity.

The first and simplest model incorporating gas exchange is summarized as follows:

<u>Gas exchange model 1</u>:

single mono-exponential tissue, having time constant τ;

1 parameter in gas exchange model: τ;

1-3 other parameters: A, P_{thr} (?), k_{O2} (?).

Thus, the risk model contains a total of 2 to 4 parameters, depending upon whether P_{thr} and/or k_{O2} are used. A logical extension of the single mono-exponential tissue model is a model including two such tissues in parallel:

<u>Gas exchange model 2</u>:

two mono-exponential tissues, having time constants τ_1 and τ_2;

2 parameters in gas exchange model: τ_1 and τ_2;

2-4 other parameters: A_1, A_2, P_{thr} (?) k_{O2} (?).

In the double-exponential description of gas exchange in a single tissue, the single exponential is replaced by the sum of two exponentials. The first exponential is multiplied by the dimensionless normalized weighting factor w_1, and the second exponential is multiplied by $(1-w_1)$. This kinetic model has 3 kinetic parameters rather than the 1 of a single exponential. If only one such tissue is postulated, then the following model results:

Gas exchange model 3:

one double-exponential tissue, having time constants τ_1 and τ_2;

w_1 is the weighting given to the first exponential, and $(1-w_1)$

is the weighting on the second exponential;

3 parameters in gas exchange model: τ_1, τ_2, w_1;

1-3 other parameters: A , P_{thr} (?), k_{O2} (?).

If we postulate three single-exponential tissues, then this model results:

Gas exchange model 4:

three mono-exponential tissues, having time constants τ_1, τ_2, and τ_3;

3 parameters in gas exchange model: τ_1, τ_2, and τ_3;

3-5 other parameters: A_1, A_2, A_3, P_{thr} (?), k_{O2} (?).

Two double-exponential tissues result in the following model:

Gas exchange model 5:

two double-exponential tissues A and B, having time constants τ_{A1}, τ_{A2}, τ_{B1}, and τ_{B2};

w_{A1} and w_{B1} are the weighings given to the first exponentials in tissues A and B; $(1-w_{A1})$ and $(1-w_{B1})$ are the weighings on the second exponentials in tissues A and B.

6 parameters in gas exchange model: τ_{A1}, τ_{A2}, w_{A1}, τ_{B1}, τ_{B2}, w_{B1};

2-4 other parameters: A_A, A_B, P_{thr} (?), k_{O2} (?).

The means of computing Ptis are detailed in Report I of this series (1). Note that although reference has been made to recognizable physical processes in formulating these models, the models are not to be taken as literal representations of the truth and the parameter values obtained by fitting them to data are not to be regarded as having significance outside of their use with these models.

III. DATA SOURCES AND HANDLING

Summaries of the data used in this study are offered in Table 1. Somewhat more detailed summaries will be offered in a future report. The dives in data sets whose names begin with "DC" or DD" were performed at the Defense and Civil Institute of Experimental Medicine under the direction of R.Y. Nishi (6-11). All data sets whose names begin with "EDU" are based on dives at the Experimental Diving Unit in Panama City, Florida, and were collected under the direction of E.D. Thalmann (12-14). Data set NMR8697 was collected at the Naval Medical Research Institute under the direction of P.K. Weathersby (15). All of the above data are from wet chamber, working dives. Dry dives were excluded because of the possibility that immersion is one of the factors that controls the risk of DCS (16). In almost all cases, moderate physical work was done at depth, not during decompression.

Automated recordings of the depth vs time profiles were available for all of the dives. These were converted to the format suitable for our analysis by use of a computer algorithm that simplifies each depth/time plot to a sequence of up to 76 connected line segments. This simplified profile was required to agree with the original depth/time recording to within 1 ft in depth and 0.1 min in time; also, a portion of the original recording was considered eligible for representation as a single line segment only if it was linear to within 10-15%. Depth of water in a suspended wet pot was taken to be the height of water above mid-chest level of a diver of average height. Divers used the Mark 15 or Mark 16 breathing apparatus during the 0.7 dives, so that the composition of the diver's breathing gas was regulated via the continuous-feedback control afforded by this system, which typically is assumed to maintain the partial pressure of O_2 within 0.1 atm of the set point. The divers breathed O_2 by mask (9-11) during decompression in the DC8AOW data set (the gas composition was assumed to be 99.5% O_2 , 0.5% N_2). Gas changeovers were encoded by representing the gas composition as a linear function of time. During the changeovers between O_2 and air in the DC8AOW data, it was assumed that the simultaneous washout of the breathing apparatus and the lungs required a total of 1.3 min; all other gas changeovers in all other data sets were assumed to require 1 min.

A post-dive surface time of either 12 or 24 h was included with each dive profile. This number defines the upper integration limit for computing the risk integrals defined in Part II. It represents the minimum length of time spent on the surface between dives, based on the best information provided by the people who directed the dives. It is highly probable that the tissue supersaturation (and hence the risk function) decreases to zero for all of these dives before 12 h has elapsed post-dive, even when much longer-than-usual time constants are used in the models. Questions about the data were resolved through consultation with the men in charge of the dives. Each dive outcome was set to zero for a definitely safe dive, 0.5 for marginal symptoms (skin itch or discoloration, mild pain of brief duration, and moderate fatigue), and 1.0 for any more severe symptoms ascribed to DCS. When a dive outcome was seriously in doubt, the dive was excluded altogether from the analysis. Cases of recompression without symptoms were deemed cases of unknown outcome and were excluded, because it was considered that symptoms could have appeared if the dives had gone to completion. For those cases in which a stricken diver was recompressed, his dive was encoded as though the intended schedule had been completed. This convention was followed out of necessity: as a consequence of the use of cumulative risk integrals, a dive that had been truncated for recompression therapy would always be computed by any of our models as being safer than a completed dive on the same schedule. Thus, since the truncated dive is associated with a case of DCS and the completed dive generally is not, the model would be forced to fit dose-response data in which decreased dose apparently results in higher response. We have observed that the fit of our models to data is markedly degraded by the inclusion of dives which have been encoded as truncated and have outcome equal to 1. Although the procedure we have followed seems contrived, it is the most rational we have yet devised.

There are some instances of repeat dive trials in which a diver suffered DCS during the surface interval or before completing the first dive, and was therefore recompressed for treatment without descending for the second dive in the series. These were encoded as single dives and were put into data sets with the other single dives. This seems to us the most logical way to treat these cases, but note that it biases the data by making the single dive sets appear more hazardous while simultaneously making the repeat dive sets appear safer. Our decision about how to organize the data into sets changes nothing when we fit models to combined single and repeat data; the data were not changed, only their arrangement into subsets was.

IV. DATA ANALYSIS

The evaluation of the data in Table 1 begins with their being fitted individually by the models described in Part II using likelihood maximization (17). Simply put, an iterative numerical algorithm [more specifically, a modified Marquardt nonlinear least-squares minimization algorithm (18)] is employed to determine the set of parameter values that maximizes the probability of the observed family of outcomes. Since, in general, the global maximum will be surrounded by a host of lesser maxima on the likelihood surface, it is always necessary to make multiple attempts at fitting, using a variety of initial guesses of the parameter values, before one can be reasonably assured of having achieved convergence at the global maximum. Following the fitting of individual data sets, various relevant combinations of those sets were also fitted by likelihood maximization. The fits to these combinations were compared with the fits of the original, smaller data sets, and this allowed us to apply one of the statistical tests for comparing single dives with repeat dives or air dives with 0.7 dives. The test is as follows (17).

Let a data set be fitted using likelihood maximization by two models such that the first model is a subset of the second, that is, the second model consists of the first model plus one or more additional adjustable parameters. Then, if the second, more elaborate, model is *not* intrinsically superior to the first model for this data set, then the test statistic $2(LL_2 - LL_1)$ is distributed approximately as

$$\chi^2, \qquad \nu = (n_2 - n_1) \qquad [4]$$

where LL_1 = ln(maximum likelihood) by the first model;
LL_2 = ln(maximum likelihood) by the second model;
χ^2 = the chi-square function having ν degrees of freedom;
n_1 = number of parameters in the first model;
n_2 = number of parameters in the second model.

In words, if the two models are equivalent for this data set, then twice the difference in the log likelihoods is a random variable approximately distributed as the chi square probability density function having a number of degrees of freedom equal to the difference in the number of parameters. Thus, to compare the models we reject the null hypothesis that they are equivalent if $2(LL_2 - LL_1)$ is an improbably large χ^2 variable with $\nu = (n_2 - n_1)$ degrees of freedom. For example, if $(n_2 \cdot n_1) = 3$, then even if the models are equivalent there is still a 0.05 probability that $2(LL_2 - LL_1)$ will be greater than 5.99, because the area under the χ^2 curve to the right of 5.99 is equal to 0.05. The above procedure is the "likelihood ratio" test.

Now, if the two data sets are each fitted by a 3-parameter model and then their combination is also fitted by the same model, we can consider the results as basis for comparing a 3-parameter model with a 6-parameter model for the superset. If the 6-parameter model is not demonstrated to be significantly superior to the 3-parameter model, then we accept that the two subsets are from the same population and call them "combinable". The sense to this is that if two data sets can be "combined", then one model can describe all of the data about as well as it can describe the individual data sets. This is a measure of the similarity of the two data sets, or at least of how similar they seem to the model.

A second statistical test for similarity between two data sets is accomplished by first fitting a model to a data set to determine the optimal parameter values, and then using the same model with these parameter values to predict the P(DCS) of the dives in the other data set. The predicted average P(DCS) is then compared with the observed average P(DCS), which is simply equal to the raw incidence of DCS.

The uncertainty on the predicted P(DCS) is estimated using a propagation of error that follows reference #19. Let the predicted P(DCS) be represented by *P*; then *P* can be written as a function of the adjustable parameters in the risk model used to calculate P(DCS):

$$P = P\,(B_i\,,\, i = 1, 2, 3 \ldots N_{PRM}) \qquad [5]$$

where B_i = an adjustable parameter;

N_{PRM} = total number of adjustable parameters in the risk model.

Then the variance on the estimate of P(DCS) for dive k is determined from the covariance matrix as follows:

$$\mathrm{var}\,(P_k) = \sum_{i=1}^{N_{PRM}} \sum_{j=1}^{N_{PRM}} \frac{\partial P_k}{\partial B_i} \frac{\partial P_k}{\partial B_j}\ \mathrm{cov}\,B_i\ \ \mathrm{cov}\,B_j \qquad [6]$$

The average predicted P(DCS) for an entire data set simply equals the sum of *P* for all dives divided by the number of dives:

$$P_{avg} = P_{sum} / N_{DIV},$$

where

$$P_{sum} = \sum_{k=1}^{N_{DIV}} P_k \qquad [7]$$

where N_{DIV} = number of dives in the data set. To compute the variance on P_{sum} we write an expression analogous to equation [6]:

$$\mathrm{var}\,(P_{sum}) = \sum_{i=1}^{N_{PRM}} \sum_{j=1}^{N_{PRM}} \frac{\partial P_{sum}}{\partial B_i} \frac{\partial P_{sum}}{\partial B_j} \mathrm{cov}\, B_i \;\; \mathrm{cov}\, B_j \qquad [8]$$

into which we make the following substitutions:

$$\frac{\partial P_{sum}}{\partial B_i} = \sum_{k=1}^{N_{DIV}} \frac{\partial P_k}{\partial B_i} \qquad [9a]$$

$$\frac{\partial P_{sum}}{\partial B_j} = \sum_{k=1}^{N_{DIV}} \frac{\partial P_k}{\partial B_j} \qquad [9b]$$

Then from equation [7] we have

$$\mathrm{var}\,(P_{avg}) = \mathrm{var}\,(P_{sum}) / (N_{DIV})^2 \qquad [10]$$

When converting var(P_{avg}) to a confidence interval on P_{avg}, we assume P_{avg} to be normally distributed.

V. DISCUSSION OF RESULTS

A. Comparing and Combining Data Sets

Likelihood maximization was used to fit models to the original data sets summarized in Table 1 and to various supersets formed by combining some of the original data sets. Tables 2-7 contain selected results; these tables list the ln(likelihoods) and optimal parameter values obtained via the above procedure for certain key supersets. Appendices 1-10 contain the same data-fitting information for all of the sets and supersets to which likelihood maximization was applied.

The aim of this study is to determine whether a single model can, with satisfactory accuracy, predict the decompression risks of single, repeat, and multilevel dives on any N_2/O_2 breathing mixture. An examination of the table entries allows one to draw several conclusions central to this aim. However, the useful information can be extracted only by comparing entries between tables as well as within each table. The authors well recognize how tedious this is and will try to select the most significant results for mention in the main text.

One note on the tabulated results: in Tables 2-10 and Appendices 1-10, the symbol "////" indicates that the parameter values converge such that the model becomes equivalent to model 1, the single-tissue monoexponential model, which is our simplest risk accumulation model. All of the more complicated risk accumulation models reduce to model 1 when certain of their parameters equal zero.

Table 2 lists the highest ln(likelihood) values obtained for the largest data sets that can be formed without mixing data from different "categories". In other words, single dive data are not mixed with repeat dive data, dives on different breathing mixes are not mixed, etc. Data set EDU1180R, which contains our only multilevel dive data, has been omitted from Table 2 and from all subsequent tables because it is not "combinable" with other data sets according to the likelihood ratio test (see "Data Analysis" section). We will elaborate on this point in Part B of this section. Table 3 lists the LL values obtained for the largest possible groupings of single dive data, repeat dive data, air dives, and 0.7 dives, where data from different categories have been mixed. Table 3 also contains LL values obtained for still larger groupings of dives from all categories.

Appendix 1 contains the ln(likelihood) values obtained for all data groupings in which data from different categories has not been mixed; Appendix 2 lists the LL values for combinations of data from different categories and Appendix 3 is for groupings of data from all categories. The results in Appendix 1-3 were obtained specifically to assess the combinability of various groupings of data using the likelihood ratio test. Only the relatively simple models, having no more than 4 adjustable parameters, were applied because many of the data sets are so small that there is no advantage to using more complex models. Note (in Appendix 1) that the original data sets EDU1180R, EDU885M, DDREPWET, and DC8AOW were not dealt with individually because they had too few cases of DCS (no more than 4) to be fitted meaningfully by any of the models. Strictly speaking, this makes it impossible to assess their combinability with other data sets using the likelihood ratio test.

One conclusion is possible immediately: given a data set large enough to support the use of models having multiple parameters, it is always true that at least one of the models based on integrated risk fits the data substantially better than the null model. As an illustration, note the entries in Table 2 for single air dives. For the null model, which has 1 adjustable parameter, the ln(likelihood) is -154.9. Model 1 (the 1 mono-exponential model) without a threshold overpressure is a 2-parameter model; the maximum LL obtained with this model is -153.9. To evaluate the improvement in fit afforded by model 1, we make use of the likelihood ratio test (equation [4]), which uses the chi-square function with 1 degree of freedom. We find that we can be only 80% confident in considering model 1 to be intrinsically superior to the null model for these data. Adding the threshold overpressure to model 1, for a total of 3 adjustable parameters, fails to improve the fit at all. However, the 4-parameter models are considerably more effective: model 2 (the 2 mono-exponential model) improves on the null model by 9.6 LL units, and model 3 (with 1 bi-exponential) is 7.2 LL units "better" than the null model. Both results are significant at the $p<0.005$ level.

Note that a difference in LL's means that two models differ in their predictions of the likelihood of the observed family of dive outcomes. For a difference of 9.6 LL units this difference in predicted likelihoods is a factor of $\exp(9.6) = 15{,}000$. Since the null model assumes a uniform risk of DCS regardless of dive profile, the superior fit of our more sophisticated models reflects their ability to discriminate among dives with regard to their riskiness.

For the data listed in Table 2, with the exception of the single air dives, noted above, neither of the 4-parameter models provides an improvement of more than 1.6 LL units ($p<0.25$) over the fit of model 1. For the generally larger and more diverse data sets in Table 3, we see that model 2 usually provides the best fit. For example, for the most complex data set, containing 1878 single and repeat dives on various gas mixtures, the fit of model 2 is 11.7 LL units better than any other model's. In fact, for the data sets in Tables 2 and 3 we find that model 2 always provides the best fit for data sets having more than 500 dives, but never improves significantly on model 1 when $n<500$. This illustrates that the amount of information one gets from a model depends on how much information is contained in the data set to which it has been fit; a simple data set cannot support an elaborate model.

Tables 4-7 list the optimal parameter values, with their standard errors, obtained for the selected data groupings that appear in Tables 2 and 3. Tables 4 and 5 list the optimal parameter values obtained by fitting the 1 mono-exponential tissue models, either with the threshold pressure difference P_{thr} treated as an adjustable parameter (3 adjustable parameters) or with P_{thr} fixed at zero (2 adjustable parameters). Tables 6 and 7 contain the optimal parameter values obtained by fitting the 2 mono-exponential tissues model and the 1 bi-exponential tissue model, both with P_{thr} fixed equal to zero (4 adjustable parameters).

Appendices 4-6 give the complete listing of the optimal parameter values obtained for the 2- and 3-parameter models. Appendices 7-9 have the parameter values for the 4-parameter models.

An important observation is that the optimal time constant(s) for a given data set depend on the time scale of the dives in that set. The air dives (EDU885A, EDU885AR, DC4W, and DRREPWET) are good examples. In DC4W the dives are as short as 0.5 h and never run as long as 2 h, from initial descent to surfacing. In EDU885AR the shortest dives last almost 2 h, most run over 3 h and more than one-sixth of them last about 8 h. EDU885A contains a very diverse collection of dives lasting anywhere from 0.3 to almost 7 h, with an average duration intermediate between those of the other two data sets. The significance is that the fitting algorithm cannot use large time constants to much advantage when describing short dives, and likewise, small time constants will not be used in fitting long dives. (This is equivalent to saying that very "slow" tissues are unimportant in short dives and that "fast" tissues tend not to affect the outcome of long dives, if one assumes each time constant to be truly associated with a distinct tissue). Again, the parameter values must reflect the sort of information contained in the data for which they were optimized. Not surprisingly, then, Appendices 4 and 7 show that DC4W wants the shortest time constants and EDU885AR wants the longest ones. For example, for the single tissue mono-exponential model (model 1) τ = 46 min for DC4W, τ = 281 min for EDU885AR, and τ = 173 min for EDU885A. In view of the disparity in fitted parameter values among the air data sets, it is not surprising also that they generally cannot be combined with one another under models having just one or two adjustable time constants, regardless of whether we are comparing single dive data sets with other single dive sets or singles with repeats. For example, by applying the likelihood ratio test to data in Appendices 1 and 2, we find that DC4W and

EDU885A (both single air sets) are not combinable under any of the models, that data sets EDU885A (single air) and EDU885AR (repeat air) are not combinable under either model 2 or model 3, and that DC4W does not combine with EDU885A+EDU885AR according to any of the models. More elaborate models, having 3 or more adjustable time constants, probably could accommodate all of the air data simultaneously, but no such models were applied to the air data exclusively.

There is no reason to conclude that there is any fundamental difference in the dives from one air dive data set to the next, other than their duration. The optimal parameter values are mathematical devices, not precise descriptors of definite underlying physical or biological processes.

The most important observation, found by comparing the entries in Tables 2 and 3, is that the models do not discriminate between single and repeat dives or between dives on different N_2/O_2 breathing mixtures. According to the likelihood ratio test, data sets from different categories generally can be easily combined. For example, using model 2 (the 2 mono-exponential tissue model, 4 adjustable parameters), which appears to have the widest applicability for the data in this study, we see that combining data sets from two categories never results in a decrease of more than 4.0 log likelihood (LL) units over the sum of the LL's for the subsets. Mathematically, this statement can be written $(LL_2 - LL_1) < 4.0$, using the same notation as in equation [4]. When combining single air dives with repeat air dives we find that $(LL_2 - LL_1) = 4.0$ LL units, but the air dive data do not appear to combine as well in general as do the other data, as was discussed previously. For combining single 0.7 dives with repeat 0.7 dives, $(LL_2 - LL_1) = 0.5$

(keep in mind that the data set EDU1180R has been excluded from this combination). For the combination of single dives on both air and 0.7 $(LL_2 - LL_1) = 1.1$, and for the combination of all repeat dives (again excluding EDU1180R), $(LL_2 - LL_1) = 1.8$. By contrast, the likelihood ratio test (equation [4]) tells us that if two data sets from the same population are described using a 4-parameter model, there is still a 0.05 probability that the highest LL that will be obtained for their combination will be less than the sum of the LL's for the individual sets by an amount of at least 4.74, i.e., $(LL_2 - LL_1) > 4.74$. Therefore, the LL difference must be at least 4.74 before we would reject at the 0.05 level the null hypothesis that single and repeat dives, or air and 0.7 dives, are from the same population. Accordingly, we accept that the likelihood ratio test does nothing to dissuade us from the null hypothesis that single and repeat dives on either air or 0.7 atm N_2 are described equally well by the same models.

Table 9 summarizes our comparison of dives from different categories by using the models as predictors rather than descriptors, as outlined in the Data Analysis section. In principle, a model that correctly relates P(DCS) to dive profiles, having been fitted to some data set "A", should be able to accurately predict the outcomes of the dives in some other data set "B". The realization of this is partly confounded by the apparent randomness of dive outcomes (in both data sets), by the dependence of optimal model parameter values on the specific dive profiles contained in data set "A", and by the imperfections of the models themselves. Nevertheless, we might often gain insight into how similar are the two data sets by comparing the predicted average P(DCS) for data set "B" with the observed average P(DCS) (which simply equals the number of recorded

DCS cases divided by the number of dives). We would hope to find substantial overlap in the confidence intervals. The confidence intervals on the PREDICTED values of average P(DCS) are given in Table 9; these are calculated by the error propagation method shown in the "Data Analysis" section.

Unfortunately, there seems to be no satisfactory way to calculate a confidence interval on the estimate of average P(DCS) given by the OBSERVED average P(DCS). Many of the dive profiles have only 2 replicates and some are unreplicated, and binomial theory cannot supply useful estimates of the uncertainty on an observed proportion when the sample size is only 1 or 2. We can, however, set a very conservative lower bound on this uncertainty by assuming that all of the dives carry the same underlying P(DCS), as though the data set is composed entirely of replicates of the same dive. This assumption leads one to calculate the least possible uncertainty in the estimate of P(DCS). The confidence interval on the estimate of the underlying P(DCS) by the observed incidence is easily computed using the approximation that the observed P(DCS) is a normally-distributed random variable.

Note that in Table 9a, models fitted to single dive data are used to predict the outcomes of repeat dives and models fitted to air dive data are used to predict the outcomes of 0.7 dives, whereas in Table 9b the situation is reversed. Occasionally the 95% confidence interval on the predicted average P(DCS) does miss the observed incidence, as for example when models fitted to the repeat 0.7 dives are used to predict the outcomes of repeat air dives (see Table 9b). There is a raw incidence of 7.2% DCS in the repeat air data, whereas the predicted incidences ranges from 2.7 to 3.8%

depending on the model, with the confidence intervals extending no higher than 7.2%. However, based on the observed incidence of DCS we estimate the confidence interval on the underlying P(DCS) to span from 3.6% to 10.9%, and remember that this is a gross underestimate of the true width of this interval. In summary, we recognize no convincing evidence that single dives are incompatible with repeat dives or that air dives and 0.7 dives are incompatible.

B. Multilevel Dives

Another important observation is that the addition of EDU1180R to a data set consistently degrades any model's ability to describe the data in that set. EDU1180R consists of a set of multilevel profiles in which the diver ascends to 10-30 fsw between descents. Strictly speaking, one cannot assess the combinability of EDU1180R with other data sets without fitting the models to EDU1180R alone, which has not been done because of the sparseness of this data set (2 DCS cases recorded out of 128 man-dives). However, if one applies the likelihood ratio test on the assumption that the risk-accumulation models would fit EDU1180R just as well as the null model, then EDU1180R is found to be not combinable with any other data. Also, the addition of EDU1180R to a data set consistently results in drastic shortening of the fitted time constants for the set.

Let us use some of the repeat dive data as an illustration. The null fit to EDU1180R yields a ln(likelihood) of 10.30. In Appendix 2 we see that the combination of data sets EDU184 and EDU885AR can be fitted with model 2 so that LL = 77.84 (this makes them very easily combinable according to the likelihood ratio test). When

EDU1180R is added, the best fit of model 2 has LL = 93.35. This much degradation of the fit is significant at the $p<0.04$ level. In Appendix 8 we see that the optimized time constants for [EDU184+EDU885AR] are τ_1 = 198 min and τ_2 = 741 min, but after EDU1180R is added to the set the optimal fit is obtained with τ_1 = 0.43 min and τ_2 = 105 min. We get similar results when EDU1180R is mixed with other data sets.

Table 8 summarizes efforts to predict P(DCS) for the EDU1180R dives using parameter values optimized for other data sets. Parameters are used that have been optimized for all of the single 0.7 dives (i.e., EDU1180S and EDU885M), all of the repeat 0.7 dives (includes only EDU184), and the combination of all dives except EDU1180R. In no instance is the prediction a good one, with between 11 and 32 DCS cases predicted as compared with 2 cases observed. The poor fit is also indicated by the low LL values compared with the null model's LL, indicating that, for the parameter values obtained by fitting other data, the observed dive outcomes are far from probable.

The explanation is that EDU1180R needs considerably shorter time constants than do the other data sets (with the exception of DC4W) and that the application of longer-than-optimal time constants is unusually deleterious to the fit. Generally, lengthening the time constants in one of the models has the partially offsetting effects of reducing the gas uptake (thereby reducing the total risk of the dive) and retarding the offgassing (thereby increasing the total risk). This dichotomy acts to moderate the effect on the predicted P(DCS) of changes in the fitted time constants. For these dives, however, it seems that the former effect is overwhelmed by the latter, so that there is a strong intolerance for longer time constants. Why is this? The dives in EDU1180R contrast with our other data in that the divers remain underwater for 4-5 h before beginning decompression but then undergo a decompression of only 1-2 h duration. Thus, the time spent underwater is unusually long compared with the decompression time, so that even "slow" tissues have plenty of time to accumulate inert gas but only "fast" tissues can offgas effectively before surfacing. In our models, a time constant much longer than about 60 min results in the prediction of a substantial tissue supersaturation remaining at the end of the dive, with especially severe risk accumulation commencing at the 20- or 10-foot stop or upon surfacing (depending on the time constant). Figure 1 illustrates this. It is a plot of one of the multilevel dives in which the divers descended to 150 fsw and stayed there for 29 min, ascended to 30 fsw and stayed for 120 min, and descended again to 150 fsw for 30 min. The depth, the partial pressure of N_2 in each of the "tissues" postulated by model 2, and the accumulated P(DCS) are plotted as functions of time. The partial pressures are predicted by model 2 using the parameter values optimized for all of the single- and repeat- dive data. It is seen that the tissue having the 33-min time constant (the "fast" tissue) really does expel most of its dissolved N_2 during the stay at 30 ft, and consequently this tissue makes a relatively small contribution to the P(DCS). By contrast, the tissue with the 715-min time constant actually experiences a small net gain of dissolved N_2 during the 30-fsw stop, and the final decompression is far too rapid to allow a thorough washout of dissolved gas before surfacing. The resulting overpressure persists for 6 h versus about 1 h of overpressure in the fast tissue. In addition, the gain coefficient coupled with the longer time constant is five times greater than the gain coefficient for the short time constant (see equation [3] for the definition of the gain coefficient). The end result is that this dive profile is predicted to carry a 19.5% probability of DCS with the 715-min tissue accounting for the bulk of the risk.

Similar plots could be shown for the rest of the multilevel dives. Therefore, when EDU1180R is mixed with other data sets and the combination is fitted by one of our models, the use of long time constants results in a gross overestimation of P(DCS) for the EDU1180R dives, and the use of short time constants results in a poor fit to the remaining data. Of course, the optimized parameter values for a combination of data sets never quite equal the optimal values for any one of the subsets. However, the subsets usually appear combinable nonetheless, using "compromise" parameter values that usually are within uncertainty bounds of the parameter estimates for the individual subsets. The difference with EDU1180R is the unusual sensitivity of the fit to time constant values, and this sensitivity is a consequence of the special characteristics of these dives.

Whereas the fitted parameter values are not taken to have any definite physical significance, the only justifiable conclusion is that a fundamental difference exists between data set EDU1180R and the others in this study with respect to their description by these particular models. If we consider the models to be suitable for modelling non-multilevel dives, then it is necessary to doubt whether they are adequate for modelling multilevel dives, on the evidence available to us from this one dive series.

C. Repetitive Dive Features

An evaluation that we made of repeat dives may be of interest to the reader. In this exercise, we used the models as predictors of P(DCS) for various repeat dive profiles and varied the duration of the surface interval as an independent parameter, without changing any of the other aspects of the dive profiles. We found that P(DCS) is partly determined by two effects peculiar to repeat dive combinations. First, the descent for the second dive eliminates the tissue supersaturation persisting from the first dive, thereby halting the accumulation of risk from the first dive and reducing P(DCS) for the dive combination as a whole. This is effectively a truncation of the first dive. Note that this reduction in P(DCS) arises from our assumption of an accumulating risk, rather than a risk resulting from some single instant of supersaturation occurring during the dive. The second effect peculiar to repeat dives is the addition of risk to the second dive because of the residual inert gas supersaturation from the first dive. This effect increases the risk of the dive combination.

According to our models, for the repeat dives in this study, the lowest P(DCS) is achieved with a surface interval of infinite duration, i.e. two single dives. This is another way of saying that the second effect described above dominates the first. Consequently, according to our models repeat dives are inherently more dangerous than single dives and one should adjust the decompression time of the second dive to compensate. As an example, Figure 2 shows the predicted P(DCS) of one of the double-dives in data set EDU885AR as a function of surface interval time, according to model 2 with its parameter values optimized for all of the repeat dive data. The monotonic decrease with surface interval time of P(DCS) is typical, although maxima and minima are possible. Incidentally, the actual dive was carried out with an 86-minute surface interval; there was a 98-minute decompression following the first descent and a 208-minute decompression after the second descent.

It certainly is possible to devise dive sequences that are exceptions to the rule, that is, which are made safer by a reduction in the times allowed between descents. One example consists of a hazardous dive followed by an extremely safe dive having an extremely long decompression time -- this is equivalent to recompression therapy. Another example occurs when the second dive is a saturation dive, in which case the residual dissolved inert gas from the first dive is irrelevant.

D. Specific Oxygen Effects

One more test of our models consists of attempting to improve the fit by allowing the dimensionless parameter k_{O2} (see equation [3]) to be an adjustable variable in the curve-fitting routine. In all modelling discussed to this point, k_{O2} has been fixed at zero. If the fit can be improved significantly by allowing k_{O2} to be non-zero, it would suggest that risk accumulation depends on the partial pressure of O_2 in the breathing mix as well as on the partial pressures of any inert gases. Accordingly, the 3-mono-exponential tissue model (model 4) was fitted to all of the available data (except EDU1180R) with k_{O2} allowed to float. Table 10 and Appendix 10 show the highest ln(likelihood) and optimal parameter values obtained, and these can be compared with the results found for model 4 with k_{O2} fixed at zero. The optimal value of k_{O2} is scarcely different from zero (0.34 with a standard error of 0.31) but the improvement in fit afforded by the extra parameter is only 0.5 LL units, which is not significant. We conclude that we have no strong evidence to support the inclusion of F_{O2} in our risk formulations. Model 4 was chosen for this test because it is superior to our other models at fitting all of the data simultaneously.

VI. MORE COMPLEX MODELS; CONCLUSIONS

The summary of the discussion is that 1) our models have some substantial face value as quantitative descriptors and predictors of DCS incidents, 2) we see no compelling reason not to combine data regardless of whether it consists of single dives or repeat dives and regardless of the composition of the N_2/O_2 breathing mix, and 3) we see no compelling evidence that any of the data sets other than EDU1180R comes from a different population than the bulk of the data. All of these conclusions are based on our use of models 1, 2, and 3. It remains for us to explore whether more complicated functions can be used to advantage. Table 10 and Appendix 10 each show the highest ln(likelihood), and the optimized parameter values, obtained by fitting model 4 (the 3-mono-exponential tissue model) and model 5 (the 2 bi-exponential tissue model), each with $P_{thr}=0$ and $k_{O2}=0$, to all of the available data (except EDU1180R). Model 4, with 6 adjustable parameters altogether, actually provides a somewhat better overall fit than does the 8-parameter model 5. The excessively high standard errors on the model 5 parameters result from strong cross-correlations between parameters, suggesting that the data set may not be sufficiently large and diverse to support a model as elaborate as this. The fit of model 4 is seen to be a statistically significant improvement over that of model 2 (the 2-mono-exponential model, having 4 parameters), according to the likelihood ratio test.

It would seem that the 3-mono-exponential model with the parameter values listed in Table 10 represents our best mathematical description of the available data. Its fit improves upon the null model's fit by 20 LL units, meaning that it predicts the observed family of dive outcomes to be $\exp(20) = 4.7 \cdot 10^8$ times more probable than the null model does. The optimized time constants of 0.44 min, 129 min, and 767 min reflect the diversity of the available data. It should not be extrapolated recklessly to dives that are appreciably different from the ones in our database. That is, it should not be expected to be a reliable predictor of the risks of dives having time scales different from those in our database; as we have seen, the optimal time constants obtained for long dives do a poor job of describing short dives, and vice-versa. Our database contains dives ranging from 0.3 to 8 h, so saturation dives are not encompassed. Obviously, it should not be extrapolated to multi-level dives, which were excluded from the data set for which the parameter values in Table 10 were optimized.

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APPENDIX 1

Log Likelihoods for the 2-, 3-, and 4-Parameter Models:
Data Sets Not Combined Across Categories; $k_{O2} = 0$

In the following tables, "////" indicates that the model converges to a solution equivalent to a two-parameter DLE6 solution.

	DCS cases/dives	-ln (likelihood) null	model 1 no P_{thr}	model 1 w/P_{thr}	model 2	model 3
single air dives:						
EDU885A	30/483	112.41	109.92	////	101.88	105.37
DC4W	[8+4(0.5)]/244	41.738	40.595	////	35.514	37.054
EDU885A + DC4W	[38+4(0.5)]/727	154.88	153.86	////	145.25	147.70
single 0.7 dives:						
EDU1180S	10/120	34.420	30.495	30.474	////	30.456
EDU885M	4/81	15.932	----	----	----	----
EDU1180S + EDU885M	14/201	50.800	44.851	////	44.821	////
single dives, other gas mixes:						
NMR8697	[11+18(0.5)]/477	83.010	81.970	81.939	81.844	81.931
DC8AOW	[2+1(0.5)]/45	9.655	----	----	----	----
repeat/multilevel air dives:						
EDU885AR	11/182	41.528	38.027	36.447	////	36.390
DRREPWET	3/12	6.748	----	----	----	----
EDU885AR + DRREPWET	14/194	50.285	45.719	44.240	////	44.115
repeat/multilevel 0.7 dives:						
EDU1180R	2/128	10.302	----	----	----	----
EDU184	11/234	44.369	38.455	37.420	37.930	37.329
EDU1180R + EDU184	13/362	56.011	52.989	52.914	////	52.511

APPENDIX 2

Log Likelihoods for the 2-, 3-, and 4-Parameter Models: Combinations of Data Sets From Different Categories

	DCS cases/dives	-ln (likelihood)				
		null	model 1		model 2	model
			no P_{tnr}	w/P_{thr}		
single, air + 0.7:						
EDU1180S + EDU885A + EDU835M + DC4W	[52+4(0.5)]/928	205.98	204.17	////	191.21	195.46
single, any gas mix:						
EDU1180S + EDU885A + EDU885M + DC4W + DC8AOW + NMR8697	[65+23(0.5)]/1450	299.51	297.23	////	285.39	////
repeat/multilevel, air + 0.7:						
EDU184 + EDU885AR	22/416	86.080	78.298	75.109	77.837	75.923
EDU184 + EDU885AR + DRREPWET	25/428	95.261	86.869	83.544	86.442	83.523
EDU1180R + EDU184 + EDU885AR	24/544	98.364	93.459	92.988	93.346	////
air, single + repeat/multilevel:						
EDU885A + EDU885AR	41/665	153.94	148.63	////	144.19	146.30
EDU885A + EDU885AR + DC4W + DRREPWET	[52+4(0.5)]/921	205.55	202.28	////	194.95	197.98
EDU885A + EDU885AR + DC4W	[49+4(0.5)]/909	196.45	194.23	////	185.98	189.43
0.7, single + repeat/multilevel:						
EDU1180S + EDU1180R	12/248	48.047	47.500	41.267	46.656	////
EDU1180S + EDU184	21/354	79.685	69.096	68.571	68.619	68.287
EDU1180S + EDU1180R + EDU184	23/482	92.419	87.992	86.962	////	////
EDU1180S + EDU184 + EDU885M	25/435	101.01	83.583	////	83.216	83.395
EDU1180S + EDU1180R + EDU184 + ZDU885M	27/563	108.35	104.89	////	////	////

APPENDIX 3

Log Likelihoods for the 2-, 3-, and 4-Parameter Models:
Any Category of Dive

	DCS cases/dives	-ln (likelihood) null	model 1 no P_{thr}	model 1 w/P_{thr}	model 2	model 3
any type of dive:						
EDU885A + EDU885AR + EDU885M	45/746	169.98	165.00	////	159.53	162.04
EDU1180S + EDU184 + EDU885A + EDU885AR + EDU885M + DC4W + NMR8697 + DRREPWET + DC8AOW	[90+23(0.5)]/1878	394.87	383.79	////	377.09	////

APPENDIX 4

Optimized Parameter Values for the 2- and 3-Parameter Models: Data Sets Not Combined Across Categorier

	model 1 (1 Tissue Mono-exponential); $P_{thr} = 0$	model 1 (1 Tissue Mono-exponential) $P_{thr} \neq 0$
single air dives:		
EDU885A	τ = 173 (38) A = 0.00221 (0.00044)	////
EDU885A + DC4W	τ = 89.6 (16.8) A = 0.00220 (0.000353)	////
DC4W	τ = 46.1 (28.2) A = 0.00209 (0.00072)	////
EDU885A + DC4W	τ = 92.4 (16.8) A = 0.00222 (0.00035)	////
single 0.7 dives:		
EDU1180S	τ = 490 (140) A = 0.00489 (0.00274)	τ = 374 (516) A = 0.00680 (0.0129) P_{thr} = 2.08 (11.6)
EDU885M	-----	-----
EDU1180S + EDU885M	τ = 483 (88.6) A = 0.00586 (0.00260)	////
single dives, other gas mixes:		
NMR8697	τ = 77.9 (34.2) A = 0.00180 (0.000461)	τ = 72.9 (28.7) A = 0.00269 (0.00414) P_{thr} = 3.03 (11.2)
DC8AOW	-----	-----
repeat/multilevel air dives:		
EDU885AR	τ = 281 (88.5) A = 0.00406 (0.00249)	τ = 134 (47.9) A = 0.0816 (0.0978) P_{thr} = 9.96 (3.98)
DRREPWET	-----	-----
EDU885AR + DRREPWET	τ = 297 (83.1) A = 0.00510 (0.00280)	τ = 177 (68.7) A = 0.0491 (0.0703) P_{thr} = 6.92 (4.35)

repeat/multilevel 0.7 dives:

EDU1180R	-----	-----
EDU184	τ = 413 (90.0) A = 0.00364 (0.00194)	τ = 187 (66.5) A = 0.0102 (0.0118) P_{thr} = 5.34 (3.37)
EDU1180R + EDU184	τ = 101 (87.0) A = 0.000875 (0.000256)	τ = 104 (69.3) A = 0.00118 (0.00163) P_{thr} = 1.92 (6.96)

APPENDIX 5

Optimized Parameter Values for the 2- and 3-Parameter Models:
Combinations of Dives From Different Categories

	model 1 (1 Tissue Mono-exponential); $P_{thr} = 0$	model 1 (1 Tissue Mono-exponential) $P_{thr} \neq 0$
single, air + 0.7:		
EDU1180S + EDU885A + EDU885M + DC4W	$\tau = 101$ (15.1) A = 0.00223 (0.000307)	////
single, any gas mix:		
EDU1180S + EDU885A + EDU885M + DC4W + DC8AOW + NMR8697	$\tau = 99.6$ (13.9) A = 0.00214 (0.000255)	////
repeat/multilevel, air + 0.7:		
EDU184 + EDU885AR	$\tau = 282$ (67.0) A = 0.00272 (0.00105)	$\tau = 162$ (29.0) A = 0.0184 (0.0149) $P_{thr} = 6.64$ (2.03)
EDU184 + EDU885AR + DRREPWET	$\tau = 288$ (66.2) A = 0.00307 (0.00115)	$\tau = 160$ (27.9) A = 0.0218 (0.0165) $P_{thr} = 6.85$ (1.90)
EDU1180R + EDU184 + EDU885AR	$\tau = 93.9$ (58.4) A = 0.00105 (0.000216)	$\tau = 92.6$ (31.8) A = 0.00279 (0.00321) $P_{thr} = 5.14$ (4.62)
air, single + repeat/multilevel:		
EDU885A + EDU885AR	$\tau = 186$ (34.5) A = 0.00228 (0.000436)	////
EDU885A + DC4W + EDU885AR	$\tau = 103$ (15.9) A = 0.00202 (0.000293)	////
EDU885A + EDU885AR + DC4W + DRREPWET	$\tau = 103$ (15.8) A = 0.00210 (0.000297)	////

0.7, single + repeat/multilevel:

EDU1180S + EDU1180R	τ = 126 (169) A = 0.00112 (0.000658)	τ = 73.7 (25.3) A = 0.0575 (0.0799) P_{thr} = 15.6 (1.60)
EDU1180S + EDU184	τ = 437 (65.2) A = 0.00413 (0.00145)	τ = 232 (100) A = 0.00700 (0.00488) P_{thr} = 3.91 (3.22)
EDU1180S + EDU1180R + EDU184	τ = 201 (100) A = 0.00119 (0.000283)	τ = 172 (36.6) A = 0.00740 (0.00497) P_{thr} = 5.09 (2.34)
EDU1180S + EDU184 + EDU885M	τ = 454 (52.9) A= 0.00486 (0.00153)	////
EDU1180S + EDU1180R + EDU184 + EDU885M	τ = 231 (96.7) A = 0.00135 (0.000431)	////

APPENDIX 6

Optimized Parameter Values for the 2- and 3-Parameter Models:
Any Category of Dive

	model 1 (1 Tissue Mono-exponential); $P_{thr} = 0$	model 1 (1 Tissue Mono-exponential) $P_{thr} \neq 0$
EDU885A + EDU885AR + EDU885M	τ = 202 (31.7) A = 0.00239 (0.000446)	////
EDU1180S + EDU184 + EDU885A + EDU885AR + EDU885M + DC4W + NMR8697 + DRREPWET + DC8AOW	τ = 112 (12.7) A = 0.00194 (0.000202)	////

APPENDIX 7

Optimized Parameter Values for the 4-Parameter Models:
Data Sets not Combined Aross Categories

	model 2 (2 Tissue Mono-exponential); $P_{thr} = 0$	model 3 (1 Tissue Bi-exponential); $P_{thr} = 0$
single air dives:		
EDU885A	$\tau_1 = 22.5$ (30) $\tau_2 = 730$ (199) $A_1 = 0.00173$ (0.0016) $A_2 = 0.00940$ (0.0075)	$\tau_1 = 12.6$ (41.1) $\tau_2 = 292$ (44.6) $w_1 = 0.822$ (0.569) $A = 0.0296$ (0.0237)
DC4W	$\tau_1 = 0.389$ (0.149) $\tau_2 = 358$ (182) $A_1 = 0.553$ (0.85) $A_2 = 0.00970$ (0.00014)	$\tau_1 = 1.56$ (4.2) $\tau_2 = 160$ (158) $w_1 = 0.991$ (0.031) $A = 0.0576$ (0.023)
EDU885A + DC4W	$\tau_1 = 27.3$ (14.6) $\tau_2 = 749$ (195) $A_1 = 0.00183$ (0.00060) $A_2 = 0.00970$ (0.00083)	$\tau_1 = 14.5$ (7.6) $\tau_2 = 290$ (58) $w_1 = 0.894$ ( ) $A = 0.00921$ (0.00026)
single 0.7 dives:		
EDU1180S	////	$\tau_1 = 12.7$ (221) $\tau_2 = 375$ (516) $w_1 = 0.886$ (1.66) $A = 0.00826$ (0.0287)
EDU885M	-----	-----
EDU1180S + EDU885M	$\tau_1 = 2.51$ (310) $\tau_2 = 493$ (250) $A_1 = 0.00555$ (1.07) $A_2 = 0.00587$ (0.00321)	////
single dives, other gas mixes:		
NMR8697	$\tau_1 = 0.263$ (0.955) $\tau_2 = 86.7$ (54.1) $A_1 = 0.205$ (2.57) $A_2 = 0.00166$ (0.00120)	$\tau_1 = 1.36$ (31.2) $\tau_2 = 74.7$ (60.7) $w_1 = 0.963$ (0.718) $A = 0.00390$ (0.0119)
DC8AOW	-----	-----
repeat/multilevel air dives:		
EDU885AR	////	$\tau_1 = 120$ (68.3) $\tau_2 = 2140$ (3520) $w_1 = 0.892$ (0.203) $A = 0.209$ (0.339)
DRREPWET	-----	-----

EDU885AR + DRREPWET	////	τ_1 = 141 (92.5) τ_2 = 2900 (7910) w_1 = 0.925 (0.233) A = 0.160 (0.264)
repeat/multilevel 0.7 dives:		
EDU1180R	-----	-----
EDU184	τ_1 = 110 (634) τ_2 = 609 (282) A_1 = 0.000440 (0.00146) A_2 = 0.00642 (0.00515)	τ_1 = 69.3 (54.3) τ_2 = 854 (334) w_1 = 0.733 (0.112) A = 0.0237 (0.0374)
EDU1180R + EDU184	////	τ_1 = 121 (117) τ_2 = 8820 (2.65E5) w_1 = 0.991 (0.282) A = 0.00429 (0.00655)

APPENDIX 8

Optimized Parameter Values for the 4-Parameter Models:
Combinations of Data from Different Categories

	model 2 (2 Tissue Mono-exponential); $P_{thr} = 0$	model 3 (1 Tissue Bi-exponential); $P_{thr} \neq 0$
single, air + 0.7:		
EDU1180S + EDU885A + EDU885M + DC4W	τ_1 = 27.1 (12.6) τ_2 = 711 (147) A_1 = 0.00183 (0.000583) A_2 = 0.00872 (0.00539)	τ_1 = 13.0 (5.35) τ_2 = 312 (39.5) w_1 = 0.900 (0.0461) A = 0.0102 (0.00249)
single, any gas mix:		
EDU1180S + EDU885A + EDU885M + DC4W + DC8AOW + NMR8697	τ_1 = 25.6 (10.3) τ_2 = 729 (115) A_1 = 0.00204 (0.000534) A_2 = 0.00846 (0.00462)	////
repeat/multilevel, air + 0.7:		
EDU184 + EDU885AR	τ_1 = 198 (270) τ_2 = 741 (782) A_1 = 0.00143 (0.00248) A_2 = 0.00525 (0.0107)	τ_1 = 148 (146) τ_2 = 2690 (11600) w_1 = 0.932 (0.0224) A = 0.0347 (0.0346)
EDU184 + EDU885AR + DRREPWET	τ_1 = 0.304 (0.109) τ_2 = 322 (90.4) A_1 = 2.58 (10.8) A_2 = 0.00331 (0.00140)	τ_1 = 0.755 (0.813) τ_2 = 183 (40.1) w_1 = 0.995 (0.00570) A = 0.0351 (0.0332)
EDU1180R + EDU184 + EDU885AR	τ_1 = 0.429 (1.01) τ_2 = 105 (84.7) A_1 = 0.108 (1.23) A_2 = 0.000992 (0.000274)	////
air, single + repeat/multilevel:		
EDU885A + EDU885AR	τ_1 = 55.3 (51.4) τ_2 = 740 (217) A_1 = 0.00105 (0.000271) A_2 = 0.00827 (0.00693)	τ_1 = 21.1 (49.2) τ_2 = 351 (89.5) w_1 = 0.793 (0.410) A = 0.00620 (0.00274)
EDU885A + EDU885AR + DC4W + DRREPWET	τ_1 = 39.6 (20.2) τ_2 = 732 (212) A_1 = 0.00148 (0.00314) A_2 = 0.00807 (0.00677)	τ_1 = 13.2 (7.28) τ_2 = 249 (63.6) w_1 = 0.864 (0.0749) A = 0.00624 (0.00191)
EDU885A + EDU885AR + DC4W	τ_1 = 38.3 (19.8) τ_2 = 734 (200) A_1 = 0.00138 (0.000309) A_2 = 0.00838 (0.00675)	τ_1 = 12.5 (6.27) τ_2 = 258 (61.0) w_1 = 0.878 (0.0662) A = 0.00647 (0.00195)

0.7, single + repeat/multilevel:

EDU1180S + EDU1180R	////	////
EDU1180S + EDU184	τ_1 = 102 (569) τ_2 = 584 (255) A_1 = 0.000366 (0.00112) A_2 = 0.00579 (0.00292)	τ_1 = 73.8 (43.4) τ_2 = 743 (321) w_1 = 0.665 (0.172) A = 0.0160 (0.0229)
EDU1180S + EDU1180R + EDU184M	////	////
EDU1180S + EDU184 + EDUU885M	τ_1 = 24.8 (498) τ_2 = 505 (225) A_1 = 0.000200 (0.000425) A_2 = 0.00568 (0.00261)	τ_1 = 11.9 (94.6) τ_2 = 462 (170) w_1 = 0.684 (2.79) A = 0.00616 (0.00479)
EDU1180S + EDU1180R + EDU184 + EDU885M	////	////

APPENDIX 9

Optimized Parameter Values for the 4-Parameter Models:
Any Category of Dive

	model 2 (2 Tissue Mono-exponential); $P_{thr} = 0$	model 3 (1 Tissue Bi-exponential); $P_{thr} \neq 0$
EDU885A + EDU885AR + EDU885M	$\tau_1 = 29.0$ (45.2) $\tau_2 = 623$ (179) $A_1 = 0.00116$ (0.000636) $A_2 = 0.00642$ (0.00337)	$\tau_1 = 14.7$ (39.8) $\tau_2 = 355$ (83.1) $w_1 = 0.839$ (0.480) $A = 0.00709$ (0.00504)
EDU1180S + EDU184 + EDU885A + EDU885AR + EDU885M + DC4W + NMR8697 + DRREPWET + DC8AOW	$\tau_1 = 33.4$ (11.4) $\tau_2 = 715$ (108) $A_1 = 0.00145$ (0.000252) $A_2 = 0.00781$ (0.00375)	////

APPENDIX 10

Log Likelihoods and Optimized Parameter Values for the Models with 6 or More Parameters: Any Category of Dive

	-ln(likelihood)			
data set	null	model 4 $k_{O2} = 0$	model 4 $k_{O2} \neq 0$	model 5 $k_{O2} = 0$
EDU1180S + EDU184 + EDU885A + EDU885AR + EDU885M + DC4W + NMR8697 + DRREPWET + DC8AOW	394.87	373.91	373.41	376.93

parameter values:

model 4 (3-mono-exponential), $k_{O2} = 0$

$\tau_1 = 0.442$ (0.174)
$\tau_2 = 129$ (68.9)
$\tau_3 = 767$ (162)
$A_1 = 0.176$ (0.206)
$A_2 = 0.00117$ (0.000306)
$A_3 = 0.00735$ (0.00522)

model 4 (3-mono-exponential), $k_{O2} = 0$

$\tau_1 = 0.284$ (0.189)
$\tau_2 = 106$ (91.7)
$\tau_3 = 1180$ (599)
$A_1 = 0.241$ (0.342)
$A_2 = 0.000756$ (0.000353)
$A_3 = 0.00473$ (0.00421)
$k_{O2} = 0.340$ (0.308)

model 5 (2 bi-exponential), $k_{O2} = 0$

$\tau_{A1} = 0.125$ (6710)
$\tau_{A2} = 33.2$ (14.0)
$w_{A1} = 0.256$ (10100)
$A_A = 0.00146$ (0.00120)

$\tau_{B1} = 517$ (1960)
$\tau_{B2} = 2570$ (65200)
$w_{B1} = 0.913$ (3.54)
$A_B = 0.0110$ (0.0113)

TABLE 1

Data Summary

0.7 - 0.7 atm oxygen, the balance nitrogen

Mean values of quantities, averaged over a data set, are indicated by parentheses

data set	DCS cases / dives	gas	depth (fsw)	bottom time (min)	total decompression time (min)
DC4W	[8+4(0.5)]/244	air	50 - 265 (154)	2.9 - 100 (24)	3.3 - 99 (28)
EDU1180R	2/128	0.7	75 - 151 (123)	162 - 270 (233)	31 - 176 (102)
EDU1180S	10/120	0.7	75 - 150 (125)	38 - 126 (73)	46 - 176 (93)
EDU184	11/234	0.7	40 - 150 (89)	20 - 212 (42)	2 - 187 (14)
EDU885A	30/483	air	50 - 190 (112)	14 - 244 (78)	1.7 - 290 (102)
EDU885AR	11/182	air	80 - 150 (102)	17 - 66 (N/A)	2 - 246 (N/A)
EDU885M	4/81	0.7	100 - 150 (133)	33 - 66 (51)	35 - 222 (76)
NMR8697	[11+18(0.5)]/477	variable 10-40% O_2, the rest N_2	25 - 130 (69)	30 - 240 (112)	0.6 - 2.5 (1.5)
DRREPWET	3/12	air	59 - 177 (128)	20 - 40 (28)	4.6 - 90 (50)
DC8AOW	(2+0.5)/45	air + O_2 decompression	90 - 180 (132)	2.3 - 60 (42)	27 - 106 (46)
total	[92+23(0.5)]/2006				

TABLE 2

Log Likelihoods for the 2-, 3-, and 4-Parameter Models; Data Sets Not Combined Across Categories; k_{O2} = 0

	DCS cases/dives	-ln (likelihood)				
		null	model 1		model 2	model 3
			no P_{thr}	w/P_{thr}		
single air dives:						
EDU885A + DC4W	[38+4(0.5)]/727	154.88	153.86	////	145.25	147.70
single 0.7 dives:						
EDU1180S + EDU885M	14/201	50.800	44.851	////	44.821	////
single dives, other gas mixes:						
NMR8697	[11+18(0.5)]/477	83.010	81.970	81.939	81.844	81.931
DC8AOW	[2+1(0.5)]/45	9.655	----	----	----	----
repeat air dives:						
EDU885AR + DRREPWET	14/194	50.285	45.719	44.240	////	44.115
repeat 0.7 dives:						
EDU184	11/234	44.369	38.455	37.420	37.933	37.329

TABLE 3

Log Likelihoods for the 2-, 3-, and 4-Parameter Models;
Combinations of Data Sets From Different Categories

	DCS cases/dives	-ln (likelihood) null	model 1 no P_{thr}	model 1 w/P_{thr}	model 2	model 3
single, air + 0.7:						
EDU1180S + EDU885A + EDU885M + DC4W	[52+4(0.5)]/928	205.98	204.17	////	191.21	195.46
single, any gas mix:						
EDU1180S + EDU885A + EDU885M + DC4W + DC8AOW + NMR8697	[65+23(0.5)]/1450	299.51	297.23	////	285.39	////
repeat, air + 0.7:						
EDU184 + EDU885AR + DRREPWET	25/428	95.261	86.869	83.544	85.442	83.523
air, single + repeat:						
EDU885A + EDU885AR + DC4W + DRREPWET	[52+4(0.5)]/921	205.55	202.28	////	194.95	197.98
0.7, single + repeat:						
EDU1180S + EDU184 + EDU885M	25/435	101.01	83.583	////	83.216	83.395
any type of dive:						
EDU1180S + EDU184 + EDU885A + EDU885AR + EDU885M + DC4W + NMR8697 + DRREPWET + DC8AOW	[90+23(0.5)]/1878	394.87	388.79	////	377.09	////

TABLE 4

Cptimized Parameter Values for the 2- and 3-Parameter Models: Data Sets Not Combined Across Categories

	model 1 (1 Tissue Mono-exponential); $P_{thr} = 0$	model 1 (1 Tissue Mono-exponential) $P_{thr} \neq 0$
single air dives:		
EDU885A + DC4W	τ = 92.4 (16.8) A = 0.00222 (0.00035)	////
single 0.7 dives:		
EDU1180S + EDU885M	τ = 483 (88.6) A = 0.00586 (0.00260)	////
single dives, other gas mixes:		
NMR8697	τ = 77.9 (34.2) A = 0.00180 (0.000461)	τ = 72.9 (28.7) A = 0.00269 (0.00414) P_{thr} = 3.03 (11.2)
DC8AOW	-----	-----
repeat air dives:		
EDU885AR + DRREPWET	τ = 297 (83.1) A = 0.00510 (0.00280)	τ = 177 (68.7) A = 0.0491 (0.0703) P_{thr} = 6.92 (4.35)
repeat 0.7 dives:		
EDU184	τ = 413 (90.0) A = 0.00364 (0.00194)	τ = 114 (24.9) A = 0.0102 (0.0118) P_{thr} = 5.34 (3.37)

TABLE 5

Optimized Parameter Values for the 2- and 3-Parameter Models:
Combinations of Dives From Different Categories

	model 1 (1 Tissue Mono-exponential); $P_{thr} = 0$	model 1 (1 Tissue Mono-exponential) $P_{thr} \neq 0$
single, air + 0.7:		
EDU1180S + EDU885A + EDU885M + DC4W	τ = 101 (15.1) A = 0.00223 (0.000307)	////
single, any gas mix:		
EDU1180S + EDU885A + EDU885M + DC4W + DC8AOW + NMR8697	τ = 99.6 (13.9) A = 0.00214 (0.000255)	////
repeat, air + 0.7:		
EDU184 + EDU885AR + DRREPWET	τ = 288 (66.2) A = 0.00307 (0.00115)	τ = 160 (27.9) A = 0.0218 (0.0165) P_{thr} = 6.85 (1.90)
air, single + repeat:		
EDU885A + EDU885AR + DC4W + DRREPWET	τ = 103 (15.8) A = 0.00210 (0.000297)	////
0.7, single + repeat:		
EDU1180S + EDU184 + EDU885M	τ = 454 (52.9) A = 0.00486 (0.00153)	////
any type of dive:		
EDU1180S + EDU184 + EDU885A + EDU885AR + EDU885M + DC4W + NMR8697 + DRREPWET + DC8AOW	τ = 112 (12.7) A = 0.00194 (0.000202)	////

TABLE 6

Optimized Parameter Values for the 4-Parameter Models: Data Sets not Combined Across Categories

	model 2 (1 Tissue Mono-exponential); $P_{thr} = 0$	model 3 (1 Tissue Mono-exponential) $P_{thr} \neq 0$
single air dives:		
EDU885A + DC4W	$\tau_1 = 27.3$ (14.6) $\tau_2 = 749$ (195) $A_1 = 0.00183$ (0.00060) $A_2 = 0.00970$ (0.00083)	$\tau_1 = 14.5$ (7.6) $\tau_2 = 290$ (58) $w_1 = 0.894$ ( ) $A = 0.00921$ (0.00026)
single 0.7 dives:		
EDU1180S + EDU885M	$\tau_1 = 2.51$ (310) $\tau_2 = 493$ (250) $A_1 = 0.00555$ (1.07) $A_2 = 0.00587$ (0.00321)	////
single dives, other gas mixes:		
NMR8697	$\tau_1 = 0.263$ (0.955) $\tau_2 = 86.7$ (54.1) $A_1 = 0.205$ (2.57) $A_2 = 0.00166$ (0.00120)	$\tau_1 = 1.36$ (31.2) $\tau_2 = 74.7$ (60.7) $w_1 = 0.963$ (0.718) $A = 0.00390$ (0.0119)
DC8AOW	-----	-----
repeat air dives:		
EDU885AR + DRREPWET	////	$\tau_1 = 141$ (92.5) $\tau_2 = 2900$ (7910) $w_1 = 0.925$ (0.233) $A = 0.160$ (0.264)
repeat 0.7 dives:		
EDU184	$\tau_1 = 110$ (634) $\tau_2 = 609$ (282) $A_1 = 0.000440$ (0.00146) $A_2 = 0.00642$ (0.00515)	$\tau_1 = 69.3$ (54.3) $\tau_2 = 854$ (334) $w_1 = 0.733$ (0.112) $A = 0.0237$ (0.0374)

TABLE 7

Optimized Parameter Values for the 4-Parameter Models: Combinations of Data from Different Categories

	model 2 (1 Tissue Mono-exponential); $P_{thr} = 0$	model 3 (1 Tissue Mono-exponential) $P_{thr} \neq 0$
single, air + 0.7:		
EDU1180S + EDU885A + EDU885M + DC4W	τ_1 = 27.1 (12.6) τ_2 = 711 (147) A_1 = 0.00183 (0.000583) A_2 = 0.00872 (0.00539)	τ_1 = 13.0 (5.35) τ_2 = 312 (39.5) w_1 = 0.900 (0.0461) A = 0.0102 (0.0024[illegible])
single, any gas mix:		
EDU1180S + EDU885A + EDU885M + DC4W + DC8AOW + NMR8697	τ_1 = 25.6 (10.3) τ_2 = 729 (115) A_1 = 0.00204 (0.000534) A_2 = 0.00846 (0.00462)	////
repeat, air + 0.7:		
EDU184 + EDU885AR + DRREPWET	τ_1 = 0.304 (0.109) τ_2 = 322 (90.4) A_1 = 2.58 (10.8) A_2 = 0.00331 (0.00140)	τ_1 = 0.755 (0.813) τ_2 = 183 (40.1) w_1 = 0.995 (0.00570) A = 0.0351 (0.0332)
air, single + repeat:		
EDU885A + EDU885AR + DC4W + DRREPWET	τ_1 = 39.6 (20.2) τ_2 = 732 (212) A_1 = 0.00148 (0.00314) A_2 = 0.00807 (0.00677)	τ_1 = 13.2 (7.28) τ_2 = 249 (63.6) w_1 = 0.864 (0.0749) A = 0.00624 (0.00191)
0.7, single + repeat:		
EDU1180S + EDU184 + EDU885M	τ_1 = 24.8 (498) τ_2 = 505 (225) A_1 = 0.000200 (0.000425) A_2 = 0.00568 (0.00261)	τ_1 = 11.9 (94.6) τ_2 = 462 (170) w_1 = 0.684 (2.79) A = 0.00616 (0.00479)
any type of dive:		
EDU1180S + EDU184 + EDU885A + EDU885AR + EDU885M + DC4W + NMR8697 + DRREPWET + DC8AOW	τ_1 = 33.4 (11.4) τ_2 = 715 (108) A_1 = 0.00145 (0.000252) A_2 = 0.00781 (0.00375)	////

TABLE 8

Predictions of P(DCS) in Data Set EDU1180R Using Parameter Values Fitted to Other Data Sets; $k_{O2} = 0$

data set to which parameters are fitted	model	-LL	average P(DCS) predicted	average P(DCS) actual
	null	10.302		1.56%
all single 0.7	1	39.068	24.8%	
	1w/P_{thr}	////	////	
	2	39.146	24.8	
	3	////	////	
all repeat 0.7	1	28.409	17.9	
	1w/P_{thr}	32.125	20.4	
	2	37.087	23.5	
	3	32.029	20.3	
all but EDU1180R	1	16.199	8.89	
	1w/P_{thr}	////	////	
	2	37.948	24.0	
	3	////	////	

TABLE 9a

Predictions of P(DCS) Using Parameter Values Fitted to Other Data Sets; $k_{O2} = 0$

data set to which parameters are fitted	model	data set for which predictions are made	-LL	average P(DCS) predicted	average P(DCS) actual
	null	all repeat air	50.285		7.22%
all single air	1		48.788	9.27 (6.37-12.2)%	
	1w/P_{thr}		////	////	
	2		50.236	9.34 (5.74-12.9)	
	3		52.318	11.3 (6.89-15.8)	
	null	all repeat 0.7 except EDU1180R	44.369		4.70%
all single 0.7	1		38.936	5.28 (2.43-8.14)%	
	1w/P_{thr}		////	////	
	2		39.547	6.49 (0-100)	
	3		////	////	
	null	all single 0.7	50.800		6.97%
all single air	1		50.496	6.82 (4.59-9.06)	
	1w/P_{thr}		////	////	
	2		46.123	6.18 (4.05-8.32)	
	3		48.703	5.58 (3.27-7.88)	
	null	all repeat 0.7 except EDU1180R	44.369		4.70%
all repeat air	1		44.299	10.6 (4.96-16.3)%	
	1w/P_{thr}		43.124	10.3 (0.79-19.9)	
	2		////	////	
	3		45.254	10.8 (2.23-19.5)	
	null	all repeats except EDU1180R	86.080		5.84%
all singles	1		92.634	8.64 (6.66-10.6)%	
	1w/P_{thr}		////	////	
	2		93.875	9.40 (6.76-12.0)	
	3		////	////	
	null	all 0.7 dives except EDU1180R	101.01		5.75%
all air dives	1		93.075	7.01 (5.58-9.58)%	
	1w/P_{thr}		////	////	
	2		91.276	5.02 (5.14-8.74)	
	3		94.971	8.35 (6.16-10.5)	

TABLE 9b

Predictions of P(DCS) Using Parameter Values Fitted to Other Data Sets; k_{O2} = 0 -- continued

Note: The ln(likelihood) is undefined when the model predicts zero risk for a dive in which a case of DCS was recorded, because in this situation the likelihood of the observed family of dive outcomes, given that P(DCS) is governed by the model in question, is zero.

data set to which parameters are fitted	model	data set for which predictions are made	-LL	average P(DCS) predicted	average P(DCS) actual
	null	all single air	154.88		5.50%
all repeat air	1		undefined	7.23 (2.81-11.7)%	
	1w/P_{thr}		undefined	11.1 (2.65-19.5)	
	2		////	////	
	3		undefined	9.90 (2.50-17.2)	
	null	all single 0.7	50.800		6.97%
all repeat 0.7 except EDU1180R	1		45.504	5.77 (2.40-9.13)%	
	1w/P_{thr}		50.046	8.18 (0.32-16.1)	
	2		45.949	5.94 (1.73-10.2)	
	3		undefined	4.31 (0-10.4)	
	null	all single air	154.88		5.50%
all single 0.7	1		undefined	4.48 (2.29-6.69)%	
	1w/P_{thr}		////	////	
	2		151.42	5.27 (0-38.8)	
	3		////	////	
	null	all repeat air	50.285		7.22%
all repeat 0.7 except EDU1180R	1		52.829	2.73 (1.15-4.29)%	
	1w/P_{thr}		48.061	3.37 (0.66-6.13)	
	2		52.532	3.82 (0.46-7.18)	
	3		51.207	3.32 (1.18-5.47)	
	null	all singles	299.51		5.28%
all repeats except EDU1180R	1		undefined	4.61 (2.72-6.50)%	
	1w/P_{thr}		undefined	7.74 (3.15-12.3)	
	2		319.88	7.49 (0-22.7)	
	3		undefined	7.36 (2.96-11.8)	
	null	all air dives	205.55		5.86%
all 0.7 dives except EDU1180R	1		undefined	3.89 (2.42-5.38)%	
	1w/P_{thr}		////	////	
	2		215.31	4.16 (0.61-7.74)	
	3		undefined	3.92 (2.38-5.48)	

TABLE 10

Log Likelihoods and Optimized Parameter Values for the Models with 6 or More Parameters: Any Category of Dive

data set	-ln(likelihood) null	model 4 $k_{O2} = 0$	model 4 $k_{O2} \neq 0$	model 5 $k_{O2} = 0$
EDU1180S + EDU184 + EDU885A + EDU885AR + EDU885M + DC4W + NMR8697 + DRREPWET + DC8AOW	394.87	373.91	373.41	376.93

parameter values:

model 4 (3-mono-exponential), $k_{O2} = 0$

$\tau_1 = 0.442$ (0.174)
$\tau_2 = 129$ (68.9)
$\tau_3 = 767$ (162)
$A_1 = 0.176$ (0.206)
$A_2 = 0.00117$ (0.000306)
$A_3 = 0.00735$ (0.00522)

model 4 (3-mono-exponential), $k_{O2} \neq 0$

$\tau_1 = 0.284$ (0.189)
$\tau_2 = 106$ (91.7)
$\tau_3 = 1180$ (599)
$A_1 = 0.241$ (0.342)
$A_2 = 0.000756$ (0.000353)
$A_3 = 0.00473$ (0.00421)
$k_{O2} = 0.339$ (0.308)

model 5 (2 bi-exponential), $k_{O2} = 0$

$\tau A_1 = 0.125$ (6710)
$\tau A_2 = 33.2$ (14.0)
$wA_1 = 0.256$ (10100)
$A_A = 0.00146$ (0.00120)

$\tau_{B1} = 517$ (1960)
$\tau_{B2} = 2570$ (65200)
$w_{B1} = 0.313$ (3.54)
$A_B = 0.0110$ (0.0113)

END

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DATE: 1-92

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