A morphometrically based method for predicting water layer boundaries in meromictic lakes

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Abstract

Many general mass-balance models that simulate processes in one or two water layers have been successfully constructed, tested and used to predict effects from remediating lake pollution and other environmental disturbances. However, these models are poorly suited for meromictic lakes which consist of yet another water layer. To determine a cross-systems based algorithm for the depth of the boundary between the two lowest layers (D_{crit2}; in m), data from 24 three-layer lakes were analysed, and this depth could be predicted from the maximum depth and the lake surface area. The resulting model was tested with good results against independent data from 6 lakes which were not used for model development. Furthermore, D_{crit2} was predicted at a considerably lower depth than the theoretical wave base (a previously defined functional separator between the two top layers) in 110 out of 113 meromictic lakes. This indicates that the equation for D_{crit2} estimated in this study may be used for developing general mass-balance models for a large number of lakes which contain three stable water layers.

Key words: lakes, layers, stratification, meromixis, morphometry

1. Introduction

The physical behaviour of the water column is of great importance for understanding and predicting the fluxes of pollutants and other substances in lakes by means of mass-balance modelling. General, dynamic mass-balance models (see Bryhn & Håkanson, 2007; Blenckner, 2008) with high predictive power may be useful for managing lakes that have been exposed to various environmental disturbances because such models can make it possible to quantify expected effects from remedial action.

For shallow lakes, substance fluxes to and from one water compartment, which describes the whole water column, can be simulated with the assumption that the water column is completely mixed (Aldenberg et al., 1995; Bryhn & Håkanson, 2007). Fluxes in deeper lakes whose water columns occasionally mix over the year can instead be simulated using two water compartments; one for surface waters and one for bottom waters which are vertically separated by the theoretical wave base (also referred to as the critical depth, D_{crit}). Thus, the two compartments can be constructed to simulate the exchange of water and other substances through mixing (Håkanson et al., 2004; Håkanson & Bryhn, 2008). There is also a sedimentological definition of D_{crit}; i. e., the depth above which erosion and transport processes dominate lake sediments, and below which particle accumulation and burial dominate (Håkanson et al., 2004). D_{crit} is given in meters as

$$D_{crit} = 45.7 \cdot \frac{\sqrt{(Area)}}{21.4 + \sqrt{(Area)}} \qquad (1)$$

where $Area$ is the surface area of the lake in km^2 (Håkanson et al., 2004). The empirical depth of the wave base is highly variable over space and time in each lake. Therefore, D_{crit} according to Equation 1 has come to serve as an alternative to empirical measurements which has made it easier to construct and test general mass-balance models for stratifying lakes that are valid over wide lake domains (Håkanson et al., 2004; Bryhn & Håkanson, 2007).

However, modelling approaches with one or two water compartments are poorly suited for, e. g., meromictic lakes, in which a third water layer is sustained for long periods. Meromictic lakes are commonly defined as lakes whose bottom waters are chemically different from the rest of the water column for at least one year at a time (Wetzel, 2001; Boehrer & Schultze, 2008). They are separated from holomictic lakes which mix completely at least once a year (Walker & Likens, 1975). The stability of meromixis has been assumed to depend on several possible factors. Hakala (2004) classified meromixis according to four categories: (1) salinity gradients due to a marked salinity difference between the water column and the water input; (2) stable oxygen concentration gradients which may occur as a result of high nutrient inputs from the catchment and intensive decomposition of dead algae in bottom waters; (3) density gradients, which are usually found in lakes with significant subsurface inflow of dense groundwater; (4) morphogenesis, where, e. g., a low area to depth ratio may prevent mixing of the water column.

Generic mass-balance models for lakes with enduring three-layer stratification may need a well-motivated, operationally defined "second critical depth", analogous with D_{crit} (Equation 1). The alternative, to always use empirical data on stratification for modelling, may be much more time-consuming and uncertain since the depth of the interface between the two deepest layers may be highly variable in space and time in a meromictic lake (Hongve, 1980; Hakala, 2005) and since different indicators of stratum differences may show rather different vertical gradient patterns (Hongve, 1980). For instance, the chemocline depth in Lake Valkiajärvi was determined near 17 m by Hakala (2004), while Walker & Likens (1975) reported a 35% higher value (23 m). Similarly, the chemocline depth in Fayetteville Green Lake was reported close to 18.5 m by Fry (1986) but at 45 m (i. e., 143% deeper than 18.5 m) by Walker & Likens (1975).

This study aims at predicting the boundary depth between the two deepest water layers, D_{crit2}, in lakes with three distinct layers. Empirical measurements of this depth in 24 lakes will be related to their morphometrical parameters. The predictive model will also be tested against data from 6 lakes which will not be used for model development. The aim is to motivate an empirically based cross-systems based definition of D_{crit2}, which, together with D_{crit} (Equation 1) could make it possible to calculate functional separators between three water layers in lakes.

2. Materials and methods

A set of 24 meromictic lakes of different subtypes was compiled from various literature sources for model development (Table 1). The maximum depth (D_{max}; in m), lake surface area (*Area*; in km^2) and lake-typical values of D_{crit2} (in m) had to be provided in the literature as a criterion for including a lake in the table. Data on the mean depth (D_m; in m) was only available for 18 of the lakes. D_{crit2} was for some lakes defined at the most accentuated gradient of a chemical substance (e. g., dissolved oxygen gas, dissolved hydrogen sulphide or sodium chloride); for others it was defined at a clear conductivity gradient, while some literature sources did not specify how D_{crit2} had been measured. Lakes with a reported D_{crit2} of less than 2 m from the surface or from the maximum depth were not used, due to the high variability of D_{crit2}, which was exemplified in the introduction of this paper. An additional set of 6 meromictic lakes was used for model testing (Table 2). The lakes in Tables 1 and 2 are located in different climate regions, from the tropical lakes Arcturus (Galapagos Islands) and Miraflores (Panama) to the Antarctic Ace Lake. *Area* ranged from 0.002 km^2 (Lake Miraflores) to 31,500 km^2 (Lake Baikal) while D_{max} ranged from 3.5 m (Mekkojärvi) to 1,637 m (Lake Baikal; Table 1). To also test whether D_{crit2} may be located close to (or shallower than) D_{crit} in a larger number of three-layer lakes, D_{max} and *Area* data from another 84 reportedly meromictic lakes from Walker & Likens (1975) were used. There was, however, no given information on measured D_{crit2} values in these 84 lakes.

Some combined morphometrical parameters that were used in this study include: (i) the relative depth ($D_{rel} = D_{max} \times \sqrt{(\pi)}/\sqrt{(Area)}$; in %), which is an important determinant of meromixis type (Walker & Likens, 1975); (ii) the volume development ($Vd = 3 \times D_m / D_{max}$), which describes the shape of the hypsographic curve, and is used for estimating the relative extent of erosion, transportation and accumulation bottom areas, as well as for estimating the ratio between the surface water volume and the total lake volume (Håkanson & Bryhn, 2008); (iii) the dynamic ratio ($DR = \sqrt{(Area)}/D_m$) which is also a determinant of the relative distribution of erosion, transportation and accumulation bottom areas and can be used to predict settling velocities of particles (Håkanson & Bryhn 2008).

In this study, all of the variables described above, plus D_{crit} (Equation 1), *Area*, D_m and D_{max}, could in theory be useful predictors of D_{crit2}. However, some of these potential predictors are components or products of some of the other variables and would therefore be statistically redundant in a full multimodel inference. Therefore, potential predictors were first singled out with bivariate regression; non-significant predictors in bivariate regression were eliminated. Second, variables which did not add any significant explanatory power to the full multivariate regression were also eliminated. The analysis included the 95% confidence level as a statistical benchmark.

3. Results

D_{crit2} was positively and significantly correlated with *Area*, D_{max}, D_m, *DR* and D_{crit}. When all of these parameters were log transformed to improve the normality, the correlation between D_{crit2} and *DR* was no longer significant and, therefore, *DR* was not used in multiple regressions. Results from the multiple regression between log(D_{crit2}) and log-transformed values of D_{max}, *Area*, D_{crit} and D_m are given in Table 3. The R^2 value from this regression was rather high (89%). D_m had a very high *p*-level (0.71), indicating that D_m added no significant explanatory power to the regression. D_m was therefore not used in further model development. One can also note that *Area* entered into the regression with a negative sign, although *Area* and D_{crit2} were positively correlated in a bivariate regression (Table 3). In order to avoid a contradiction between a negative coefficient for *Area* in a multiple regression with D_{crit2} and a positive coefficient for *Area* in a bivariate regression with D_{crit2}, it was considered worthwhile to test correlations between D_{crit2} and $D_{crit}/Area^{0.5}$, since the exponents in this ratio (1 and -0.5) were close to the coefficients for D_{crit} and *Area* (1.090 and -0.534) in Table 3. Table 4 shows results after this new variable had replaced D_{crit} and *Area* in the multiple regression, and after D_m had been eliminated. It is worth noting that the R^2 values of both models are equal (89%), indicating that no predictive power was lost by introducing this new D_{crit} to $\sqrt{(Area)}$ ratio. The coefficient of log($D_{crit}/\sqrt{(Area)}$) in step 2 of Table 4 was 1.05 and thus close to 1, which raised the opportunity to attempt using the exponent 1 instead of 1.05 in a multiple statistical model to predict D_{crit2}. Including the definition of D_{crit} in Equation 1 (which is a function of $\sqrt{(Area)}$), and using the information in Table 4, the following statistical model was constructed as the definition of D_{crit2}:

$$D_{crit\,2} = 6.70 \cdot \frac{D_{\max}^{\;1.23}}{21.4 + \sqrt{(Area)}} \qquad (2)$$

To determine whether the slight simplification of exponents used to motivate Equation 2 was warranted, a bivariate regression between log-values of empirical and estimated D_{crit2} was run and plotted in Figure 1. The regression line received a slope close to 1 (0.97) and an intercept close to 0 (0.01) which suggested that estimated log(D_{crit2}) did not deviate systematically from empirical log(D_{crit2}) to any conspicuous extent. When lakes with morphogenetic meromixis ("Type M" according to Table 1) were removed from the regression in Figure 1, the R^2 value remained at 90%, while the slope of the regression line decreased to 0.96 and the intercept decreased to -0.02. When only lakes with reportedly morphogenetic meromixis were used in the regression, the R^2 value increased to 91% while the slope increased to 1.005 and the intercept was 0.0004.

The lakes listed in Table 2 were not used for model development, and log-values of estimated and observed D_{crit2} in these lakes were regressed and displayed in Figure 2, as an independent test of Equation 2. The R^2 value was higher in Figure 2 (95%) than in Figure 1 (90%), the slope closer to 1 (0.99) and the intercept closer to 0 (-

0.01), indicating that Equation 2 yielded better predictions for the six independent lakes in Table 2 than for the lakes in Table 1 which were used to develop Equation 2.

Expressed in percentage deviation between estimated and observed data, the prediction error regarding the lakes in Table 1 ranged from 4% to 113% (mean: 34%, median: 21%, standard deviation: 29 percentage units), and was thus lower for all of these lakes than the uncertainty in one of the examples mentioned in the introduction. The prediction error regarding the six independent lakes in Table 2 ranged from 1% to 71% (mean: 17%, median: 6%, standard deviation: 27 percentage units) and was thus lower than the prediction error of the lakes in Table 1.

From the definitions of D_{crit} (Equation 1) and D_{crit2} (Equation 2), one can note that it was possible to calculate which conditions would be required for D_{crit} and D_{crit2} to have an equal value. An algebraic transformation of Equations 1 and 2 gave:

$$\frac{D_{crit\ 2}}{D_{crit}} = 0.1466 \cdot \frac{D_{\max}^{\ 1.23}}{\sqrt{(Area)}} \tag{3}$$

Equation 3 formed the basis of another new concept, the morphometric mixolimnion factor (*MMF*, dimensionless):

$$MMF = 0.1466 \cdot \frac{D_{\max}^{\ 1.23}}{\sqrt{(Area)}} - 1 \tag{4}$$

Thus, D_{crit} equals D_{crit2} when *MMF* equals zero, indicating that there is no middle water layer which is separated from the surface and from deep sediments). D_{crit2} is located deeper than D_{crit} only when *MMF* has a positive value, which could be seen as a theoretical precondition for the existence of three distinct water layers.

To determine whether D_{crit2} may be close to, or shallower than, D_{crit}, all lakes from Walker & Likens (1975) and one lake from (Goldman et al., 1967) with data on $Area$, D_{max} and stratification type (O or M; see Table 1) were merged together with Tables 1 and 2, adding up to a total of 114 meromictic lakes. Four of the lakes with very low *MMF* values were removed from this analysis, for reasons which will be stated below. The remaining 110 lakes had *MMF* values ranging from 0.23 to 240, indicating that their middle layer thickness was 23%-24,000 % of the upper water layer thickness. The mean and median *MMF* value among these lakes were 27 and 18, respectively, which suggested that most of the lakes had mid-level water layers which were many times thicker than their surface water layer.

As previously mentioned, four of the 114 reportedly meromictic lakes were removed from this analysis. They were listed in Walker & Likens (1975) and all four had *MMF* values which were below, or less than 0.1 unit above, zero, indicating that D_{crit} is very close to, or below, D_{crit2}. Lake Hamana is actually not a lake but an estuary (Taguchi & Nakata, 1998). Meromixis in Lakes Abashiriko, Harutoriko and Togo-ike has not been described in any modern studies in other languages than Japanese, but was reported by Walker & Likens (1975), who in turn cited works that were too old for the author of the present study to access. Hence, the reason for low MMF values in these three remaining lakes could not be investigated in detail.

4. Discussion

Most of the total variability in log (D_{crit2}) was explained by the model developed in this study (Equation 2). A test with independent data from six other lakes (Table 2, Figure 2) yielded high explanatory power (95%) from model predictions. Prediction errors in Figure 1 and Figure 2 were not greater than the difference in reported empirical data from different literature sources (see the introduction of this paper). The regression in Figure 1 was only marginally affected when lakes of morphogenetic or non-morphogenetic meromixis were omitted, which indicated that D_{crit2} showed little systematic variability between lakes of different meromixis types. Furthermore, the small change in the regression coefficients suggests that morphometry plays a great role not only for morphogenetic meromixis but for other meromixis types as well (also reported by Hakala, 2004).

The definition of D_{crit2} (Equation 2) allows us to draw some general conclusions about the depth of the interface between the two deepest layers. This equation implies that deep meromictic lakes often have high D_{crit2} values and deeply located monimolimnia (the lowest water layer). The exponent 1.23 in Equation 2 tells us that large lakes are more likely to have deeper D_{crit2} than small lakes with the same D_{max} to $\sqrt{}$(Area) ratio, which may be attributed to differences in effective fetch, wind exposure and wave base depths. Finally, small lakes have thinner and more deeply located monimolimnia (deeper D_{crit2}) than larger lakes with similar D_{max}.

The model developed here (Equation 2) also has some obvious practical limitations. Gradients of specific variables, such as conductivity or sulphide, may not be predicted with this model but have to be examined by other means. However, since different variables may indicate different chemocline depths, D_{crit2}, as defined and motivated in this work, may be used to provide a reference value regarding where the chemocline can be expected to appear over time and as a mean value emanating from different indicators of meromixis.

A cross-systems validated indicator such as D_{crit2} may also be very useful for constructing management-related mass-balance models that can predict environmental effects in three-layer lakes from foodweb disturbances, polluting substances, or climate change. The predictive success of dynamic mass-balance models that are valid without tuning for wide ranges of holomictic lakes has previously been demonstrated, e. g., regarding radiocesium (Håkanson et al., 2004), suspended particulate matter (Håkanson, 2006) and nutrients (Aldenberg et al. 1995; Bryhn & Håkanson 2007; Blenckner, 2008). It remains a challenge to examine whether such generalised modelling can also be applied to meromictic lakes.

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Table 1. 24 meromictic lakes used for model development. Stratification type M indicates that morphogenesis was reported as the main cause of stratification, while type O indicates other causes.

Lake name	***Area***	D_{max}	D_m	D_{crit2}	**Stratification type**	**Source**
Arcturus	0.2	30	n. a.	25	M	a
Baikal	31500	1637	688	250	M	b
Big Soda	1.616	64.5	26.2	60	O	a
Blue	0.443	34	19.4	34	O	a
Encantada	0.083	14	n. a.	6	O	c
Fayetteville Green Lake	0.26	52.5	28	18.5	M	d
Hännisenlampi	0.015	16	5.2	10.5	M	e
Långsjön	1.43	18	6.3	7.5	O	e
Laukunlampi	0.08	27	6.3	16.5	M	e
Lovojärvi	0.051	17.5	7.7	12.5	M	e
Mahoney	0.216	18.9	7.16	16.5	M	a
Mary	0.012	25.2	7.7	20	M	a
Mekkojärvi	0.0035	3.5	2.2	0.7	M	e
Miraflores	0.002	26	n. a.	21	O	a
Nitinat	27.6	205	99.6	120	O	a
Ö Kyrksundet	2.00	22	n. a.	13.5	O	e
Sakinaw	3.39	140	8.6	80	O	a
Sunfish	0.083	20	10.4	18	M	a
V Kyrksundet	0.60	18	n. a.	6.5	O	e
Vähä-Pitkusta	0.011	35	12	21	M	e
Valkiajärvi	0.078	25	8.4	17	M	e
Vargsundet	1.10	35	n. a.	13	O	e
White	0.996	15	4.62	10.5	M	a
Yellow	0.323	40	20.45	34.5	M	a

a: Walker & Likens (1975); b: Straškrábová et al. (2005), Sherstyankin et al. (2006); c: Brezonik & Fox (1974); d: Fry (1986); e: Hakala (2004); n. a.: no information available.

Table 2. Six meromictic lakes used for model testing. Stratification type M indicates that morphogenesis was reported as the main cause of stratification, while type O indicates other causes.

Lake name	*Area*	D_{max}	D_m	D_{crit2}	Stratification type	Source
Ace	0.14	23	n. a.	15	O	a
Bourget	42	145	80	125	M	b
Cadagno	0.3	20	9.0	12	M	c
Garrow	4.18	49	24.5	20	O	d
La Cruz	0.0145	24	13.1	17	M	e
Vilar	0.011	9	n. a.	4.5	M	f

a: Burton (1980); b: Vinçon-Leite et al. (2002), Jacquet et al. (2005); c: Bossard et al. (2001); d: Ouellet et al. (1989); e: Rodrigo et al. (2001); f: Casamayor et al. (2000). n. a.: no information available.

Table 3. A multiple regression with $\log(D_{crit2})$ as a response variable. $R^2 = 0.89$, $n = 24$, $p < 0.001$.

	Coefficient	**Standard error of coefficient**	***p*-level**
Intercept	-0.79	0.30	0.02
$\log(D_{max})$	1.12	0.23	0.0003
$\log(Area)$	-0.53	0.16	0.005
$\log(D_{crit})$	1.09	0.36	0.01
$\log(D_m)$	0.08	0.21	0.71

Table 4. A multiple regression with $\log(D_{crit2})$ as a response variable, and including $\log(D_{crit}/\sqrt{(Area)})$ as an explanatory variable. $R^2 = 0.89$, $n = 24$, $p < 0.001$.

	Coefficient	**Standard error of coefficient**	***p*-level**
Intercept	-0.86	0.22	0.001
$\log(D_{max})$	1.22	0.11	< 0.0001
$\log(D_{crit}/\sqrt{(Area)})$	1.05	0.27	0.0008

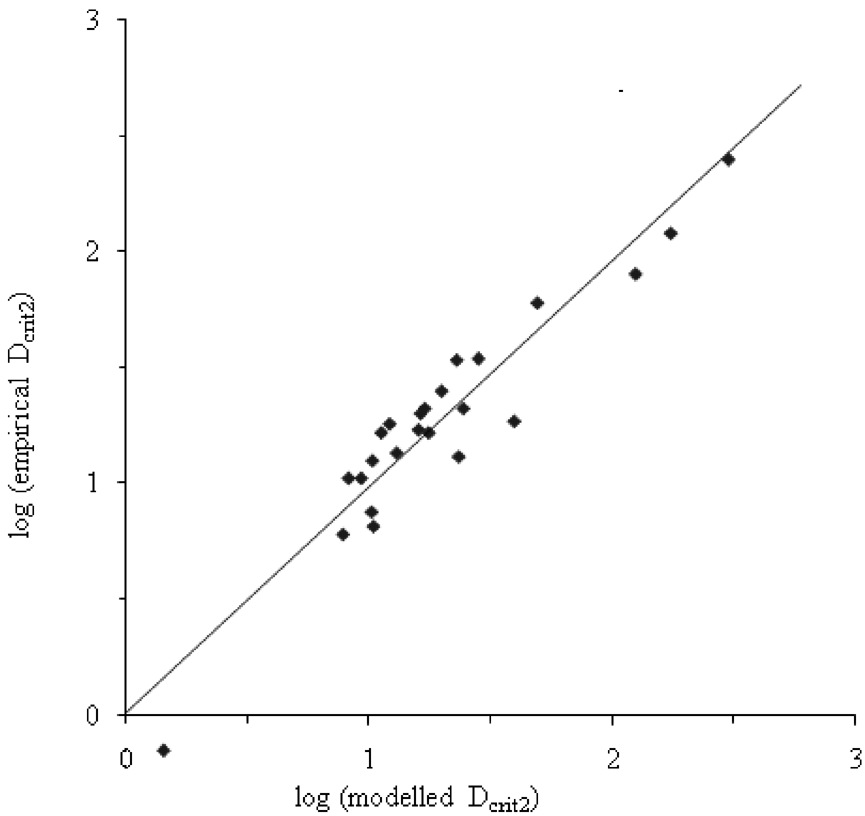

Figure 1. Relationship between log-transformed values of estimated and observed D_{crit2} values in 24 meromictic lakes listed in Table 1.

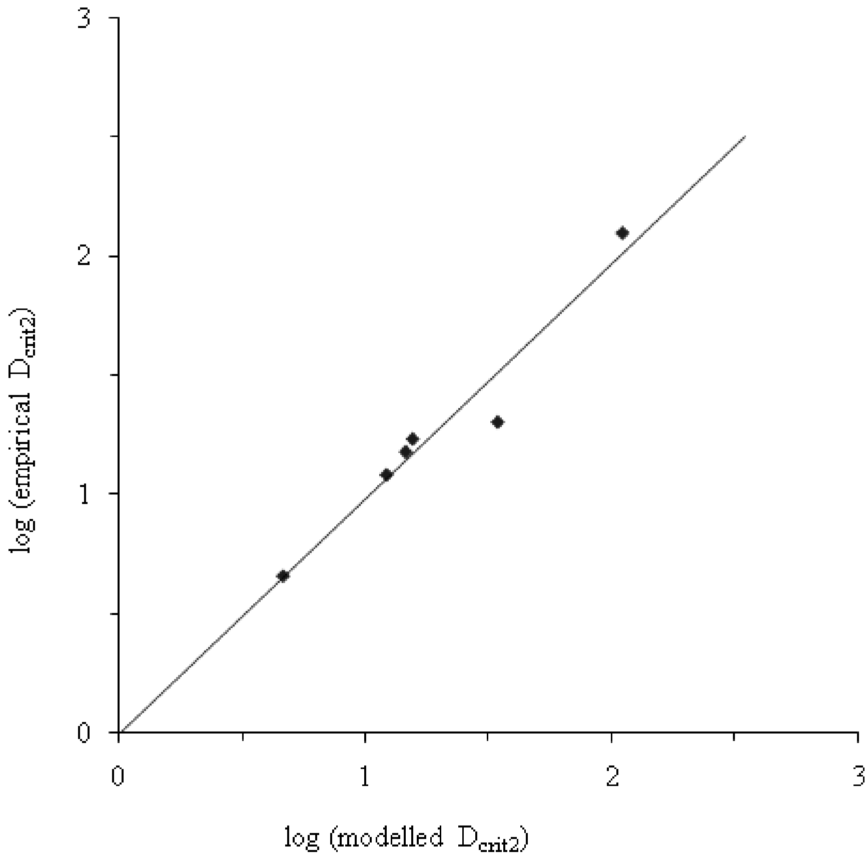

Figure 2. Relationship between log-transformed values of estimated and observed D_{crit2} values in 6 meromictic lakes listed in Table 2.