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Calibrating the Dynamic Reservoir Simulation Model (DYRESM) and filling required data gaps for one-dimensional thermal profile predictions in a boreal lake

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Abstract

One-dimensional vertical heat transfer and mixing models, such as the Dynamic Reservoir Simulation Model (DYRESM), have seldom been applied to lakes in the boreal region even though this region houses the majority of global freshwater lakes. In order to employ DYRESM to predict the thermal structure of a boreal lake located near Sudbury, Ontario, Canada, we overcame two methodological challenges. First, we developed models to predict the vertical light extinction coefficient (K_d) from dissolved organic carbon (DOC) concentrations and hydraulic retention time. We also developed models to predict stream temperatures from local meteorology, and to predict the discharge of lake inflows and the lake outflow from runoff per unit area at gauged streams nearby. We then re-calibrated several DYRESM parameters which had been tested previously primarily in the Southern Hemisphere, and explored the sensitivity of the re-calibrated model to all of the remaining uncalibrated inputs implicated in heating and mixing processes. The mean difference between values predicted with the re-calibrated model and field measurements (± 1 standard deviation), 1.09 m (± 0.89 m) for thermocline depth and 1.98°C (± 1.58°C) for bottom water temperature, was relatively small compared with other North American studies, and likely due to the model rather than our parameterization. Our calibration of DYRESM for Clearwater Lake, and supplementary models, provide a demonstration for and guidance to those wishing to simulate changes in thermal regimes of boreal lakes in response to climate change or other broad-scale environmental stressors of importance both to local fisheries and freshwater resource management.

Despite the fact that boreal lakes, the majority of which are located in Canada, may retain at least 80% of unfrozen freshwater globally (Schindler 1998), process-based physical models have seldom been applied to lakes of this region. One such model, the Dynamic Reservoir Simulation Model (DYRESM) is a numerical one-dimensional model used to simulate changes in lake thermal structure. Originally developed for Australian reservoirs (Imberger et al. 1978; Fischer et al. 1979; Imberger and Patterson 1981), the application of DYRESM to northern latitudes (>45°) represents a potentially rigorous test of model performance. If Coriolis effects and forcing parameters do not have the same functional dynamics as at lower latitudes, then the performance of DYRESM may diminish when applied to boreal regions. Regional environmental influences, i.e., groundwater intrusions or wind sheltering, also may confound mixing and forcing processes, potentially further influencing model simulations. Previous calibrations of DYRESM in Wisconsin (De Stasio et al. 1996; Hamilton et al. 2002; Yeates and Imberger 2003), a region with significant groundwater fluxes (e.g., Anderson and Cheng 1993), may not be broadly applicable to the boreal shield of Canada with its dominance by surficial drainage. Hence, calibrating DYRESM for boreal lakes presents a unique opportunity to model and simulate one-dimensional changes in thermal profiles for a very important subset of global lakes.

This study employed a medium-sized lake located near Sudbury, Canada, to demonstrate calibration and parameterization of DYRESM for a boreal lake. A prerequisite was the synthesis of input data of an appropriate time scale and suitable quality for the model, as some required data were missing on occasion. Removing uncertainty in model forcing data was another important part of establishing confidence and robustness in calibrated

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parameters and model simulations. Thus, the objectives of this study were: (1) to model the one-dimensional thermal structure of Clearwater Lake; (2) to develop models to predict vertical light attenuation, stream temperature, and flow volume, which were rarely included in our measured data sets; and (3) to calibrate and test the sensitivity of model parameters in DYRESM.

Materials and procedures

Clearwater Lake is a medium-sized (area, 76.5 ha; mean depth, 8.4 m; maximum depth, 21.5 m), single-basin lake located 12 km south of Sudbury, Ontario, Canada (46°22′N, 81°03′W). The principal inflows are from surface runoff and two small streams, and a single outflow drains the lake into adjacent Lohi Lake. Monitoring of chemistry, biota, and thermal regimes in Clearwater Lake has been uninterrupted, with the exception of 1992, since 1973, with weekly sampling during the 1970s, and later, monthly visits during the ice-free season (Yan and Miller 1984). Water temperatures were recorded at 1-m intervals through all depths at the site of maximum depth with a YSI model 432D telethermometer from 1973 to 1976, a Montedoro-Whitney TC-5C thermistor from 1976 to 1981, a Mark II Telethermometer from 1982 to 1998, and either a YSI Model 52 or 54 dissolved oxygen/temperature meter since 1998. Thermistors were calibrated annually with a NBS-certified 0.1°C sensitivity thermometer. Thermocline depths were defined as the top of the 1-m measurement interval (or within a 0.20–0.22 m resolution in the modeled results, depending on water levels in the lake), over which the greatest decline in temperature occurred. Dissolved organic carbon (DOC) and pH were collected as whole-lake volume-weighted composites (Yan 1983).

To model the thermal profile of Clearwater Lake, we employed a vertical heat transfer model (DYRESM) which simulates vertical water temperature, salinity, and density with horizontal Lagrangian layers that vary in thickness and number. The model's predictions are driven by volume changes produced by inflows, outflows, and mixing, and are dependent on the thickness of the horizontal layers to detect changes in vertical density stratification (Imberger et al. 1978). The model adopts a one-dimensional layer structure based on common dominance of vertical density stratification over horizontal density variations, with destabilizing forces such as wind stress and surface cooling abbreviated to ensure a one-dimensional structure (Antenucci and Imerito 2003). Mixing and surface layer dynamics are modeled at the confluence of adjacent layers, and are dependent on a turbulent kinetic energy budget and potential energy required for mixing (Sherman et al. 1978; Hamilton and Schladow 1997).

DYRESM was configured to simulate temperature for Clearwater Lake on a daily interval during the ice-free season for each year from 1973–2001. Simulation start dates were chosen as the earliest date in May for which temperature profiles were recorded, except 1973, 1974, 1993, and 1996 when the earliest temperature profiles were collected in June. The last simulation day for each year was chosen to be 1 November. Model inputs

Table 1. Values of DYRESM parameters and model simulation specifications.

Parameter	Set Value
albedo	0.08
benthic boundary layer thickness (m)	0
bulk aerodynamic momentum transport coefficient	0.00139
critical wind speed (m s^{-1})	4.3
effective surface area coefficient	1.0×10^7
emissivity of a water surface	0.96
non-neutral atmospheric stability correction switch	No
potential energy mixing efficiency	0.2
shear production efficiency	0.06
vertical mixing coefficient	200
wind stirring efficiency	0.8
Following calibrations	
minimum layer thickness	0.25 m
maximum layer thickness	0.6 m
wind stirring efficiency	0.06
potential energy mixing efficiency	0.2
vertical light attenuation coefficient (K_d)	+0.01 m^{-1}

all were based on data collected from long-term monitoring of Clearwater Lake or constants included in Antenucci and Imerito (2003) and assigned values in Table 1, with the exception of the mean annual vertical light attenuation coefficient (K_d), inflow temperatures, and flow volumes (Fig. 1). Therefore, regression models were constructed from other long-term data sets to predict values for missing model input data for K_d and inflow temperatures, and flow volumes were estimated based on runoff per unit area from nearby gauged streams.

Predicting the vertical light extinction coefficient—A model to predict the mean annual vertical light extinction coefficient (K_d) was developed from a data set of 14 lakes situated in Killarney Provincial Park, approximately 80 km SW of Sudbury (Appendix 1). Non-volume-weighted water samples were collected from the epilimnia of these lakes in July 1998 and July 1999, and whole lake volume-weighted tube composite samples were collected in November each year (Snucins 1999). By November, these lakes are fully vertically mixed; hence, whole lake volume-weighted samples will not differ from discrete non-volume weighted samples. Downwelling light measurements (400–700 nm) were collected throughout the ice-free season at all lakes with a cosine-corrected flat sensor (model LI-2SB, Li-Cor) connected to a Li-Cor LI-188B Integrating Quantum Photometer (Girard et al. 2006), with the exception of one sampling trip in July 1998 when an Optronics Laboratory Inc. scanning spectroradiometer was used at four of the Killarney Park lakes (Gunn et al. 2001). These light profiles were then employed in calculating an annual average K_d as the slope of the linear regression between the natural logarithm of downwelling irradiance versus negative depth.

To compensate for the influence of ultraviolet-induced (UV-induced) photodegradation of chromophoric DOC

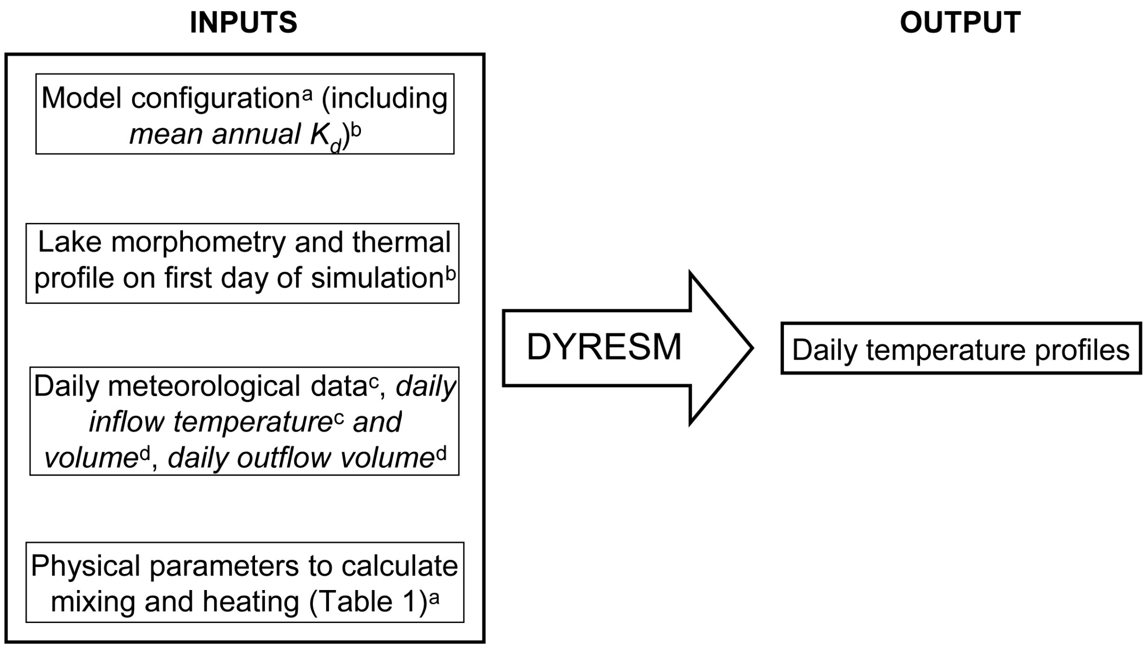

Fig. 1. Schematic of inputs into DYRESM and resulting output. Italicized text indicates modeled inputs. Data sources: [a]Antenucci and Imerito 2003; [b] Ontario Ministry of the Environment; [c] Environment Canada; [d] Water Survey of Canada.

(Molot and Dillon 1997; Beauclerc and Gunn 2001), retention time was considered as a secondary predictor of K_d. Retention times were calculated with Eq. 1 (B. Keller, unpubl. data). All lakes considered in the model possessed a retention time less than Clearwater Lake (5.04 yrs).

$$R = V / (RO \times A), \tag{1}$$

where R = retention time (yr), V = lake volume (m^3), RO = unit runoff coefficient (m yr^{-1}), and A = watershed area – lake area (m^2). RO was designated as 0.35 m yr^{-1} for the Sudbury region including Killarney Provincial Park (International Hydrological Decade 1978).

The Killarney Provincial Park model was a good predictor of K_d according to a backward stepwise multiple regression. July DOC concentrations at Killarney in 1998 and 1999, and retention time (R), exhibited the strongest correlation with annual average K_d in 1998 and 1999 ($r^2 = 0.881$; $P < 0.001$). Curve fitting regressions revealed that a cubic transformation of DOC (mg L^{-1}; $0.15 - 0.0117DOC + 0.0454DOC^2 - 0.0037DOC^3$) and inverse transformation of retention time (years; $0.1895 + 0.1055R^{-1}$) improved the model ($r^2 = 0.952$; $P < 0.001$; Eq. 2; Fig. 2).

$$K_d(m^{-1}) = -0.049 + 0.681DOC \text{ (transformed)} + 0.457R \text{ (transformed)} \tag{2}$$

Values of K_d derived from the Killarney model required epilimnetic DOC concentrations, as opposed to the whole lake measurements routinely recorded for Clearwater Lake (Girard et al. 2006). As epilimnetic DOC was recorded at Clearwater Lake only from 1995–2003, a linear regression was developed between whole lake DOC (DOC_W) for July 1995–2003 and epilimnetic DOC (DOC_E) to allow for pre-1995 estimates of epilimnetic DOC concentrations (Eq. 3). However, at low observed DOC values the linear regression diverged from linearity (Fig. 3). To correct for this, the differences between predicted and observed DOC at low concentrations (Table 2) were subtracted from values predicted with Eq. 3, ensuring less deviation from the 1:1 line (Fig. 3).

$$DOC_E(mg\ L^{-1}) = 0.018 + 0.671e^{0.511DOCW(mg\ L^{-1})}$$
$$r^2 = 0.875;\ P < 0.001 \tag{3}$$

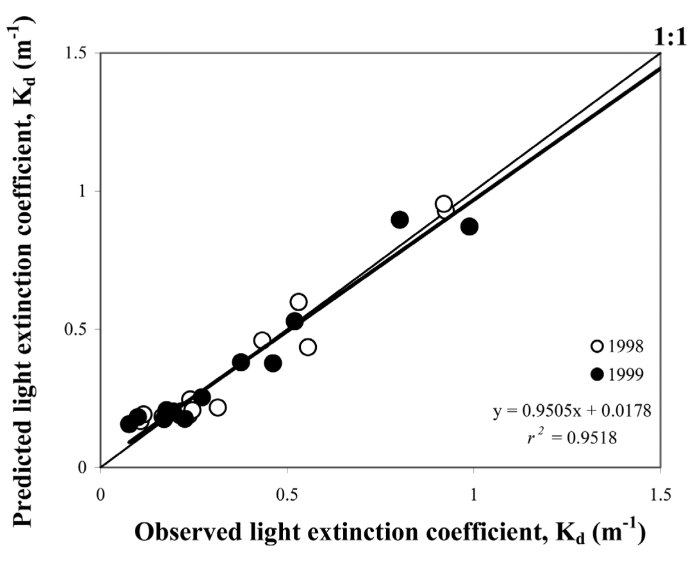

Fig. 2. Predicted versus observed light extinction coefficient values for lakes in the Killarney Provincial Park model.

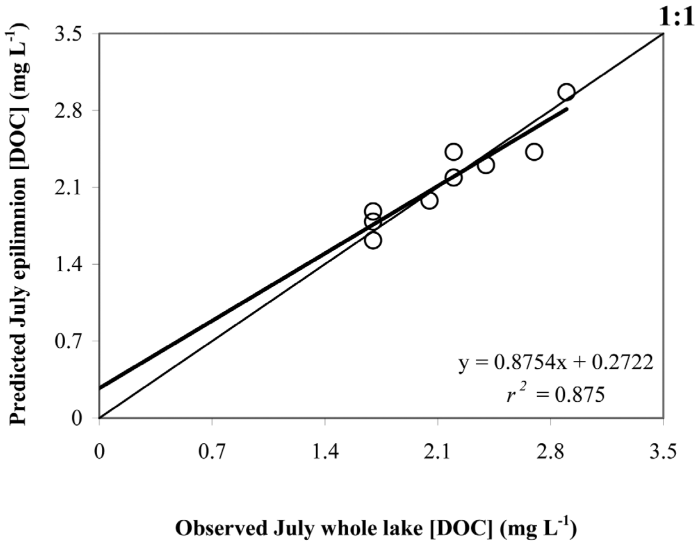

Fig. 3. Observed versus predicted July epilimnion DOC concentration for Clearwater Lake, 1995–2003.

Lastly, our predictions of pre-1995 DOC from Eq. 3 could extend back only to 1981 as DOC was not measured in Clearwater Lake samples between 1973 and 1980. Strong positive correlations exist between DOC concentration and pH for Canadian Shield lakes (Dillon et al. 1987; Schindler et al. 1996; Yan et al. 1996; Keller et al. 2003; Keller et al. 2005), including Clearwater (Dixit et al. 2001), because of enhanced DOC flocculation and precipitation with metals such as Al at low pH (Yan et al. 1996) and/or because low pH increases photodegradation by UV (Gennings et al. 2001). As the pH of Clearwater Lake was measured frequently prior to 1981, a linear regression between July concentrations of epilimnetic DOC and pH was developed for the 1981–2000 data and used to predict epilimnetic DOC concentrations from the pH measured in July from 1973–1980 (Eq. 4).

$$DOC_E = -4.15 + 1.04\ pH \quad r^2 = 0.927;\ P < 0.001 \tag{4}$$

Prediction of stream temperatures in central Ontario—DYRESM requires quantification of inputs of heat via stream flow, but inflow temperatures for Clearwater Lake were never recorded. We reasoned that stream temperature could be derived from appropriate meteorological variables, and numerous studies have identified air temperature as the strongest correlate of stream temperature (e.g., Cluis 1972; Smith 1981; Crisp and Howson 1982; Stefan and Preudhomme 1993) because of its influence on heat budget components such as atmospheric longwave radiation, evaporation, and convection (Bartholow 1989). Other meteorological parameters such as relative humidity, percent possible hours of bright sunshine, and wind speed also may influence stream temperature (Bartholow 1989).

In May 2005, three StowAway TidbiT (Onset Computer) water temperature loggers (TBI32-05+37) were anchored at three separate locations in each of the two streams that feed Clearwater Lake. Locations were selected as close as possible to the mouth of the streams while attempting to avoid locations vulnerable to any back-flushing of Clearwater Lake water into the streams. Water temperatures were recorded hourly from May 20, 2005 to June 22, 2005. A multiple linear regression then was used to predict mean daily stream temperature (T_S) from mean daily values of air temperature (T_A) and total rain (RN), the daily ratio of hours of bright sunshine to the maximum possible hours of bright sunshine for the specific day (S), calculated according to Allen et al. (1998), and daily wind speed (W) and relative humidity (RH) averaged from hourly data. All meteorological data were recorded at the Sudbury Airport and accessed online from Environment Canada (http://www.climate.weatheroffice.ec.gc.ca/).

Table 2. Correction factor for DOC concentrations predicted with Eq. 3.

Whole lake DOC (mg L^{-1})	Amount subtracted from predicted epilimnion DOC (mg L^{-1})
0.3	0.235
0.4	0.222
0.5	0.210
0.6	0.197
0.7	0.185
0.8	0.173
0.9	0.160
1.0	0.148

Highly significant relationships ($P < 0.001$) were found between daily stream temperature and meteorological parameters at both Clearwater Lake inflows (Eq. 5 and Eq. 6). Ungauged surface flow was estimated with Eq. 6, as it would most closely resemble the smaller, shallower, low-flow input (Inflow 2; mean depth = 0.14 m; mean width = 1.40 m).

$$T_{S\ inflow\ 1}(°C) = 8.12 + 0.421T_A(°C) - 0.101RN(mm) - 0.831S - 0.024W(km\ h^{-1}) + 0.031RH(\%)\quad r^2 = 0.791 \tag{5}$$

$$T_{S\ inflow\ 2}(°C) = -9.37 + 0.801T_A(°C) - 0.307RN(mm) + 1.05S + 0.052W(km\ h^{-1}) + 0.154RH(\%)\quad r^2 = 0.846 \tag{6}$$

Estimating inflow and outflow volumes from runoff coefficients—Inputs of heat in stream waters require estimates of stream temperature and discharge rates; however, daily discharges were measured only in the two inflow streams and the outflow stream in 1978 and 1979. To predict daily inflow and outflow volumes for Clearwater Lake, five reference locations with continuously gauged hydrology were selected from the Water Survey of Canada online database (http://www.wsc.ec.gc.ca/) based on proximity to Clearwater Lake (Appendix 2). Discharge at the reference locations (FR; m^3 s^{-1}) was divided by the watershed area of the reference site (AR; m^2) to generate water yield normalized by watershed area (m s^{-1}), and mean

Table 3. Comparison of predicted and observed discharges for Clearwater Lake inflows and outflow (1978–1979) with a paired *t*-test.

Location	Statistic	Inflow 1	Inflow 2	Outflow
Junction Creek below Kelley Lake	significance (*P*)	**0.833***	0.661	<0.001
	t-value	0.212	–0.439	–15.344
	degrees of freedom	701	701	701
	Avg. % difference from predicted	**1.05**	2.40	31.26
Junction Creek at Sudbury	significance (*P*)	0.136	**0.791**	<0.001
	t-value	1.494	0.265	–5.022
	degrees of freedom	729	729	729
	Avg. % difference from predicted	5.19	1.06	23.76
Nolin Creek at Sudbury	significance (*P*)	0.001	0.003	0.024
	t-value	3.891	2.984	–2.262
	degrees of freedom	729	729	729
	Avg. % difference from predicted	15.73	12.05	10.00
Wanapitei River near Wanup	significance (*P*)	0.001	0.005	**0.970**
	t-value	3.22	2.803	–0.038
	degrees of freedom	729	729	729
	Avg. % difference from predicted	23.25	19.90	**0.18**
Whitson River at Chelmsford	significance (*P*)	<0.001	0.002	0.836
	t-value	4.125	3.055	–0.207
	degrees of freedom	729	729	729
	Avg. % difference from predicted	22.92	19.55	0.62

*Values in bold indicate reference location with least significant difference and lowest average percent difference between predicted and observed discharge.

runoff per unit area (m s^{-1}) was assumed to be the same in the reference watershed as at Clearwater Lake. Therefore, the area of each of the individual Clearwater inflows or outflow watersheds (AP; m^2) could be multiplied by the water yield for the watershed to estimate discharge (FP; Eq. 7).

$$FP(m^3\ s^{-1}) = (FR\ /\ AR) \times AP \qquad (7)$$

Reference locations were selected by comparing daily flow volumes at each inflow and at the outflow, predicted from each of the five possible reference locations, with measured values at Clearwater in 1978 and 1979, the only years for which water flows of inputs to the lake were measured. Additionally, the average daily percent difference between predicted and actual flow rate for each site was calculated. The reference location with the least significant difference and highest *P*-value between predicted and observed values, as determined from a paired two-sample *t*-test, was chosen to predict flow volumes for 1973–1977 and 1980–2001. It was assumed that any changes over time in the morphometry of the streambeds and surrounding watersheds, including general patterns of afforestation (Tanentzap et al. 2007), would not have influenced flow rates significantly.

Hydrologic data from Junction Creek below Kelley Lake, Junction Creek at Sudbury, and the Wanapitei River near Wanup were excellent predictors of daily flow volumes at Clearwater Lake Inflow 1, Inflow 2, and Outflow, respectively in 1978 and 1979 (Table 3). Following discontinuation of the Junction Creek monitoring station at Sudbury on April 25, 1996, Junction Creek below Kelley Lake was used to predict flow volume for Inflow 2. Ungauged surface flow was estimated as the sum of flow at Inflow 1 and 2, multiplied by the ungauged area and divided by the gauged area.

Calibration—Although it was possible to parameterize missing values for DYRESM inputs such as K_d, stream temperatures, and flow volumes, there were several remaining inputs which could be evaluated only through calibration due to the nature of the parameter, e.g., minimum and maximum layer thickness (Hornung 2002), and ranges previously employed in the literature, e.g., values of the wind stirring efficiency parameter have been set to 0.06 (Imberger 1998, pers. comm. in Antenucci and Imerito 2003), 0.4 (Yeates and Imberger 2003), and 0.8 (Hornung 2002; Gal et al. 2003). Using the parameterized model, we performed two calibrations with a subset of years from our data set to reduce computational demands while reflecting all periods in the modeling record, (1) early; 1978 and 1980; (2) middle; 1986, 1987, 1988; and (3) late; 1996, 1998. The mean absolute difference between predicted and actual water temperature at all depths for which field data existed (W_T), thermocline depth (Z_T), and bottom water temperature (T_B; 17-m depth), and standard error of the mean absolute difference between predicted and actual temperatures and thermocline depths, were calculated.

We performed two separate calibrations, the first for layer thickness and the second for the wind stirring efficiency parameter, to identify the values of these settings which would result in the least amount of error between observed and predicted temperature profiles. Minimum layer thickness was varied from 0.25, 0.5, and 1.0 m and maximum layer

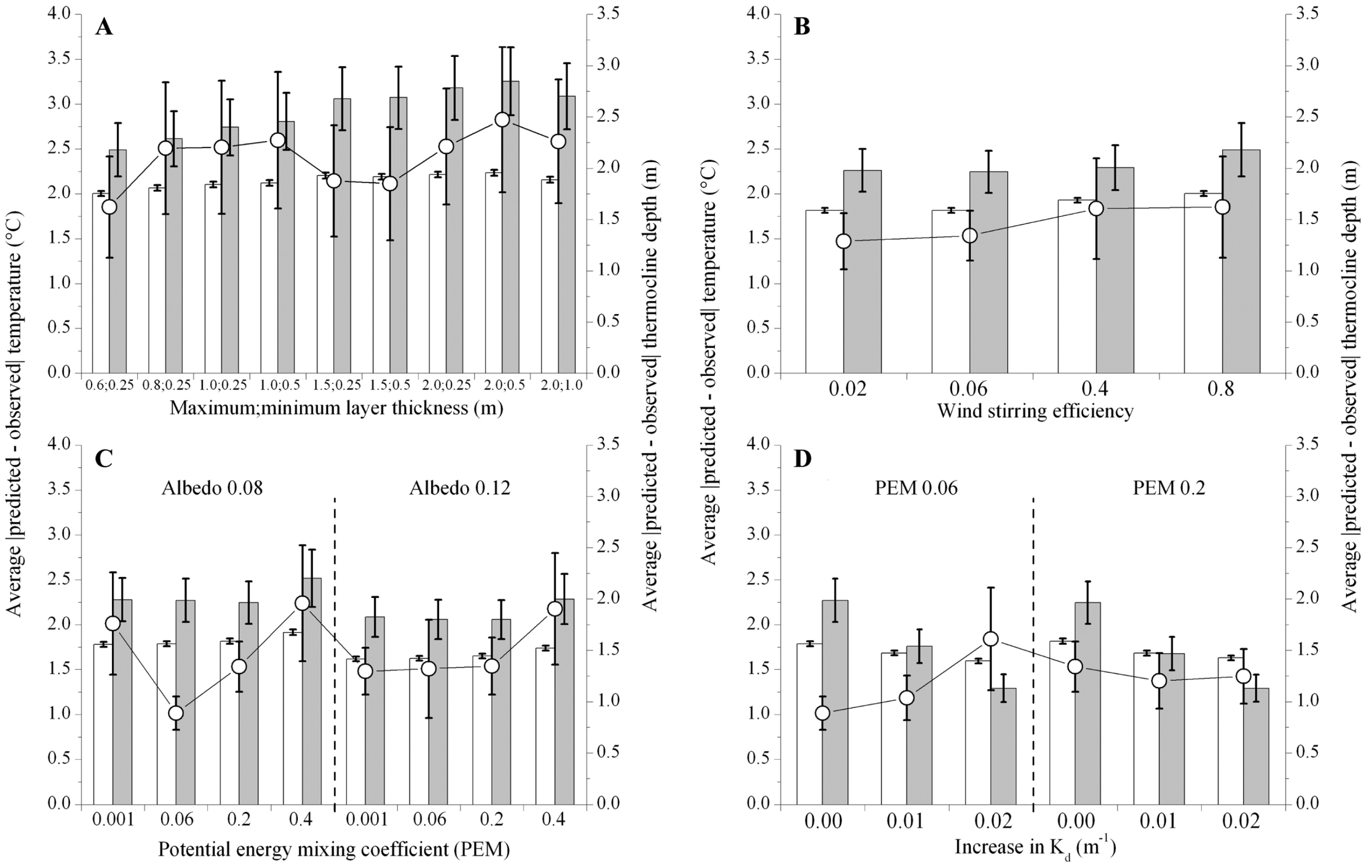

Fig. 4. Average absolute difference ± standard error of the mean between DYRESM predicted and observed water temperature (white column, $n = 2111$), bottom water temperature (gray column, $n = 46$), and thermocline depth (line, $n = 16$) at various layer thickness settings (A), wind stirring efficiency values (B), albedo and potential energy mixing coefficient (PEM) values (C), and additions to K_d predicted with Eq. 2 and employing a PEM value of 0.06 or 0.2 (D).

thickness from 0.6, 0.8, 1.0, 1.5, and 2.0 m. For the calibration of layer thickness, all simulations involved maximum layer thickness set to less than twice the minimum layer thickness, and a wind stirring efficiency of 0.8. The second calibration tested values of 0.8, 0.4, and 0.06 for the wind stirring efficiency, all values that have been previously employed, with layer thickness set at the values identified in the preceding calibration.

DYRESM validation—Once we calibrated DYRESM, simulated thermocline depths and near-bottom water temperatures (17-m depth) for Clearwater Lake from 1973 to 2001 were compared to measured values on days when thermal profiles had been measured in the field. A regression of observed daily thermocline depth, from 15 July to 5 September, and bottom water temperature, from 15 May (or start date of yearly simulation for 1973, 1974, 1993, and 1996) to 31 October, on modeled values, tested the ability of DYRESM to predict thermal profiles of Clearwater Lake. If the regression generated a high r^2 (≥0.65), an intercept not significantly different from zero (α = 0.05), and a slope significantly different from zero (α = 0.05) and approaching one, DYRESM was considered to adequately predict thermal profiles.

Assessment

DYRESM calibrations—Sixty-three simulations were performed to identify the layer thickness settings that would yield the least amount of deviation between predicted and observed thermal profiles. A maximum layer thickness of 0.6 m and minimum layer thickness of 0.25 m were the best settings to predict water temperature at all depths (Fig. 4A).

Twenty-eight simulations for the seven calibration years demonstrated that wind stirring efficiency parameters of 0.02 and 0.06 performed equally well as predictors of W_T, Z_T, and T_B (Fig. 4B). This led us to adopt a value of 0.06 to remain consistent with the recommendation in the DYRESM operating literature (Antenucci and Imerito 2003). However, predicted values of W_T, Z_T, and T_B were consistently larger than observations. Warmer temperatures and deeper thermoclines were a result of either too much heat input or mixing in the simulation. Therefore, additional calibrations were applied.

Reducing heat and mixing through calibration—Fifty-six simulations were performed with an albedo of 0.08 or 0.12, and a potential energy mixing (PEM) coefficient of 0.001, 0.06, 0.2, or 0.4. The simulations demonstrated that no single setting

Table 4. Repeated-measures ANOVAs to compare original input values of uncalibrated parameters with changes of ±10%.

	Temperature at 1-m depth			Temperature at 17-m depth			Thermocline depth		
Parameter	**F**	**DF**	***P***	**F**	**DF**	***P***	**F**	**DF**	***P***
air temperature	1.450	21.758, 43.516	0.147	1.202	23.893, 47.787	0.288	0.979	16.222, 32.443	0.500
benthic boundary layer thickness	2.895	52, 104	**<0.001**	11.950	8.742, 17.485	**<0.001**	1.295	52, 104	0.133
critical wind speed	0.905	41.967, 83.934	0.633	1.755	10.370, 21.340	0.129	1.156	17.104, 34.208	0.348
effective surface area coefficient	1.080	59.129, 118.259	0.357	0.899	11.533, 23.066	0.558	1.318	51.243, 102.485	0.119
inflow temperature	1.031	31.204, 62.407	0.447	0.760	10.448, 20.896	0.669	1.313	54.263, 108.526	0.116
net longwave radiation	1.113	57.906, 115.812	0.310	1.325	15.021, 30.041	0.248	0.973	30.151, 60.302	0.520
non-neutral atmospheric stability switch	1.295	19.182, 38.364	0.242	2.316	11.792, 23.584	**0.040**	1.059	8.853, 17.707	0.435
rainfall	0.976	23.940, 47.880	0.511	1.739	16.219, 32.438	0.088	1.006	7.535, 15.070	0.468
shear production efficiency	1.053	36.369, 72.739	0.416	0.906	10.589, 21.177	0.548	1.312	26.995, 53.996	0.195
shortwave radiation	1.059	19.915, 39.831	0.425	4.619	7.528, 15.056	**0.006**	1.030	37.086, 74.172	0.446
vertical mixing coefficient	1.094	19.072, 38.144	0.394	1.166	15.769, 31.537	0.345	1.325	64.282, 128.564	0.090
water vapor	0.982	37.036, 74.072	0.513	0.684	16.029, 32.058	0.788	1.176	17.750, 35.501	0.660
wind speed	0.746	21.270, 42.539	0.763	1.711	7.132, 14.264	0.184	1.063	8.142, 16.285	0.433

*Degrees of freedom were adjusted with the Huynh-Feldt correction. Bolded values are significant at α = 0.05.

was best at predicting W_T, Z_T, or T_B (Fig. 4C). Whereas an increase solely in albedo decreased differences between predicted and observed temperatures, thermocline depth was less accurately predicted than at lower albedo. Similarly, increases in the PEM coefficient tended to increase error in water temperature slightly, as well as the difference between predicted and observed thermocline depth. It appeared from these results that the interaction between albedo and the PEM coefficient would most successfully counter error in the model at an albedo of 0.08 and PEM of 0.06. However, we were reluctant to accept the PEM coefficient as the main source of error.

An additional 42 simulations were performed to identify whether an under-predicted K_d was responsible for overestimates of actual water temperatures. Temperature profiles predicted with yearly K_d calculated from Eq. 2 were compared with simulations employing increases in K_d of either 0.01 or 0.02 m^{-1} at a PEM coefficient of both 0.06 and 0.2. Whereas increases in K_d decreased the error of predicted water temperatures at all depths (Fig. 4D), thermocline depth was best predicted when K_d was increased by 0.01 m^{-1}. Both a PEM coefficient of 0.06 and 0.2 performed almost identically with an increase in K_d of 0.01 m^{-1}, whereas 0.2 was the better setting for PEM when K_d was increased to 0.02 m^{-1}. Although an increase in K_d of 0.02 m^{-1} and a PEM coefficient of 0.2 predicted T_B better than settings with a K_d increase of 0.01 m^{-1}, the improvement (<0.5°C) increased Z_T error slightly, which we felt was still too high and took precedence in reducing error. Thus, K_d was increased by 0.01 m^{-1}, and the PEM coefficient was maintained at 0.2. Overall, the calibrations demonstrated that the model could have been adjusted differently depending on what was being predicted. The ideal parameterization for T_B did not result in the least amount of error for predicting Z_T.

Sensitivity testing of inputs implicated in heating and mixing—Several input parameters implicated in thermal processes were not tested for their influence on heating and mixing in DYRESM. Therefore, additional simulations with the years 1978, 1988, and 1998 were performed while varying one of the meteorological parameters (air temperature, radiation, rainfall, vapor pressure, and wind speed), inflow temperature, critical wind speed, shear production efficiency, or the effective surface area and vertical mixing coefficients. Inflow salinity was not included in the sensitivity analyses as the model would be insensitive at the low salinity of the inflows (<0.005 practical salinity units [psu], as estimated from conductivity). Remaining inputs were parameterized according to Table 1. Tested input parameters were designated as highly sensitive when relatively small changes in the original values (±10%) resulted in significantly different daily water temperatures at depths of 1-m and 17-m, and daily thermocline depth, based on a repeated-measures one-way analysis of variation (ANOVA) for the late-summer period (15 July – 5 September). Temperature or thermocline depth was input as the within-subjects variable, with treatment as the between-subjects variable. Year was blocked and included as a between-subjects variable, thus eliminating a two-way repeated-measures design. Where an original parameter value was zero, as for benthic boundary layer thickness, sensitivity analyses were performed comparing values of zero and 0.10.

Sensitivity testing revealed that the majority of uncalibrated input parameters were insensitive to changes of ±10% (Table 4). Only changes to benthic boundary layer thickness resulted in significantly different surface water temperatures (Table 4). However, these changes produced surface water temperatures that were not consistently more accurate than those predicted with the original input value. Increases in benthic boundary layer thickness and activation of the non-neutral atmospheric stability switch also increased bottom water temperatures significantly, causing them to deviate further from actual values

Table 5. Comparisons of DYRESM-predicted thermocline depths and temperatures at 17-m (depth) versus measured values on dates with corresponding field data, 1973–2001.

metric	r^2	P	intercept (P)	slope	n
thermocline depth	0.65	<0.001	–0.27 (0.771)	1.00	76
bottom water temperature	0.77	<0.001	0.58 (0.235)	1.12	204

*In linear regression, P values for slopes are same as for r^2.

(Table 4). Significantly different bottom water temperatures resulting from changes in shortwave radiation did not differ from predictions with the original input values, rather, temperatures predicted with a 10% increase in shortwave radiation were significantly different from those predicted with a 10% decrease (Tukey post-hoc test, $P = 0.004$). Thus, the uncalibrated parameters identified as highly sensitive (Table 4) could not have caused the elevated amount of mixing and heating in DYRESM, as both increases and reductions to the original values increased error. Settings within the source code or errors in field data and predicting model input data, particularly K_d, must therefore be responsible for the modeled deviations in water temperature and thermocline depth.

Validation of DYRESM for Clearwater Lake—Following calibration, DYRESM could accurately simulate both the thermocline depth and bottom water temperature of Clearwater Lake. Prediction error ± 1 standard deviation was 1.09 m ± 0.89 m (10.5% ± 8.5%, $n = 76$) for thermocline depth and 1.98°C ± 1.58°C (18.5% ± 16.8%, $n = 204$) for bottom water temperature. Regressions modeled on observed values generated coefficients of determination with $r^2 > 0.6$, intercepts that were not significantly different from zero, and slopes significantly different from zero, and approaching one (Table 5). Error was comparable to DYRESM studies for other small North American lakes (De Stasio et al. 1996). Sensitivity and calibration testing of mixing and heating parameters was not able to identify consistent parameter changes to reduce error in the model, and thus, error was likely due to process representation in the model structure or errors in the field data, such as drift in calibration of the thermistor. Some of the error could, however, be attributed to intra-annual variations in K_d contributed by, for example, changes in color, phytoplankton biomass, or inorganic suspended sediments.

Discussion

Our calibration of Clearwater Lake is the first to demonstrate applicability of DYRESM to a boreal lake on the Canadian Shield. We show that large gaps in required input data can be overcome with several simple, yet effective models, to predict limnological parameters such as K_d or inflow volumes and temperature. Once the model was parameterized, deviations between DYRESM-modeled and observed field data remained, but they did not impede our ability to distinguish long-term trends in thermocline depth and bottom water temperature (Table 5). These errors were likely due to one or more of the following factors: (1) a lack of additional multivariate model calibrations; (2) the internal structure of DYRESM; (3) errors in field measurements; and (4) bias in predictions of field data from regression models.

Changes in K_d have been shown to be important in determining differences in temperature between predicted and observed values (i.e., Hocking and Straskraba 1999). For example, an increase in K_d of 0.02 m^{-1} improved predictions of summer temperature profiles in the summer of 1978, but not in the spring of the same year (Fig. 5). However, seasonal variations in K_d are generally less than 0.01 m^{-1} in Clearwater Lake (mean standard deviation of seasonal K_d = 0.005 m^{-1}), and would account for less than 0.15°C of variation in modeled temperatures and 0.6 m in modeled thermocline depths (Fig. 4D). Seasonal variation in chlorophyll *a* (Chl *a*) also is not important in determining K_d at Clearwater (Beauclerc and Gunn 2001), and the effect of chlorophyll was likely minimal early in the record, as phytoplankton were located deep in the water column (Yan and Miller 1984). Although these factors may matter in some lakes, i.e., eutrophic lakes or lakes with strong seasonality in the main driver of K_d, in our case, where DOC is the dominant light-attenuating constituent and its concentration varies little seasonally, the inter-annual changes in K_d at Clearwater greatly exceeded any within-year

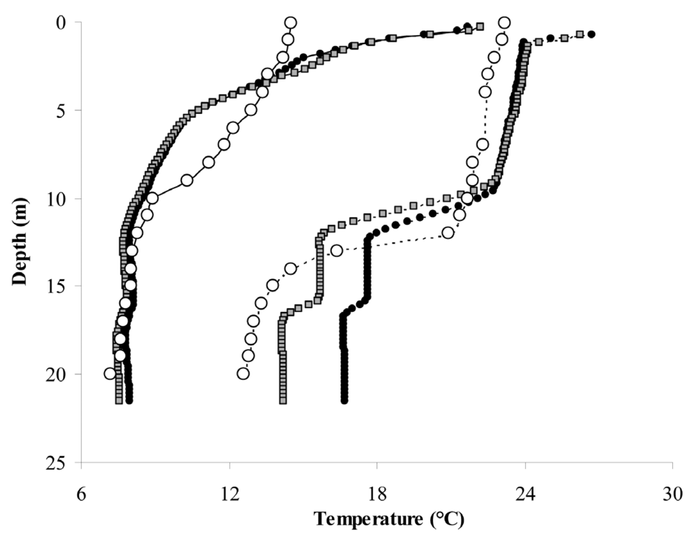

Fig. 5. Seasonal improvement in thermal profile prediction due to intra-annual K_d variation. Thermal profiles for 25 May (solid line) and 14 August (broken line) 1978, predicted with no change in K_d (black circle) and an increase in K_d of 0.02 m^{-1} (black square), compared to field measurements (white circle).

changes to K_d that may have occurred. Photodegradation over the course of the summer heating season also did not appear to influence K_d to a significant extent in Clearwater Lake (Beauclerc and Gunn 2001). We found that K_d was underestimated later in summer in our model rather than overestimated (Fig. 5), as would occur due to decreased light attenuation via photodegradation of DOC (De Haan 1993; Wetzel et al. 1995; Morris and Hargreaves 1997).

In lakes where intra-annual variation in K_d is large, repeated measurements of K_d should be considered in refining thermal profile modeling. Application of a fully coupled water quality model (e.g., DYRESM-CAEDYM; Bruce et al. 2006) would implicitly incorporate intra-annual effects on K_d, as K_d values are simulated as a function of selected state variables (e.g., Chl *a*) in the model. Further, consideration also could be given in future studies to the use of measured values of K_d as forcing input to the model, so as to reduce this source of error. The deterministic nature of output from a model such as DYRESM will not capture some of the variability inherent in measured field data taken under a specific set of conditions at one particular time of day. A stochastic approach that quantified variation due to different parameter settings, to generate a statistical distribution of model output, may be a better reflection of some of the variability of measurements.

Most small stratified lakes generally reflect the widely accepted paradigm of DYRESM of one-dimensionality of field data as they tend to lack large horizontal temperature gradients (Imberger and Patterson 1981). However, exceptions exist, primarily in short-term deviations of thermocline depth, for large lakes with significant internal wave activity and at lake monitoring stations that are not centered about the fulcrum of internal wave activity (e.g., Ryan et al. 2005). Three-dimensional effects, such as circulation associated with convective heating and cooling also may disrupt vertical density structures implicit in the one-dimensional assumption. For example, upwelling and differential heating (Monismith et al. 1990), or spatial variations in wind stress (Imberger and Parker 1985), i.e., wind sheltering, can produce significant horizontal variations in thermal profiles.

Surface heat exchange processes form one of the underlying mechanisms for thermal profile predictions with DYRESM. Although bulk aerodynamic fluxes incorporated in DYRESM appear to adequately represent most boundary fluxes, representations of these fluxes have changed little in more than 35 years of model applications. Greatly improved capacity for high-resolution, high-frequency measurements suggests that there is scope to consider adopting improved transfer functions (MacIntyre et al. 1995). The exclusion of sediment heat fluxes and heat fluxes associated with groundwater intrusions from DYRESM also may influence model performance. Mitigating this influence somewhat for our application is the fact that these fluxes are likely to be most significant in winter (Ellis et al. 1991; Tsay et al. 1992), especially during ice cover, when other boundary heat fluxes will be reduced greatly, and for our study, groundwater intrusions do not exist (Scheider 1984). Current attempts to incorporate ice cover into DYRESM (Hamilton et al. 2002) may resolve this issue, and further improve model predictions in deep lakes where heat content may be retained over years and even decades producing a climatic 'memory' (Livingstone 1993; Ambrosetti and Barbanti 1999).

Through applying DYRESM to a boreal lake, we have provided a starting point for broad-scale predictions of the thermal structure of the majority of global freshwater lakes, i.e., for lakes on the boreal shield. Integration of DYRESM across the landscape could provide a powerful tool to simulate the response of many of these lakes to climate change or other broad-scale environmental stressors. Long term data, as for our study lake, also provides an exceptional opportunity of running the model over extended periods of time for comparative purposes. Additionally, the regression models we have developed also could be used for many other biological and hydrological processes, other than predicting thermal profiles, including prediction of the vertical migration of organisms (Ringelberg 1999) or the effect of climate change on stream temperatures and the life history of macroinvertebrates (Hogg and Williams 1996). Tanentzap et al. (2008) provide an example of how these models and DYRESM can be used to identify the joint impacts of changes in wind speed and K_d on lake thermal structure, a demonstration that is difficult to provide using statistical procedures alone (e.g., Keller et al. 2005).

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