A multi-lake comparative analysis of the General Lake Model (GLM): Stress-testing across a global observatory network

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Highlights

- General Lake Model (GLM) stress tested against 32 globally distributed lakes.
- Uncertainty in input data not greatest determinant of model performance.
- Model performance related to lake morphometry and climate.
- Temperature predictions less sensitive to model parameters than prediction of thermocline depth and Schmidt number.
- Developed a common and collaborative approach to answering global lake science questions.

Abstract

The lake modelling community has identified challenges for the integration and assessment of lake models due to the diversity of modelling approaches and lakes. In this study, we develop and assess an open source, one-dimensional lake model and apply it to 32 lakes from a global observatory network to simulate lake water balance and thermal structure. The data set included lakes over broad ranges in latitude, climatic zones, depth, volume, residence time, mixing regime and trophic level. To our knowledge, this is the first time that one lake model has been rigorously tested and applied to such a large number of test cases. Model performance was evaluated using several error assessment metrics, and a sensitivity analysis was conducted for nine parameters that governed the surface heat exchange and mixing efficiency. The model performance and parameter sensitivity were found to correlate with several lake characteristics related to morphometry and climatic regime. The study highlights applications where the common model approach and associated assumptions work, and those where adjustments to model parameterisations and/or structure are required. The international collaboration using a community model facilitated the sharing of ideas and data and led to improved model development.

Key Words: Lake model, GLM, model assessment, global data, cross collaboration.

1 Introduction

Vörösmarty et al. (2000) urged the international "water sciences community" to work together in the collation and dissemination of hydrological data and modelling techniques to improve our understanding of freshwater ecosystems and "secure a more complete picture of future water vulnerabilities". Lakes, in particular, are highly valued ecosystems as they provide important water and food resources, in addition to numerous other ecosystem services (Wilson and Carpenter 1999). However, human activities such as fresh water diversion and increased nutrient loading, in addition to indirect pressures from climate change, have led to an increased vulnerability of lakes on a global scale (Folke et al. 2004). These challenges have given rise to international networks of scientists such as the Global Lake Ecological Observatory Network (GLEON: gleon.org). Collaborative networks can take advantage of shared data, techniques, and expertise to enable scientists to address the ecological challenges facing lakes globally (Eigenbrode et al. 2007; Adams 2012; Goring et al. 2014). GLEON was initiated in 2005 as a grassroots science community with a vision to observe, understand and predict freshwater systems at a global scale (Weathers et al. 2013).

Collaboration between scientists and synthesis of data collected through GLEON has led to advances in our understanding of how lake ecosystems respond to external changes and contribute to effective lake management on a local (Gal et al. 2009), regional (Read et al. 2014; Trolle et al. 2015) and global scale (O'Reilly et al. 2015). Analyses based on data from a broad spectrum of lakes across the globe have provided insight into metabolism and carbon cycling in lakes (Hanson et al. 2011; Solomon et al. 2013), the role of wind and heat exchange in lake physics (Read et al. 2012), the impact of climate change (Adrian et al. 2009), response and recovery of lakes to extreme events (Jennings et al. 2012; Klug et al. 2012), and assisted in development of models (Staehr et al. 2010; Read et al. 2011; Kara et al. 2012; Hipsey et al. 2014a). Further interrogation of the emerging multi-lake datasets offers the potential to advance our understanding of how lakes respond to pressures such as climate or land use change from the individual to global scales.

The collaborative network also creates opportunities for developing and testing modelling tools. Aquatic ecosystem models are recognised as essential instruments to improve understanding of processes, analyse relationships, test hypotheses and predict the state of a system (Trolle et al. 2012). These models have evolved since the first attempts in the early 1920s, with a recent review of aquatic ecosystem models revealing the incredible diversity of existing models from simple 0-D to complex 3-D coupled hydrodynamic-biogeochemical models (Janssen et al. 2015). This diversity creates challenges for integration and synthesis of model approaches (Mooij et al. 2010). The Aquatic Ecosystem Modelling Network (AEMON: https://sites.google.com/site/aquaticmodelling/home) was formed to foster collaboration and improve model development, predictability, transparency and reliability. One of the major challenges facing modellers is how to develop generic models that can capture the diversity of ecosystems while allowing prediction with confidence of the processes of each system. In order to undertake analytical synthesis across multiple sites, there is a need to assess the transferability of the underlying model and standardise its structure, parameterisation, development and examination. While the need to develop a set of standards for model assessment and reporting is widely recognized (Bennett et al. 2013; Grimm et al. 2014), the ability to test these standards across multiple systems and highlight both strengths and limitations of a particular model remains a challenge.

For lakes and reservoirs in particular, one-dimensional (1-D) models that resolve vertical profiles of temperature and density have found widespread use due to their computational efficiency and minimal calibration. The reduced complexity of 1-D models, is advantageous whenever greater computational efficiency is needed, e.g., in ensemble modelling (Trolle et al. 2014), model inter-comparison projects such as LakeMIP (http://www.unige.ch/climate/lakemip) (Stepanenko et al. 2010; Thiery et al. 2014), probabilistic studies (Schlabing et al. 2014), for long-term scenario analysis (Gilboa et al. 2014) or when linking lake models to global climate models (Balsamo et al. 2012) or catchment models (Hipsey et al. 2015). Moreover, lake managers and reservoir operators prefer models having a simpler application and often rely on 1-D models.

Here we introduce the Multi-Lake Comparison Project (MLCP), an AEMON initiative. The MLCP is a community driven project, where teams of modellers simulate lakes using common approaches for model setup, assessment and analysis. The underlying purpose of the project was to bring together an international network of scientists and modellers with diverse experience in order to improve our ability to predict how lake ecosystems respond to external drivers. In the first stage, the MLCP took advantage of GLEON and AEMON member data from numerous, diverse lakes to stress test the recently developed General Lake Model (GLM) (Hipsey et al. 2014a). GLM is a 1-D hydrodynamic model for use in a broad spectrum of enclosed aquatic ecosystems such as lakes, reservoirs and wetlands. The model is simple in nature and is based on assumptions that are common to previous model applications (Imberger and Patterson 1989; Hamilton and Schladow 1997; Coats et al. 2006). The model conducts a lake water and energy balance to compute vertical profiles of temperature, salinity and density while accounting for the effect of inflows and outflows, surface heating and cooling, mixing and ice cover on the lake. GLM can be coupled with biogeochemical models to explore the impact of temperature, stratification, and vertical mixing on the dynamics of lake ecology.

This paper summarises the first phase of the MLCP to develop and stress-test GLM. The stress-test involved applying a single standardised procedure for model set-up, simulation, performance testing and analysis to 32 lakes from across the global network. The main objective of this study was to undertake cross lake, model comparison analysis on a scale never achieved before in order to advance our limnological understanding and contemporary modelling practices. The specific aims of the study were to:

1. ascertain a typical level of model performance and relate to model input uncertainty;
2. identify lake attributes (e.g. depth, inflows, and climate) that correspond with high (or low) prediction accuracy;
3. relate sensitivity of model output variables to changes in surface exchange, heating and mixing parameters that characterise 1-D lake models;
4. to document the transferability of the model without recalibration of single parameters between lakes strongly differing in their properties; and
5. provide guidance to lake modellers as to how to focus data collection and model application efforts to improve predictions for lake ecosystems.

2 Methods

2.1 Study site selection

Lakes were not chosen a priori based on their attributes, but rather AEMON and GLEON members were invited to participate in the MLCP by volunteering details of their candidate lake to the group (shared via open access spreadsheet). The requirement for inclusion of a lake was specified based on the following three conditions:

1. sufficient temperature data exists for validation (2 years of at least monthly/regular thermistor chain and/or profile data);
2. high-resolution meteorological forcing data from an on-lake buoy or local terrestrial based station was available; and
3. gauged or well-estimated inflows and outflows were available over the simulation period to form a realistic lake water balance.

Participants were also required to have a basic knowledge of lake modelling. Instructions as to how to set-up the GLM, test cases and a common binary executable (GLM v2.2.0) were made available for download from the Aquatic EcoDynamics (AED) website (http://aed.see.uwa.edu.au/). Pre- and post-processing MATLAB scripts were provided to all participants to ensure a common model setup and assessment approach, and all GLM lake setups were available to other members via a, cloud-based, shared folder.

A total of 32 lakes were chosen for the analysis, with an alphabetic listing of the lakes used and their physical characteristics outlined in Table 1. Each lake is associated with a two letter abbreviated code, and for brevity when presenting model results, the lakes are frequently referred to by this code. To illustrate the range of sizes in the lakes included in this study, lake outlines have been drawn to scale in Figure 1. With the exception of lakes Geneva and Kinneret, all lake simulations were run for two years, with the start year and date indicated in Table A3. For Lake Geneva and Lake Kinneret, analyses were performed separately for two alternative 2-year time periods with significant differences in climate and inflows. For Lake Geneva, 2003 to 2004 had higher than average summer air temperatures, precipitation and inflows as well as an uncharacteristically high winter inflow in early 2004. In contrast, 2001 to 2002 experienced closer to the "normal" seasonal cycles of climate and inflows (Anneville et al. 2010). These simulations are referred to as Geneva03 and Geneva01 respectively. For Lake Kinneret, 1997 to 1998 had generally average climatic conditions(Bruce et al. 2006). In contrast, 2003 to 2004 had a rainy winter (Feb-Mar 2003, Jan-Feb 2004), large changes to lake level and lower than normal water temperatures (Berger and Telzch 2005). These simulations are referred to as Kinneret97 and Kinneret03, respectively.

Lake depths ranged from 2.4 to 440 m, and lake surface areas from 104 $\times 10^3$ m^2 to 579 $\times 10^6$ m^2, (Table 1). A comparative plot of the hypsographic curves for each of the 32 lakes shows diversity in lake size and bed slope (Figure A1 Appendix). Annual average inflows ranged from 0 to 33×10^6 m^3 s^{-1} and residence times from 1 month to 67 years (Table A3). Lake elevation ranged from 209 m below to 747 m above sea level (Table 1). Annual average air temperature ranged from below freezing (min: -9.1˚C) to a maximum of +23.2˚C (Table A3). While the majority of the lakes in the MLCP are mid-latitude (both northern and southern hemisphere), two lakes are located in the Arctic.

2.2 GLM set-up

GLM has several configuration options for simulating surface heating, mixing and inflow and outflow (Hipsey et al. 2014a). For this assessment, model set-ups were configured based on the site specific conditions (e.g., hypsographic curve and number of inflows and outflows), but all simulations adopted the same model algorithms and parameters for mixing, surface heat fluxes, and ice cover. Default parameters adopted are summarised in Table 2.

All simulations were run for 2 years or 730 days starting with initial conditions in the winter or when the lake was closest to well mixed. For the northern hemisphere lakes the start date was the 1st of January and for lakes located in the southern hemisphere the start date was set at 1st July. The standardised start date was chosen to simplify cross lake comparisons. For the majority of the lakes in the MLCP mid-winter is also associated with complete mixing thus reducing error associated with uncertainty in initial profiles.

Box plots are used to present monthly means and range of input data across all 34 simulations (Figure 2). For input data for each lake, refer to references listed in Table 1 and/or the institutions listed in Table D1. Inflow and outflow are also plotted as monthly averages based on time from the beginning of the simulation (Figure 3a&b). There are no seasonal patterns apparent in the monthly inflows and outflows averaged over the MLCP lakes due to the large variation in peak flow months.

While an effort was made to use lakes with high quality input data, lakes where input data was estimated were still selected for the MLCP in order to ensure a sufficient variation in lake characteristics. For seven lakes either inflow, outflow or both were estimated (Bourget, Emaiksoun, Feeagh, Mendota, NamCo, Stechlin and Woods) and the parameter of light attenuation (K_w) was estimated for three lakes (Alexandrina, Muggelesee and Woods). In an attempt to assess the errors associated with input data limitations, a qualitative weighting system was used to assess each input variable or constant, where a minimum score is associated with the best available input or observation data (Table A1). Table A2a lists the method of determining the hypsographic curve, distance from lake and frequency of meteorological and observed data and method of determining inflow, outflow and extinction coefficient for each lake in the MLCP. This information is used to determine the relative error scale associated with boundary forcing and observed data for each lake (Table A2b) where low refers to low uncertainty in forcing data and high, a higher level of error associated with model input.

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2.3 Model assessment approach

Measures of model fit used to evaluate model performance included five alternatives listed below. This set of measures of model fit enabled us to standardise comparisons among lakes, track trends in deviations from observed data (Bennett et al. 2013) and to compare against similar lake modelling studies previously published, (e.g. Rigosi et al. 2010).

Measures of model fit were calculated as:

1) Root mean square error (*RMSE*):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{N}} \qquad (2\text{-}1)$$

2) Model Efficiency (*MEFF*; Murphy, 1988; Nash and Sutcliffe, 1970):

$$MEFF = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \qquad (2\text{-}2)$$

3) Correlation coefficient (r):

$$r = \frac{\sum_{i=1}^{N}(P_i - \bar{P})(O_i - \bar{O})}{\left[\sum_{i=1}^{N}(P_i - \bar{P})^2 \sum_{i=1}^{N}(O_i - \bar{O})^2\right]^{1/2}} \qquad (2\text{-}3)$$

4) Percent relative error (*PRE*) :

$$PRE = \frac{\sum_{i=1}^{N}(P_i - O_i)/O_i}{N} * 100 \qquad (2\text{-}4)$$

5) Normalised mean absolute error (*NMAE*) :

$$NMAE = \frac{\sum_{i=1}^{N}|(P_i - O_i)/O_i|}{N} \qquad (2\text{-}5)$$

where N is the number of observations, O_i and P_i, the "ith" observed and model predicted data and $\bar{O}$ and $\bar{P}$ the mean observed and model predicted data, respectively.

A further advantage of calculating alternative measures of model fit is that different methods of model evaluation highlight different aspects of model performance (Bennett et al. 2013). *RMSE* is a standard measure of the average deviation of simulated values from observations with values near zero indicating a close match and units that correspond to those of the variable. *MEFF* is a measure of the square of the deviation of simulated values from observations, normalized to the standard deviation of the observed data. One indicates perfect fit and zero indicates that the model provides equal predictive skill as assuming mean observed data. The correlation coefficient r gives an indication of the linear relationship between observed and predicted data and is the most common measure for assessing aquatic models (Arhonditsis and Brett 2004). *PRE* is a measure of the relative deviation of simulated from observed values and can be used to determine the bias in predictions (Bennett et al. 2013). Finally, *NMAE* is both normalised to the mean, enabling like comparisons between variables and is absolute so that under and over estimations are not cancelled out.

Initial manual calibration focused on refining input data and adjusting wind factor and river inflow slope. Wind factor calibration was used to adjust for wind stations located some distance from the lake and to account for wind sheltering. River inflow slope was adjusted to correct the magnitude of momentum and entrainment associated with plunging inflows. For lakes where few or no light attenuation or Secchi depth readings were available, K_w was adjusted until simulated thermocline depth matched that of observed data. Initial calibration was carried out until an *RMSE* (calculated for all observed temperature data over the simulation period) of less than 2°C was achieved.

We chose a range of thermodynamic metrics to assess model performance at each site: observed full profile temperature data; epilimnion temperature; hypolimnion temperature; thermocline depth and Schmidt Stability. Schmidt Stability (S_T) and thermocline depth (T_D) were calculated for both model output and observed thermistor data using Lake Analyzer (http://lakeanalyzer.gleon.org/), an open source software tool that computes indices of mixing and stratification for lakes and reservoirs (Read et al. 2011). S_T was calculated using Lake Analyzer as a measure of lake stability and breakdown of stratification. The comparison of T_D calculations was included in the analysis as it is a simple, widely-used metric of mixed depth while acknowledging the calculation of T_D can be challenging for weakly stratified and polymicitic lakes. While not used as a direct gauge of model performance, the daily Lake Number (L_N) output as a GLM diagnostic parameter was used in the cross lake comparison analysis as a measure of both lake stability and to test the one-dimensional assumption of the model.

Derived measures of lake properties were calculated as:

1) Schmidt Stability (S_T):

$$S_T = \frac{g}{A_S}\int_0^{z_D} (z - z_v)\rho_z A_z \partial z \qquad (2\text{-}6)$$

2) Lake Number (L_N):

$$\mathrm{L_N} = \frac{\mathrm{S_T}(z_e - z_h)}{2\rho_h u_*^2 A_s^{1/2} z_v} \qquad (2\text{-}7)$$

where g is the acceleration due to gravity, A_s is the surface area of the lake, A_z is the area of the lake at depth z, z_D is the maximum depth of the lake, and z_v is the depth to the centre of volume of the lake and z_e and z_h are the depths to the top and bottom of the metalimnion, respectively, ρ_z is the water density at depth z, ρ_h is the average density of the hypolimnion and u_* is the surface friction velocity. S_T represents resistance to mechanical mixing due to the potential energy inherent in the stratification of the water column. L_N balances the strength of stratification to wind induced mixing across the thermocline and is a measure of the potential for mixing across the thermocline (Imberger and Patterson 1989).

2.4 Sensitivity analysis

Sensitivity of model output to nine parameters of mixing and heat exchange was evaluated for each lake. Three of the parameters influence surface heat and momentum exchange: bulk aerodynamic coefficient for sensible heat transfer, (C_H), bulk aerodynamic coefficient for latent heat transfer (C_E), coefficient of wind drag (C_D). The remaining six parameters control surface and hypolimnetic mixing: mixing efficiency for convective overturn (C_C), mixing efficiency of wind stirring (C_W), mixing efficiency of shear production (C_S), mixing efficiency of unsteady turbulence (C_T), mixing efficiency of Kelvin-Helmholtz turbulent billows (C_{KH}), and mixing efficiency of hypolimnetic turbulence (C_{HYP}), (Table 2). To gauge a response to parameter change, the one-at-a-time (OAT) method (Bruce et al. 2008) was adopted for the first stage of the MLCP, where the model was first run with the model default value to each parameter and then run again increasing and decreasing parameter values by 20%.

Sensitivity to changes in parameter values for each of the five lake variables used in the model assessment described above (temperature of the full water column, epilimnion, hypolimnion, T_D and S_T) was analysed. Normalised sensitivity coefficients (S_{ij}) to assess the relative sensitivity of variable i to parameter j were calculated according to:

$$S_{ij} = \frac{\Delta C_i / C_{is}}{\Delta \beta_j / \beta_{js}} \qquad (2\text{-}8)$$

where ΔC_i is the change in output variable i from the standard or reference value C_{is} (Table 2) and $\Delta\beta_j$ is the change in parameter j from the reference value β_j (Fasham et al. 1990).

Sensitivity coefficients were then related to ten lake properties describing the morphometry, climatic conditions and trophic state of the lakes. These lake properties include maximum depth, lake volume, ratio of area to maximum depth, ratio of length to width, annual average inflow, residence time, mean air temperature, mean short wave radiation, mean wind speed and extinction coefficient (Table 1).

3 Results

3.1 Model Performance

Using the simulated results from running GLM with the standard set of parameters, five model fit metrics (*RMSE*, *MEFF*, *r*, *PRE* and *NMAE*) were calculated for five data sets (full profile, epilimnion, hypolimnion temperature, T_D and S_T) for each lake. The full set of results is provided in Appendix B (Table B1) with *NMAE* results given in Table 3. A comprehensive description of model performance for each lake can be found in the plots of modelled versus observed temperature data included in Appendix B.

An analysis of model performance in the prediction of full temperature profiles, (full profile) demonstrated a robustness for GLM across all model fit metrics with an average *RMSE* of 1.36°C, *MEFF* of 0.88, *r* of 0.96, *PRE* of 0.01% and *NMAE* of 0.11 (Table B1). The lakes with the lowest *RMSE* included Feagh, Tarawera and Emaiksoun. The highest *RMSE* values were calculated for Ravn, Ammersee and Woods. Ammersee also recorded the lowest values for *MEFF* along with NamCo and Toolik. All values of r were > 0.9, with the exception of Toolik. The *PRE* values ranged from +18% for NamCo to -15% for Rassnitzersee. Because lakes had both positive and negative *PRE* (representing a temperature bias, warm and cold respectively) the mean *PRE* was -0.16%. The lowest absolute *PRE* was for GrosseDhuenn (0.33%) which also performed well on all five measures of model fit.

In general, the model performance predicting the epilimnion temperatures was of similar magnitude to the full temperature profiles (*RMSE* mean = 1.62˚C). By analysing the *PRE*, it is clear that the GLM tended to produce both warm and cold temperature biases in the epilimnion, slightly favouring a cold bias (mean *PRE* = -0.07%). For most lakes, model performance metrics were similar for the epilimnion as the full profile with the exception of Windermere and Zurich which performed worse and Oneida which performed better in the computation of epilimnion temperatures.

For the hypolimnetic temperature simulations, average *RMSE* and *NMAE* values were relatively low, 1.31˚C and 0.14 respectively. Typically small seasonal variation across all lakes led to greater percentage error between model and simulated data with both warm and cold temperature biases and a tendency to bias warm (mean *PRE* = 1.97%). The mean *r* value of 0.73 was the lowest of the three temperature-associated hydrodynamic properties. Lakes with the highest model performance for hypolimnion temperature included Geneva01, Geneva03 and Como with the lowest being Rassnitzersee, Esthwaite and Blelham. Model efficiency values for the calculation of hypolimnion temperatures were poor with less than a third greater than 0.5 and 44% of lakes recording a value of less than zero.

Thermocline depth (T_D) was the most difficult to model parameter with the poorest *PRE* and *NMAE* values (Tables 3 & B1). Measures of model performance comparing calculations of observed and simulated T_D ranged in value across the lakes with *PRE* values from -16% to +52% and *NMAE* ranging from 0.10 to 0.76 and (Tables 3 & B1). The *PRE* values indicate a bias towards over prediction of T_D by the model compared to the observed data. This was most apparent in Lake Geneva over the winter months when GLM predicted full mixing (i.e. T_D = lake depth) and the field data recorded a shallow T_D (<5m). As the lake depth was >300m this resulted in large relative error of greater than 6000% leading to unfavourable mean measures of fit.

The *NMAE* values for calculation of S_T were generally low with exceptions Ammersee, Oneida and Pusiano associated with lower overall values of S_T. The mean *MEFF* and *r* were both quite high (0.83 and 0.96, respectively) indicating that the general seasonal patterns for S_T prediction across the majority of lakes were well simulated by the model. For a number of lakes with high error associated with the calculation of T_D had much better fit with S_T (e.g. Como, Harp and Iseo).

Analysis of the relationship between indices of model fit and input quality showed some correlation for the prediction of full profile, epilimnion and hypolimnion temperatures and T_D (Table B2). Analysis of measures of *PRE* indicates a cold bias in prediction of both full profile and hypolimnion temperatures when input error is greatest (Figure 4b). In addition for lakes where the meteorological measurement station was near or at the lake edge, there was a warm bias and for lakes where meteorological input was sourced from further away, there was a cold bias (Figure 4a). Similarly there was a warm bias for the prediction of hypolimnetic temperatures for lakes with high frequency meteorological data and a cold bias for lakes with daily meteorological data (Figure 4c). Lakes with lowest input error associated with the estimation of K_w corresponded with lowest values of *r* with respect to the prediction of full temperature profiles (Figure 4d) and similarly lakes that had close to ideal ranking of input error scored the lowest values of *r* for epilimnion temperatures (Figure 4e). Similarly high frequency observed data also correlated with high *NMAE* scores for the prediction of hypolimnion temperatures (Figure 4f).

When comparing model performance for simulations using the standard set of mixing and surface exchange parameters there were a number of significant correlations linking model performance to lake characteristics (Table B3). For comparison of absolute model performance, the *RMSE* metric was used for temperatures and *MEFF* for T_D and S_T. Whilst measurements of *PRE* can be a deceptive measure of model performance for lake variables where under and over prediction occurs in equal measure, they are useful to observe patterns of bias in model prediction. A number of significant correlations between lake characteristics and model error are illustrated in Figure 5 and Figure 6 and described below.

The *RMSE* error associated with the prediction of both full profile and hypolimnion temperatures was generally higher for eutrophic lakes (K_w > 0.8 m^{-1}) and lower for oligotrophic lakes (K_w < 0.3 m^{-1}) (Figure 5a&b). A general correlation was observed between the *RMSE* associated with the prediction of hypolimnion temperatures and lake depth (Figure 5c) with deep lakes (>100m) calculating lowest levels of *RMSE* (<1˚C). In terms of relative measures of model performance, for lakes with both low inflows (< 10^5 m^{3}s^{-1}) and low levels of incident short wave radiation (<120 Wm^{-2}) there was a cold bias in prediction of full profile and epilimnion temperatures, respectively (Figure 5c&d). Whilst correlation was relatively low, there was some indication that for lakes with low residence time there was a cold bias in the GLM predicted hypolimnetic temperatures (Figure 5f).

For prediction of S_T, the lake depth, residence time and extinction coefficient all had a significant impact on model performance (Figure 6a, b & c). Generally oligotrophic, deep lakes (>100m), with residence times > 2 years recorded the lowest values of *NMAE*. A reverse pattern of correlation was observed for the prediction of T_D with deep lakes calculating the highest values of *NMAE* and shallow lakes (<40m) showing highest levels of T_D predictive accuracy (Figure 6e). There was a small but significant trend where GLM over estimated S_T in lakes with high incident short wave radiation (>200 Wm^{-2}) (Figure 6e). For prediction of T_D, GLM tended towards over-prediction which was more pronounced in colder lakes (air temperature < 10˚C) (Figure 6f).

3.2 Sensitivity Analysis

The sensitivity analysis (SA) on each of the nine surface exchange and mixing parameters highlighted differences both between lakes and thermodynamic properties (Figure 7a-e). For all three temperature metrics (full profile, epilimnion or hypolimnion) there was little sensitivity to perturbations in physical parameters, when the SA was applied one at a time and averaged over the 2 year simulation period. There was some degree of sensitivity to changes in C_d in the calculation of hypolimnion temperatures and to C_e in the calculation of epilimnion temperatures. Calculation of sensitivity index (*SI*) for prediction of both T_D and S_T, , were significant (>1) across a broader range of lakes (Figure 7d-e). While there was some variability across the lakes and parameters, model output for both T_D and S_T had greatest sensitivity to perturbations of C_d and for S_T there was a consistent level of sensitivity to perturbations of C_e.

Sensitivity of each parameter were compared to a gradient of physical and climate lake properties (Table C1-5) and a number of significant correlations were observed. For each thermodynamic metric, the three most significant correlations to lake characteristics were compared (Figure 8-12). A common significant ($p<0.05$) trend was recorded for maximum lake depth (Figure 9b, 12a-c). For the prediction of full profile and epilimnion temperatures, deeper and larger lakes were more sensitive to changes in C_{KH} than small, shallow lakes (Figure 9b). Similarly for the prediction of T_D, deeper lakes were more sensitive to changes in C_c, C_w and C_{KH} than shallow lakes (Figure 11).

A significant correlation with air temperature indicated that lakes with low air temperatures were more sensitive to changes in C_h and C_s for the prediction of full temperature profile than lakes in warm climates (mean air temperature > 10˚C) (Figure 8c), epilimnion (Figure 9a) and hypolimnion temperatures (Figure 10a). Lakes with low inflow were more sensitive to changes in C_h for the prediction of hypolimnion temperatures than those with larger inflows (Figure 9c). Finally, lakes with highest wind speed recorded greatest SI to C_e in the prediction of S_T (Figure 12).

4 Discussion

Historically, lake modellers have adopted simplistic methods to justify model performance and suitability, rarely reporting statistical measures of model fit (Arhonditsis and Brett 2004; Arhonditsis et al. 2006). For individual lake applications, these have been adequate to undertake scenario simulations and further our understanding of site specific dynamics. However, a common approach to model assessment, both in terms of metrics that should be applied and identification of a commonly agreed level of model performance, is necessary to further enhance model development (Bennett et al. 2013). Undertaking a standardized method of assessment of the community lake model, GLM, over a diversity of lakes has led to an improved level of understanding of the strengths and weaknesses in the predictive capacity of simple 1-D lake models. By first ascertaining an acceptable model error, we were able to elucidate the relationship between model performance and data input uncertainty or lake characteristics. For lakes where a similar 1-D model has been applied and statistical measures of model performance reported these have been compared to the results from this study (Table 4). For most lakes, GLM performs as well as or better than other models despite the standardisation of model structure and parameterisation used in this study.

A key finding when comparing the various model assessment metrics was that, in general, the quality of input data was not as significantly related to model performance as expected. Lakes using daily meteorological input, rather than hourly, did have the largest values of *NMAE* in the prediction of full profile temperature and T_D, which is not surprising given the importance of diurnal forcing as an important factor in 1-D model predictive capability. It was found that greater meteorological observation distance to the lake tended to result in both cold-biased temperatures and under prediction of S_T. The cause of warm-biased temperatures and over prediction of lake stability resulting from lakes with nearby or on-lake meteorological observations requires further investigation. The strong correlation between accuracy of *Kw* measurements and model performance in the prediction of both full profile temperature and T_D emphasises both the importance of light extinction in the determination of thermocline depth and the need to include measurements of *Kw* in routine lake monitoring. The GLM can be coupled to water quality models such as the Aquatic EcoDynamics Model (AED: http://aed.see.uwa.edu.au/research/models/AED/index.html Hipsey et al. 2013) to feedback seasonal changes in *Kw* that we surmise would also improve model prediction particularly in relation to T_D.

The 1-D nature of the model implicitly assumes a predominance of surface forcing, and relative insignificance of horizontal gradients. A simple quantification of this assumption was established by Imberger and Patterson (1989 eq. 2.7) during the early development of the 1-D lake model approach with computation of the Lake Number. As the Lake Number is a relative measure of the strength of stratification to surface wind energy, the 1-D model assumption is said to hold true for $L_N >> 1$ (Imberger and Patterson 1989; Yeates and Imberger 2003). Over the past three decades, the 1-D model approach has been applied to a wide diversity of sites due to its simplicity and tractability relative to 3-D models. However, given that L_N can be highly variable, it has remained unclear what significance the 1-D assumption has on model prediction error for various lake attributes and under what conditions would this assumption no longer hold. Comparing the mean

L_N over the 2-year simulation period of 34 GLM simulations to measurements of model performance for lake temperatures and thermocline depth found no significant relationship (Table B3). A time series of *RMSE* for temperature against L_N for each individual lake (data not shown) did not show elevated *RMSE* corresponding to $L_N < 1$. Even when temperature *RMSE* for individual lakes were plotted against L_N for stratified periods only there was no discernible correlation. This highlights the need to go beyond a simple assessment of L_N when determining whether a lake meets the 1-D model assumption.

A comparison of *PRE* against L_N for the calculation of simulated versus observed S_T indicated that lakes with mean L_N closest to 1 tended to underestimate S_T. This is in itself an interesting observation since for these lakes the 1-D assumption as defined by L_N, does not hold. Yeates and Imberger (2003) demonstrated that for lakes where deep mixing is important, the traditional 1-D lake model structure similar to GLM tended to overmix the water column and thus underestimate lake stability and therefore S_T. A solution put forward by Yeates and Imberger (2003) included a pseudo two-dimensional algorithm in the 1-D model DYRESM to parameterise internal and boundary fluxes, similarly Gaudard et al. (2016) proposed a method of adding a seasonal component in the parameterisation of internal seiches that led to improved accuracy in the prediction of deep mixing in the 1-D model SIMSTRAT. Whilst compromising computational efficiency, lake modellers could consider a similar approach when conditions for improved deep mixing accuracy are necessary. For example, in lakes where upwelling or internal nutrient loading is deemed important or simulation of water quality variables such as deep chlorophyll maxima are the focus of the modelling study.

Further exploration of individual lake properties compared to measures of model performance found strongest correlations against K_w and lake depth. Lakes with high K_w (> 0.5), recorded greatest error in the prediction of lake temperatures particularly in the hypolimnion. While there was no significant correlation between the accuracy in prediction of epilimnion temperatures and lake depth, there was a strong negative correlation for the magnitude of error in prediction of hypolimnion temperatures and depth. That is, for deeper lakes (>40 m) where surface mixing dynamics have less influence on hypolimnion temperatures, GLM predicts temperatures with greater accuracy. This suggests that while the surface thermodynamics are better represented by the model, prediction of rates of mixing across the metalimnion requires attention and further development. Relatively shallow, well-mixed lakes, such as Feeagh and Emaiksuon, had the highest overall model performance. These lakes are dominated by surface exchange with no thermocline and associated deepening.

The prediction of the lake thermocline depth proved harder to achieve than the lake temperatures. Particularly in moderately deep lakes, small relative deviations in predictions can result in large changes to error magnitude. As the thermocline depth was predicted both biased deep and shallow in different lakes, it is not consistent bias in the mixing algorithms, rather, it may be driven by high sensitivity to input parameter uncertainty. The positive correlation between *NMAE* of thermocline prediction and lake depth was significant with best fit occurring for lakes less than 50-80 m deep. A tendency to over-predict thermocline depth in the majority of lakes could be attributed to an over prediction of penetrative heat and may be related to both the application of a standard minimum layer thickness for all lakes and the use of a single average K_w value over 2 annual seasonal cycles. The positive correlation with K_w indicates that a single K_w for all seasonal conditions is not appropriate particularly for lakes with high mean or seasonally variant K_w values. A consideration for using a K_w weighted towards the summer stratified period could be a solution or coupling to a water quality model with explicit light extinction feedback properties could improve thermocline prediction particularly in eutrophic lakes ($K_w > 0.5$).

The absence of strong sensitivity to parameterisation of surface exchange and mixing algorithms in the prediction of temperature profiles is indicative of the dominance of boundary conditions in the thermal budget of individual lakes. Alternatively, the prediction of thermocline depth and Schmidt Stability were more sensitive than temperatures to changes in parameterisation suggesting that these parameters had a greater effect on the determination of the structure of the thermodynamic profile of the lake. When calculating T_D and S_T, the model was sensitive to the shear mixing efficiency and wind drag coefficient parameters. Both parameters are directly related to the transfer of wind energy to mixing. Care should therefore be taken in both the measurement accuracy in wind speed data as well as the parameterisation and classification of these parameters in relation to lake characteristics to improve model performance across a wide variety of lake properties.

In general, simulations of deep lakes with large volumes and residence times were most sensitive to changes in mixing efficiency parameters (as measured by changes in T_D and S_T), which was expected since larger lakes require greater efficiency in transfer of surface momentum input to thermocline deepening and subsequent mixing. Lakes with low K_w were most sensitive to changes in surface exchange parameters. This is logical given that in lakes with low extinction coefficient light will penetrate deeper and increase the transport of heat to the lower layers influencing stratification dynamics. Lakes with lower K_w are also known to be more sensitive to climate variability (Snucins and Gunn 2000) which ties with sensitivity to surface exchange parameters.

An appealing alternative to the minimal calibration presented here (i.e., input data refinement, wind factor and river inflow slope adjustment) will be the relaxation of the assumption of globally common parameter values for the core hydrodynamic parameters and the adoption of a Bayesian hierarchical calibration framework that reflects the more realistic notion that each lake (or group of lakes) is unique but shares some commonality of behavior with other lakes (Zhang and Arhonditsis 2009; Cheng et al. 2010; Shimoda and Arhonditsis 2015) The proposed approach represents a pragmatic compromise between system- or group-specific and globally common parameter estimates and may be a conceptually more sound strategy to accommodate within- and among-lake variability (Figure 13). Recent work has shown that the delineation of more homogeneous subsets of lakes with respect to their morphological characteristics/hydraulic regimes and their subsequent integration with hierarchical frameworks may give models with better predictive capacity (Cheng et al. 2010; Shimoda and Arhonditsis 2015). In particular, our sensitivity analysis patterns could be used to identify groups with similarities in behavior (e.g., deep versus shallow lakes, high versus low water transparency) as well as to identify the candidate parameters for the calibration exercise. The prior distributions of the hyper-parameters (or global priors) can be easily formulated on the basis of existing knowledge (e.g., field observations, laboratory studies, and information from the modeling literature) of the relative plausibility of their values. Moreover, the proposed incorporation of mathematical models into Bayesian hierarchical frameworks can also assist the effective modeling of systems with limited knowledge by enabling the transfer of information across systems. With the hierarchical model configuration, we can potentially overcome problems of insufficient local data by "borrowing strength" from well-studied lakes on the basis of distributions that connect systems in space (Zhang and Arhonditsis 2009). On a final note, another advantage of a Bayesian calibration configuration will be the ability to express the input uncertainty in the form of probability density functions which can then be propagated through the model structure and may ultimately shape the moments of the posterior predictive distributions.

Through international collaboration, this work allowed us to test and to improve the process and performance of a 1-D open source model by simulating thermal structure in lakes with varying physical and climatic characteristics. Initial efforts in setting up a collaborative network of lake modellers were rewarded with improved user based support as well as model feedback, development and testing to the development team. From its initiation as v1.0.0 in the MLCP, using feedback and re-coding by network members, the GLM evolved through numerous improvements to the current v2.2.0 described in this study. The study also identified the most sensitive parameters related to surface exchange and mixing that affect model prediction and therefore performance for each individual lake. These sensitives could then be correlated to lake characteristics such as residence time, meteorological conditions and trophic status. Additionally, this work opens a new challenge for the community of limnologists involved in ecosystem modelling. Indeed the next step would be cross lake comparison project including biogeochemical processes simulation using a similar open source community biogeochemical model such as the Framework for Aquatic Biogeochemical Models (FABM: Bruggeman et al. 2011) and/or AED (Hipsey et al. 2013). The establishment of a strong global data base of modelling techniques (set up, output analysis), lakes and scientists is just the beginning of what can be achieved through collaborative modelling networks of aquatic ecosystem modellers. The significance of the MLCP resides in a common and collaborative approach to answering global lake science questions.

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Table 1 - Lakes includes in the Multi-Lake Comparison Project Stage 1, abbreviation, maximum depth, surface area at maximum depth, crest elevation and latitude.

Lake Name	Abv.	Maximum Depth (m)	Surface Area at Crest (m^2)	Crest Elevation (m)	Latitude	Reference
Lake Alexandrina	AL	9.4	655,755,315	3.4	-35	(Hipsey et al. 2014b)
Ammersee	AM	83.7	47,250,000	533.5	48	(Bueche and Vetter 2014a; b; Weinberger and Vetter 2014)
Blelham	BL	14.5	104,000	14.0	54.4	(Woolway et al. 2015)
Lake Bourget	BO	146.0	42,575,000	230.5	45.4	(Vinçon-Leite et al. 1989, 2014; Kerimoglu et al. 2016)
Cannonsville Reservoir	CA	52.0	19,000,000	351.0	42.1	(Samal et al. 2012)
Lake Como	CO	440.0	147,012,649	410.0	46	(Laborde et al. 2010; Copetti et al. 2013; Guyennon et al. 2014)
Lake Constance	CN	253.3	472,650,000	395.0	47.6	(Wessels 1998; Frassl et al. 2014)
El Gergal	EG	55.0	4,732,669	50.0	37	(Rigosi et al. 2011)
Emaiksoun	EM	2.4	1,860,000	2.4	71.2	(Potter 2011)
Esthwaite	ES	15.5	1,000,000	15.5	54.4	(Woolway et al. 2015)
Feeagh	FE	43.0	3,942,266	9.0	53.4	(Dalton et al. 2014)
Lake Geneva 2001-2	G1	309.0	578,560,865	371.4	46.4	(Anneville et al. 2010)
Lake Geneva 2003-4	G3	309.0	578,560,865	371.4	46.4	(Anneville et al. 2015)
Grosse Dhuenn	GD	48.5	3,750,100	177.5	51.1	Weber et al. (2016)
Harp Lake	HA	37.5	713,800	327.0	45.4	(Yao et al. 2014)
Lake Iseo	IS	256.0	60,880,350	185.2	45.7	(Pilotti et al. 2013, 2014; Valerio et al. 2015)
Lake Kinneret 2003-4	K3	44.0	173,000,000	-208.9	32	(Gal et al. 2009)
Lake Kinneret 1997-8	K7	44.0	173,000,000	-208.9	32	(Bruce et al. 2006)
Lake Mendota	ME	25.0	39,581,170	400.0	43	(Magnuson et al. 2006)
Mount Bold Reservoir	MB	45.4	3,080,000	246.9	-35.1	(van der Linden and Burch 2016) Rigosi et al. 2015
Muggelsee	MG	8.0	7,318,000	32.4	52	(Huber et al. 2008)

Lake Nam Co	NM	98.9	2,018,230,000	4718.0	30.7	(Wang et al. 2009)
Oneida	ON	17.0	207,100,000	112.0	43	(Hetherington et al. 2015)
Lake Pusiano	PU	30.9	8,123,699	27.0	45.8	(Copetti et al. 2006, 2013; Carraro et al. 2012)
Rappbode	RP	85.6	4,344,724	423.6	51.7	(Bocaniov et al. 2014)
Rassnitzersee	RS	40.0	3,033,057	85.0	51.3	(Böhrer et al. 1998; Boehrer et al. 2014)
Ravn	RV	33.0	1,820,000	33.0	56	(Trolle et al. 2008a; b)
Rotorua	RO	22.0	79,722,140	280.0	-38	(Burger et al. 2008)
Stechlin	ST	69.5	4,231,549	60.0	53.2	(Kirillin et al. 2013)
Tarawera	TA	90.0	40,996,000	88.0	-38.2	(Hamilton et al. 2010) Hamilton et al. 2006
Toolik	TO	24.0	940,119	740.0	68.6	(MacIntyre et al. 2009)
Windermere	WI	66.8	14,779,600	66.8	54.4	(Woolway et al. 2015)
Woods Lake	WO	10.4	15,000,000	738.2	42	(Hydro Tasmania 2003)
Lower Lake Zurich	ZU	136.0	66,600,000	406.0	47.3	(Peeters et al. 2002; Schmid and Köster 2016)

Table 2 - Description, symbols and initial values of the parameters used in the sensitivity analysis.

Symbol	Description	Reference	Initial value
Surface Heat Exchange			
C_h	Bulk aerodynamic coefficient for sensible heat transfer	(Fischer et al. 2013)	0.0013
C_e	Bulk aerodynamic coefficient for latent heat transfer	(Fischer et al. 2013)	0.0013
C_d	Bulk aerodynamic momentum transfer coefficient	(Fischer et al. 2013)	0.0013
Mixing			
C_c	Mixing efficiency - convective overturn	(Yeates and Imberger 2003)	0.2
C_w	Mixing efficiency - wind stirring	(Spigel et al. 1986)	0.23
C_t	Mixing efficiency - unsteady turbulence (acceleration)	(Sherman et al. 1978)	0.3
C_s	Mixing efficiency - shear production	(Sherman et al. 1978)	0.51
C_{KH}	Mixing efficiency - Kelvin-Helmholtz turbulent billows	(Sherman et al. 1978)	0.3
C_{hyp}	Mixing efficiency of hypolimnetic turbulence	(Weinstock 1981)	0.5

Table 3 - *NMAE* for base simulations using standard parameter set. Note that for fully mixed lakes or for lakes where temperature profiles were shallower than the thermocline depth, *NMAE* values are listed as not applicable (N/A).

Lake	Full Prof. Temp.	Epi. Temp.	Hyp. Temp.	T_D	S_T
Alexandrina	0.07	0.07	0.07	N/A	N/A
Ammersee	0.19	0.19	0.11	0.60	0.17
Blelham	0.12	0.13	0.27	0.24	0.45
Bourget	0.08	0.10	0.06	0.42	0.09
Cannonsville	0.10	0.06	0.16	0.31	0.12
Como	0.10	0.08	0.05	0.40	0.19
Constance	0.08	0.09	0.07	0.61	0.16
ElGergal	0.08	0.07	0.07	0.59	0.27
Emaiksoun	0.08	0.08	0.08	N/A	N/A
Esthwaite	0.13	0.10	0.31	0.26	0.24
Feeagh	0.06	0.05	0.07	0.23	0.30
Geneva03	0.10	0.08	0.04	1.16	0.22
Geneva05	0.09	0.05	0.04	1.29	0.18
GrosseDhuenn	0.07	0.05	0.10	0.36	0.09
Harp	0.18	0.12	0.27	0.68	0.19
Iseo	0.08	0.07	0.07	0.46	0.16
Kinneret03	0.07	0.06	0.07	0.26	0.20
Kinneret97	0.05	0.06	0.05	0.21	0.21
Mendota	0.11	0.10	0.13	0.44	0.24
MtBold	0.08	0.08	0.07	0.82	0.43
Muggelsee	0.07	0.06	0.09	N/A	N/A
NamCo	0.30	0.33	0.39	0.43	0.85
Oneida	0.04	0.03	0.08	0.33	0.86
Pusiano	0.14	0.10	0.24	0.32	0.19
Rappbode	0.14	0.08	0.11	0.29	0.16
Rassnitzersee	0.17	0.15	0.36	0.19	0.17
Ravn	0.19	0.13	0.21	0.33	0.34
Rotorua	0.07	0.07	0.08	0.25	0.43
Stechlin	0.13	0.11	0.11	0.83	0.14
Tarawera	0.04	0.03	0.03	0.26	0.10
Toolik	0.25	0.25	0.21	0.63	0.43
Windermere	0.15	0.22	0.25	0.10	0.21
Woods	0.17	0.17	0.17	N/A	N/A
Zurich	0.12	0.12	0.15	0.65	0.17
Mean	**0.11**	**0.10**	**0.13**	**0.43**	**0.28**
Median	**0.10**	**0.08**	**0.10**	**0.32**	**0.21**

Table 4 – Comparison of measures of model fit with other 1-D models

Lake Name	Model	Years Simulated	Metric	Value	GLM	Reference
Constance	DYRESM	1995-1997	r	0.97	0.98	(Rinke et al. 2010)
Geneva	DYRESM	1996, 2000 & 2004	RMSE	2.07	1.17	(Perroud et al. 2009)
Geneva	SIMSTRAT	1996, 2000 & 2004	RMSE	1.57	1.17	(Perroud et al. 2009)
Geneva	FLAKE	1996, 2000 & 2004	RMSE	3.65	1.17	(Perroud et al. 2009)
Harp	Minlake	1978-1993	r	0.94	0.96	(Yao et al. 2014)
Kinneret97	DYRESM	1997-2000	NMAE	0.07	0.05	(Gal et al. 2003)
Zurich	SIMSTRAT	1981-2013	RMSE	0.4-1.5	1.24	(Schmid and Köster 2016)

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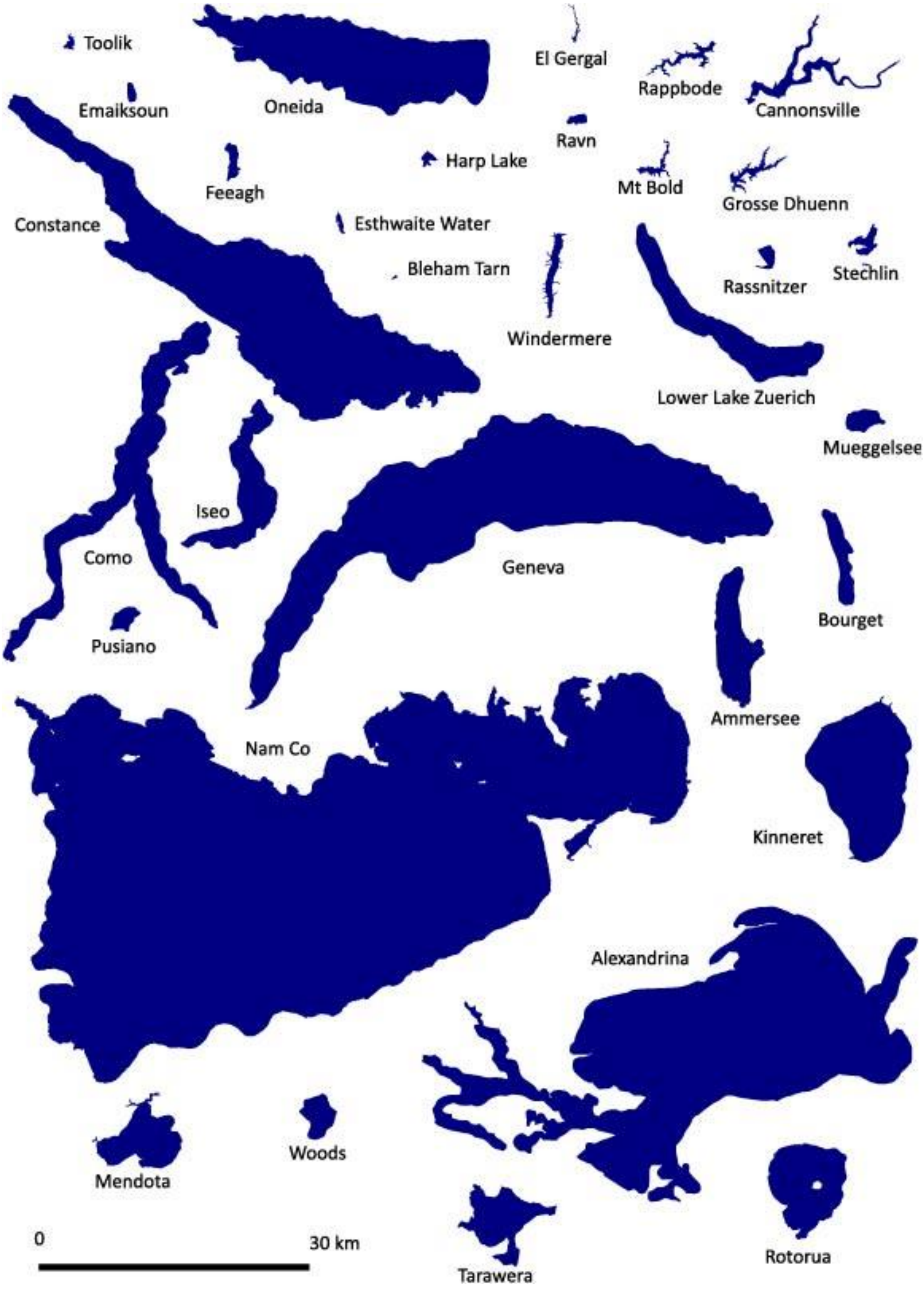


Figure 1 – Lake outlines to scale for all lakes in the current MLCP.

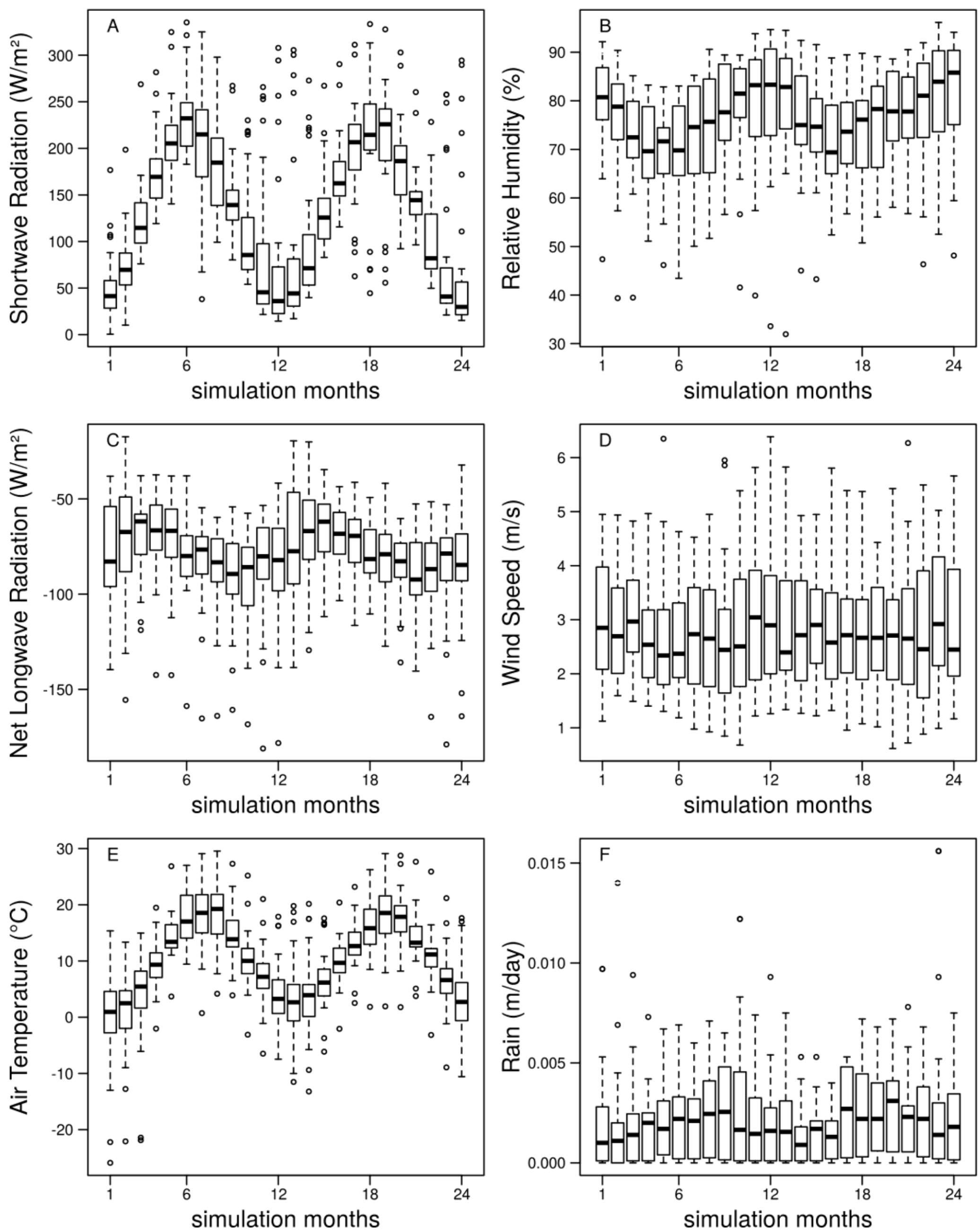


Figure 2 - Time series of monthly mean lake short wave radiation (a), relative humidity (b), net longwave radiation (c), wind speed (d), air temperature (e) and precipitation (f) where box plot indicates range and circles outliers.

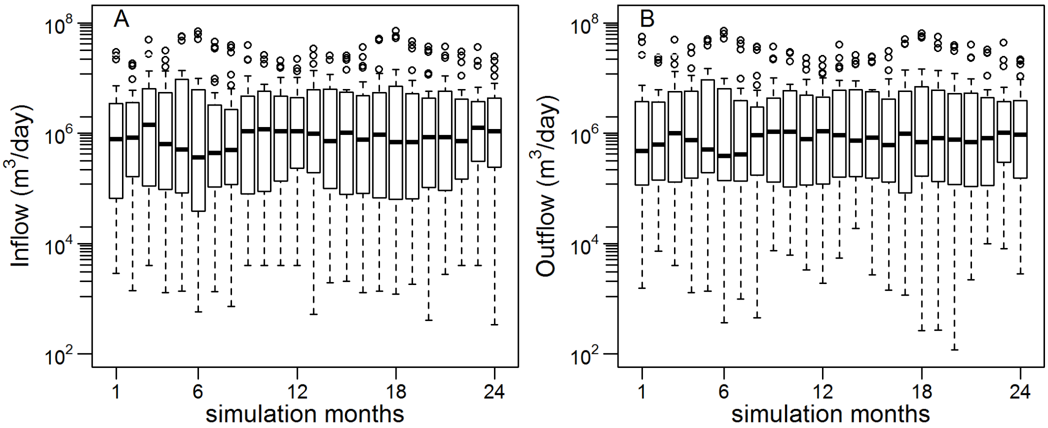


Figure 3 – Time series of monthly mean lake inflows (a) and outflows (b) where box plot indicates range and circles outliers.

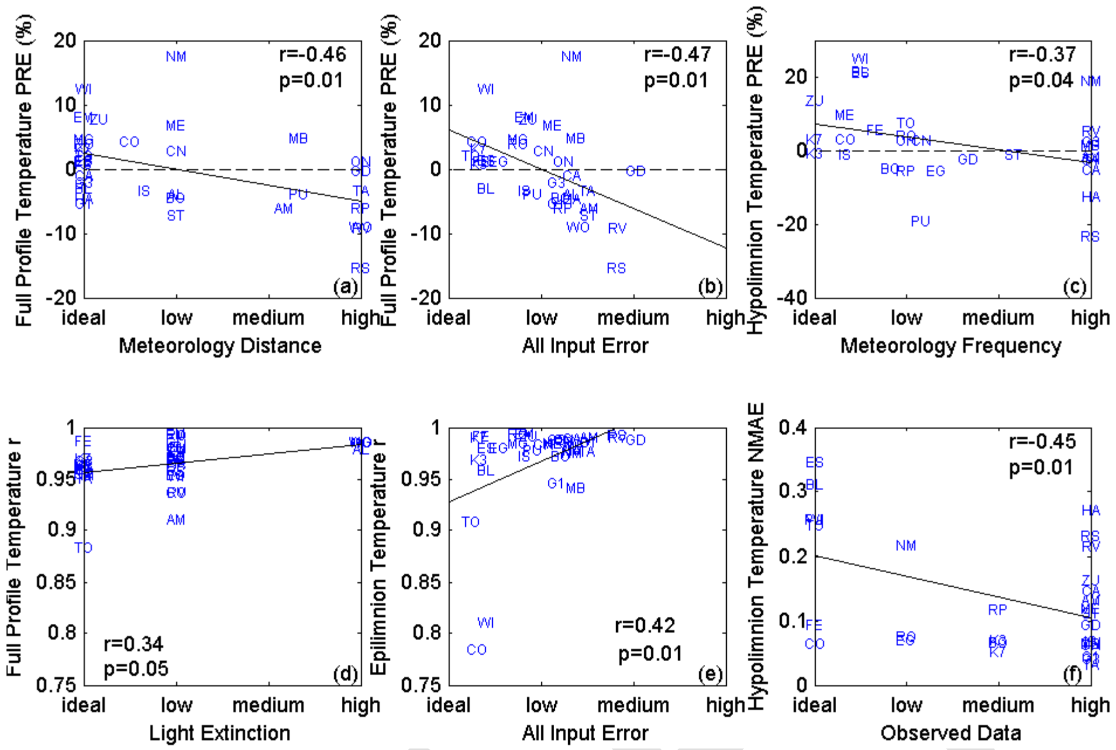


Figure 4 – Correlation between GLM model performance metrics PRE (a-c), r (d-e) and NMAE (f) for prediction of full profile temperatures (a, b & d), epilimnion temperatures (e) and hypolimnion temperatures (c & f) against rankings of input data uncertainty. Refer to Table 1 for lake acronyms and Table A1 for details of input uncertainty ranking system.

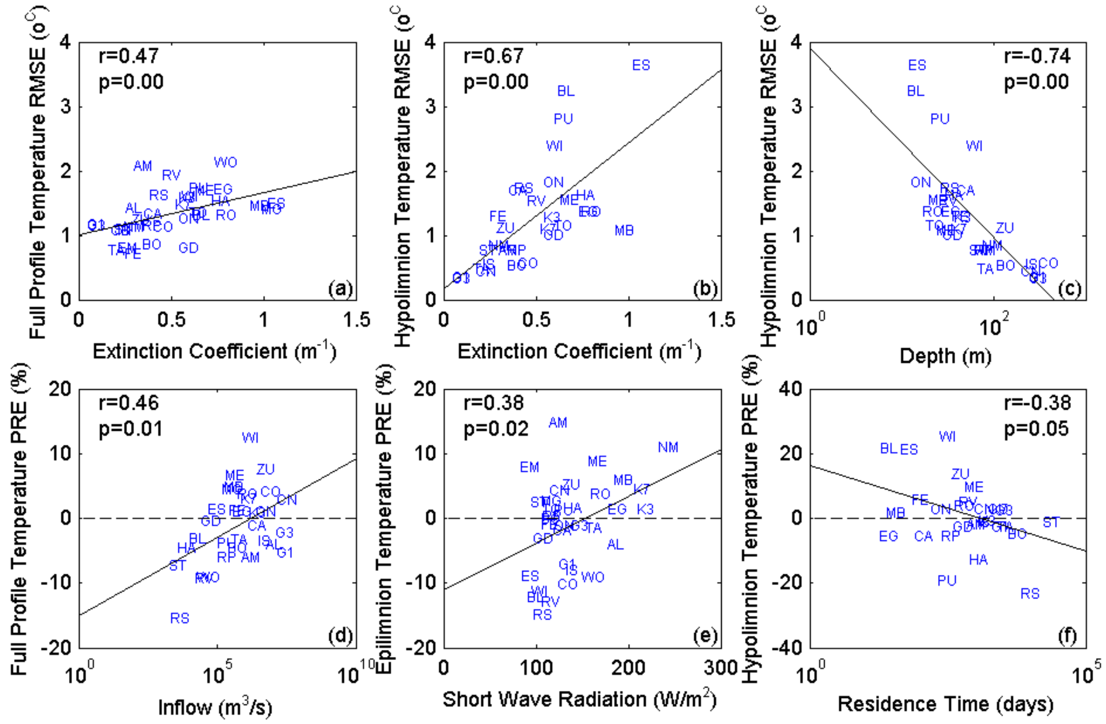


Figure 5 - GLM model performance metrics for prediction of full profile temperature (a&d), epilimnion temperature (e) and hypolimnion temperature (b,c&f) against lake characteristics. Refer to Table 1 for lake acronyms.

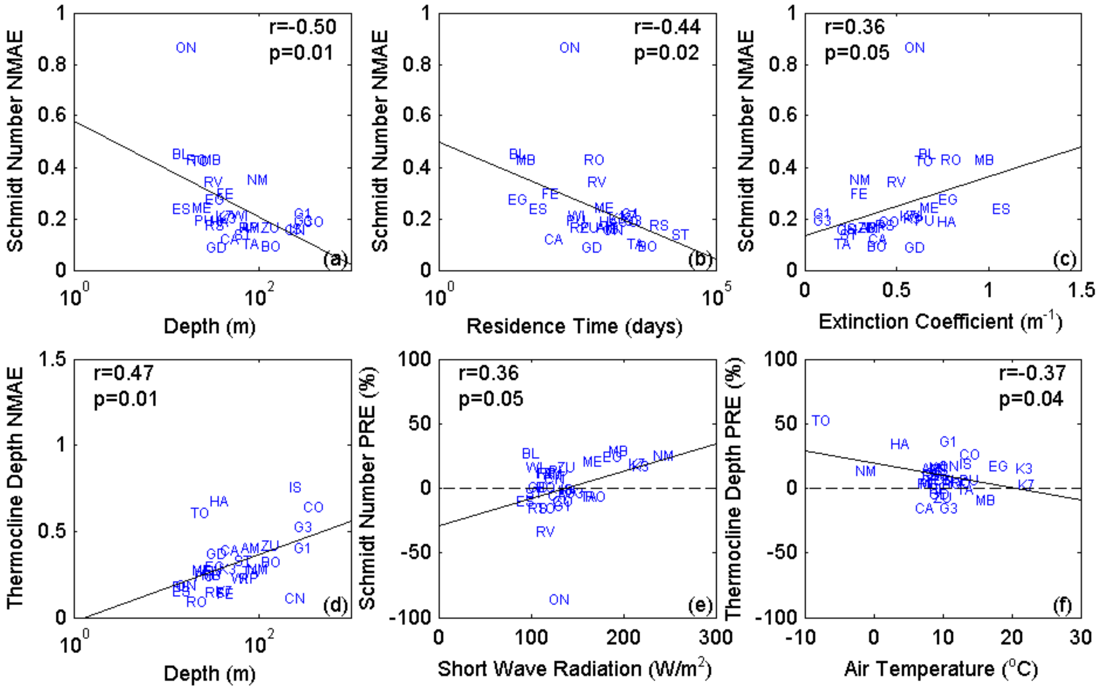


Figure 6 - GLM model performance metrics for prediction of thermocline depth (d,f) and Schmidt number (a,b,c&e) against lake characteristics. Refer to Table 1 for lake acronyms.

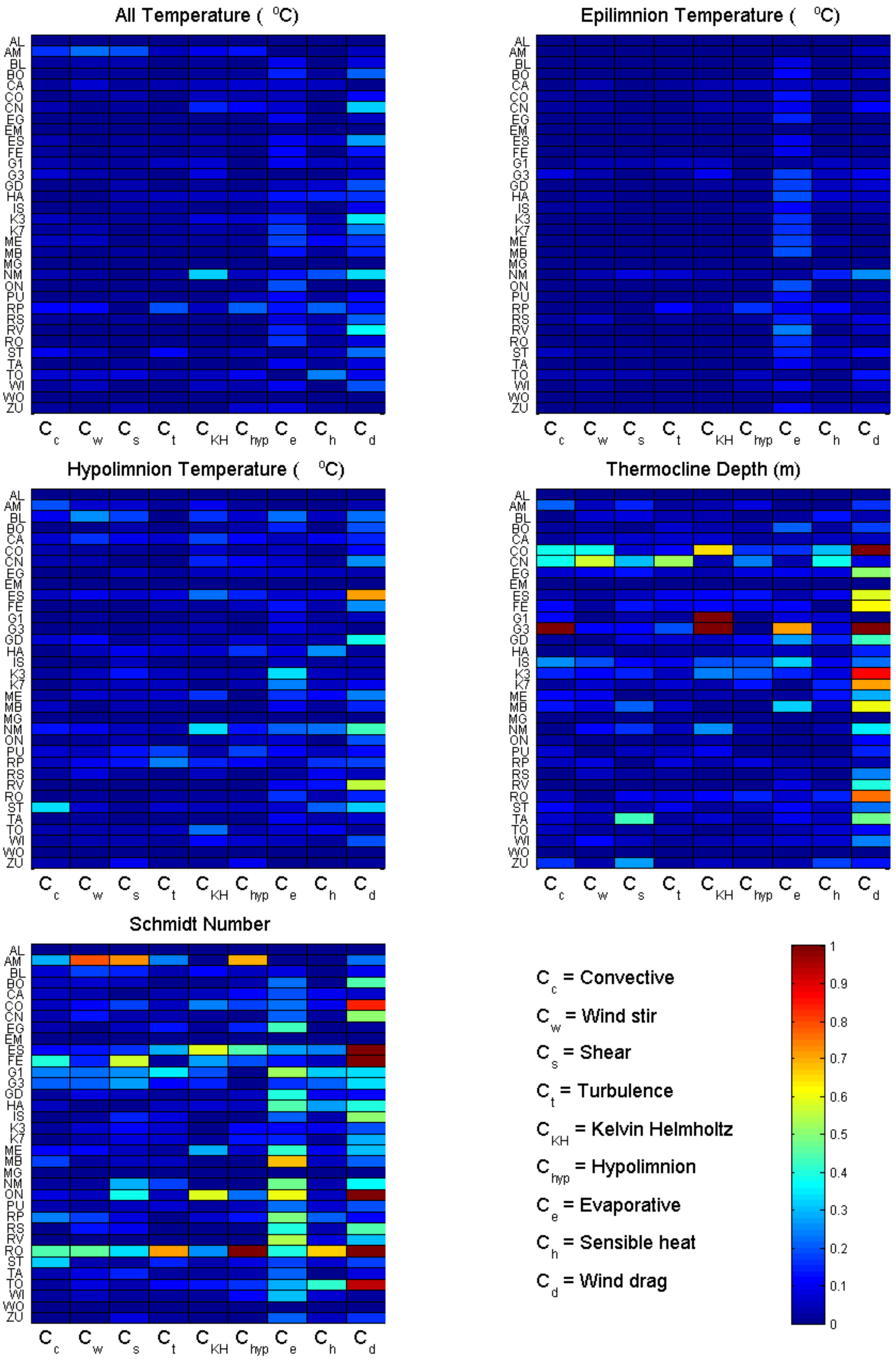


Figure 7 - Sensitivity indices for a) full profile temperature, b) epilimnion temperature, c) hypolimnion temperature, d) thermocline depth and e) Schmidt stability. The colour bar has been limited to a value of 1 so that any sensitivity index (SI) greater than one

(indicating the percent response in thermodynamic metric is greater than the change in physical parameter) has been highlighted.

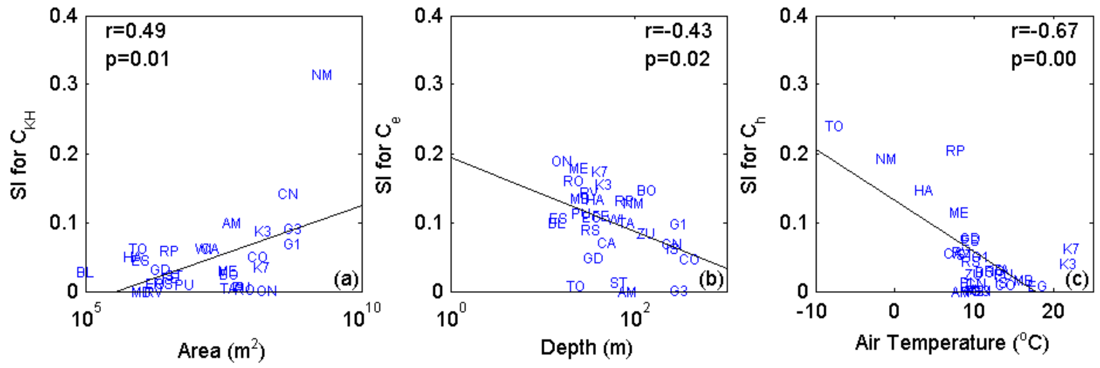


Figure 8 - Significant correlation between sensitivity indices of GLM physical parameters for the prediction of full profile temperatures and (a) surface area, (b) lake depth and (c) wind speed.

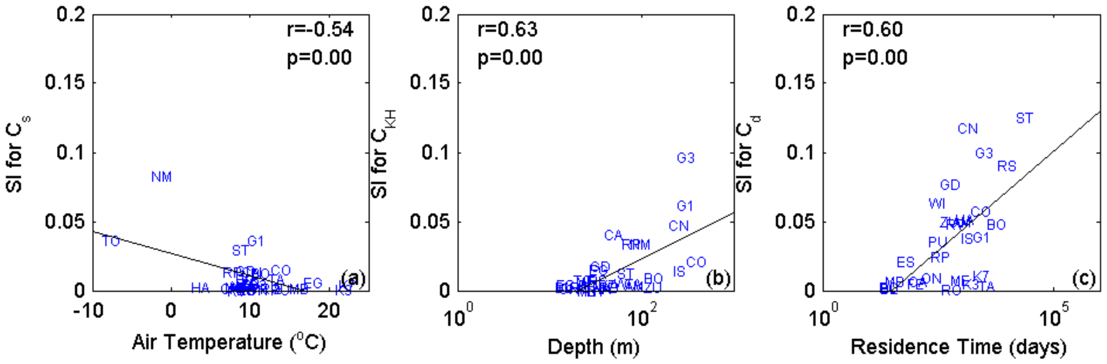


Figure 9 - Significant correlation between sensitivity indices of GLM physical parameters for the prediction of epilimnion temperature and (a) air temperature, (b) lake depth and (c) residence time.

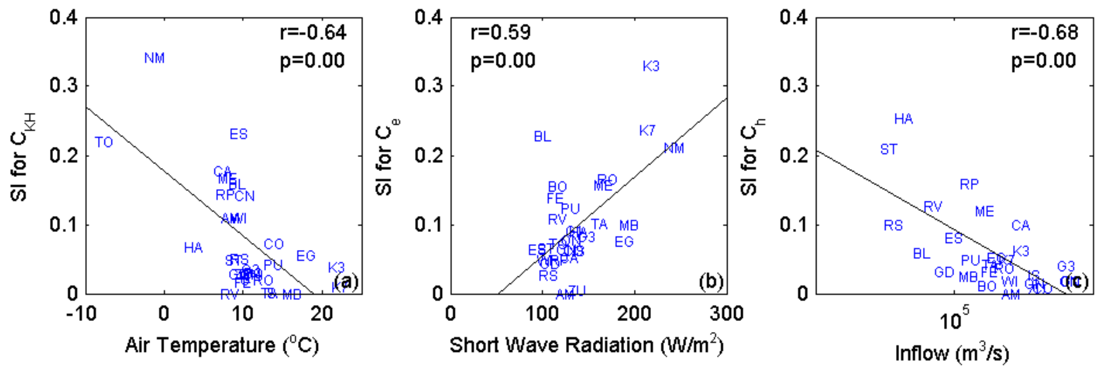


Figure 10 - Significant correlation between sensitivity indices of GLM physical parameters for the prediction of hypolimnion temperatures and (a) air temperature, (b) short wave radiation and (c) inflow.

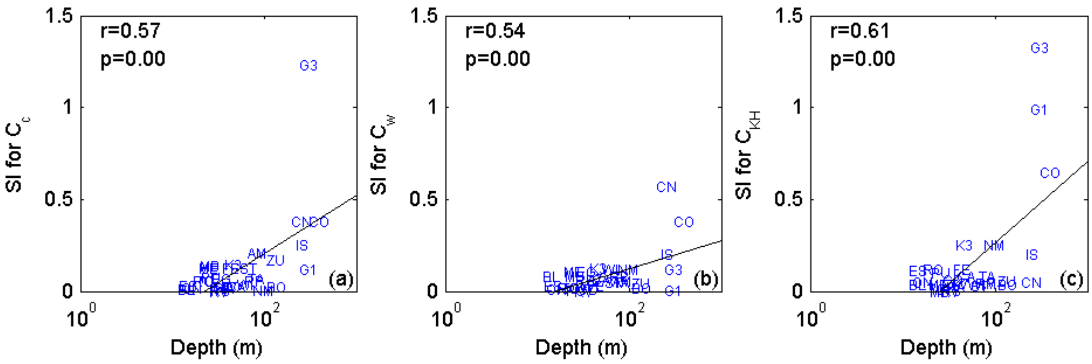


Figure 11 - Significant correlation between sensitivity indices of GLM physical parameters for the prediction of thermocline depth and lake depth.

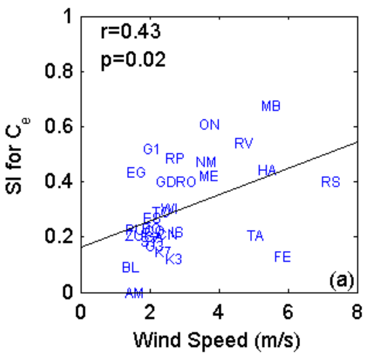


Figure 12 - Significant correlation between sensitivity indices of GLM physical parameters for the prediction of Schmidt number and wind speed.

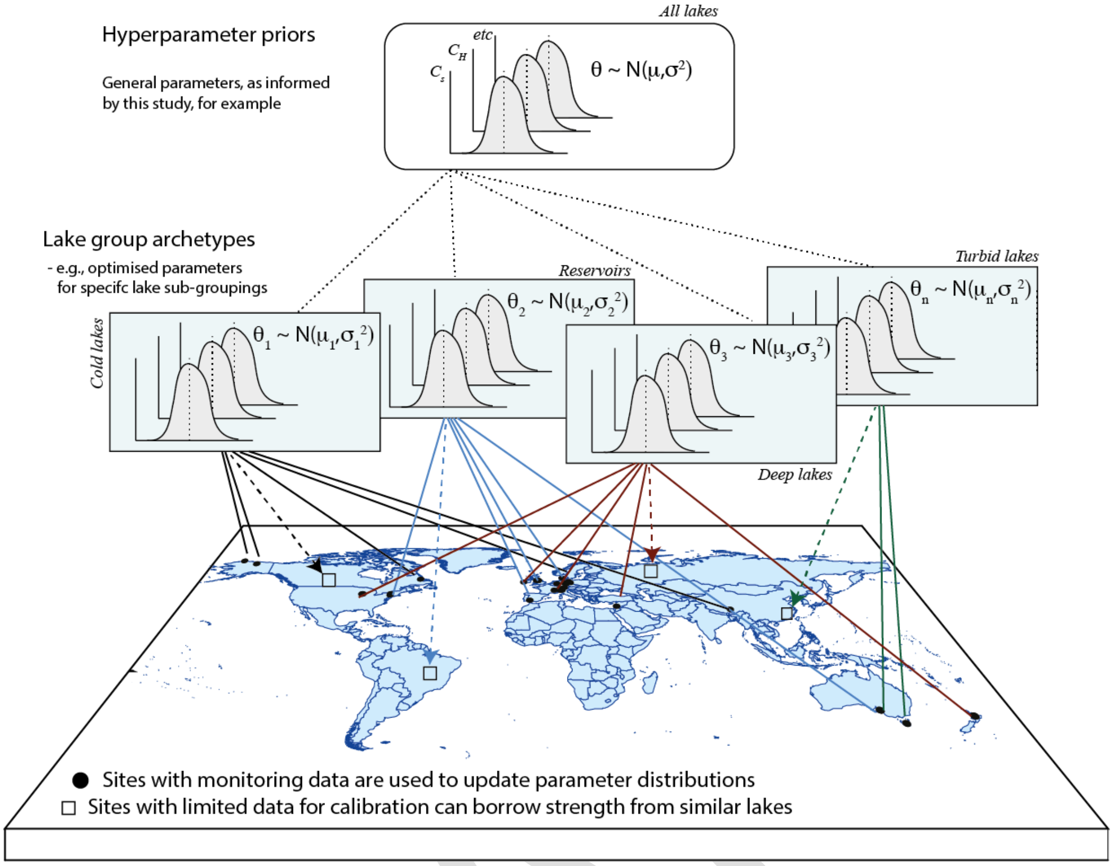


Figure 13 - A conceptual overview of future lake modelling applications to best integrate model applications with the increasing volumes of sensor data. In this study no parameter fitting was undertaken for GLM and parameters presented herein could be used as the hyperparameter prior for all lakes within the observatory network. Future applications can improve parameter accuracy within a Bayesian hierarchical framework based on suitable groupings of lakes into distinct archetypes. Other lakes with limited data for robust calibration, can adopt standard model parameters depending on the lake archetype, which it best relates to.

5 Appendix A – Model Input

Table A1 – Input uncertainty ranking system

Rank	0 - ideal	1 - high	2 - medium	3 - low
Morphometry	digitised		estimated from topographic drawing	estimated
Meteorology - Distance	on lake (< 1km)	<5km from lake	<10km from lake	>10km from lake/ estimated
Meteorology - Frequency	sub-hourly	hourly	sub-daily	daily
Flow	gauged	modelled		estimated
Kw	mean from light measurements	Secchi depth mean from > 12 measurements/year	Secchi depth mean from < 12 measurements/year	estimated
Frequency of Observed Data	>=daily	>= weekly	>=monthly	< monthly

Table A2 – Input data quality for each lake, (a) measurement, (b) rank. A value of 9999 indicates that input data has been estimated.

		Distance (km)						Sampling interval (hours)									Number of
Lake Name	Morphometry	Short Wave Rad.	Long Wave Rad.	Air Temp.	Rel. Hum.	Wind speed	Precipitation	Short Wave Rad.	Long Wave Rad.	Air Temp.	Rel. Hum.	Wind speed	Precipitation	Inflow	Outflow	Kw	Obs Data
Alexandrina	digital	1.2	1.2	1.2	1.2	1.2	1.2	0.25	0.25	0.25	0.25	0.25	0.25	model	model	estimated	14
Ammersee	digital	10	12	10	10	10	10	24.00	24.00	24.00	24.00	24.00	24.00	gauge	gauge	secchi	24
Blelham	contour	0	0	0	0	0	0	0.03	24.00	0.03	0.03	0.03	0.03	gauge	gauge	secchi	2920
Bourget	contour	2	2	2	2	2	2	1.00	1.00	1.00	1.00	1.00	0.10	gauge	estimated	secchi	74
Cannonsville	contour	0	0	0	0	0	0	24.00	24.00	24.00	24.00	24.00	24.00	gauge	gauge	secchi	31
Como	digital	0	50	0	0	0	1	0.02	1.00	0.02	0.02	0.02	1.00	gauge	gauge	secchi	2916
Constance	digital	1.2	1.2	1.2	1.2	1.2	1.2	1.00	1.00	1.00	1.00	1.00	6.00	gauge	gauge	secchi	31
ElGergal	digital	0.3	0.3	0.3	0.3	0.3	0.3	1.00	1.00	1.00	1.00	1.00	24.00	gauge	gauge	secchi	124
Emaiksoun	digital	0	0	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	estimated	estimated	secchi	467
Esthwaite	contour	0	0	0	0	0	0	0.03	24.00	0.03	0.03	0.03	0.03	gauge	gauge	secchi	2799
Feeagh	digital	0.7	0.7	0.35	0.35	0.35	0.35	0.03	24.00	0.00	0.00	0.00	1.00	gauge	estimated	light	2913
Geneva03	contour	1	1	1	1	1	1	24.00	24.00	24.00	24.00	24.00	24.00	gauge	gauge	light	30
Geneva05	contour	1	1	1	1	1	1	24.00	24.00	24.00	24.00	24.00	24.00	gauge	gauge	light	36
GrosseDhuenn	estimated	37	9999	22.5	22.5	22.5	9999	1.00	9999.00	1.00	1.00	1.00	9999.00	model	gauge	secchi	28
Harp	contour	0.5	0.5	0.5	0.5	0.5	0.5	24.00	24.00	24.00	24.00	24.00	24.00	gauge	gauge	secchi	20
Iseo	digital	0	20	0	0	0	3	0.03	1.00	0.03	0.03	0.03	1.00	gauge	gauge	secchi	25
Kinneret03	digital	0	0	0	0	0	0	0.02	0.02	0.02	0.02	0.02	0.02	gauge	gauge	light	93
Kinneret97	digital	0	0	0	0	0	0	0.02	0.02	0.02	0.02	0.02	0.02	gauge	gauge	light	78
Mendota	contour	2.5	2.5	2.5	2.5	2.5	2.5	0.00	1.00	0.00	0.00	0.00	1.00	gauge	estimated	light	30
MtBold	digital	12	22	10	10	12	5	24.00	24.00	24.00	24.00	24.00	24.00	gauge	gauge	light	46
Muggelsee	digital	0	0	0	0	0	0	0.08	24.00	0.08	0.08	0.08	0.08	model	model	estimated	1747
NamCo	digital	1.6	1.6	1.6	1.6	1.6	1.6	24.00	24.00	24.00	24.00	24.00	24.00	estimated	estimated	light	188
Oneida	digital	21	21	21	21	21	21	1.00	1.00	1.00	1.00	1.00	1.00	model	gauge	light	40
Pusiano	digital	11	9999	4	17	11	4	1.00	3.00	1.00	1.00	1.00	1.00	model	model	secchi	2320

Rappbode	digital	16	16	16	16	16	16	1.00	1.00	1.00	1.00	1.00	1.00	model	gauge	secchi	58
Rassnitzersee	digital	12	12	12	12	12	12	24.00	24.00	24.00	24.00	24.00	24.00	model	model	secchi	16
Ravn	contour	50	50	50	50	50	50	24.00	24.00	24.00	24.00	24.00	24.00	gauge	gauge	secchi	44
Rotorua	digital	0	0	0	0	0	0	1.00	1.00	1.00	1.00	1.00	1.00	gauge	estimated	secchi	677
Stechlin	digital	5	5	5	5	5	5	3.00	3.00	3.00	3.00	3.00	24.00	estimated	estimated	light	41
Tarawera	digital	15	15	15	15	15	15	24.00	24.00	24.00	24.00	24.00	24.00	gauge	gauge	light	21
Toolik	digital	0.05	0.05	0.05	0.05	0.05	0.05	1.00	1.00	1.00	1.00	1.00	1.00	gauge	model	light	2142
Windermere	contour	0	0	0	0	0	0	0.03	24.00	0.03	0.03	0.03	0.03	gauge	gauge	secchi	3040
Woods	digital	9999	9999	33.6	33.6	33.6	33.6	1.00	1.00	1.00	1.00	1.00	1.00	estimated	gauge	estimated	761
Zurich	contour	0.5	2.0	0.5	0.5	0.5	0.5	0.17	0.17	0.17	0.17	0.17	0.17	gauge	gauge	secchi	24

				Distance		Sampling interval								Number of				
Lake Name	Morphometry	Short Wave Rad.	Long Wave Rad.	Air Temp.	Rel. Hum.	Wind speed	Precipitation	Short Wave Rad.	Long Wave Rad.	Air Temp.	Rel. Hum.	Wind speed	Precipitation	Inflow	Outflow	Kw	Obs Data	Mean
Alexandrina	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	3	3	1.33
Ammersee	0	2	3	2	2	2	2	3	3	3	3	3	3	0	0	1	3	1.53
Blelham	1	0	0	0	0	0	0	0	3	0	0	0	0	0	0	1	0	0.42
Bourget	1	1	1	1	1	1	1	1	1	1	1	1	0	0	3	1	2	1.22
Cannonsville	1	0	0	0	0	0	0	3	3	3	3	3	3	0	0	1	3	1.33
Como	0	0	3	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0.31
Constance	0	1	1	1	1	1	1	1	1	1	1	1	2	0	0	1	3	1.03
ElGergal	0	0	0	0	0	0	0	1	1	1	1	1	3	0	0	1	1	0.56
Emaiksoun	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	1	1	0.83
Esthwaite	1	0	0	0	0	0	0	0	3	0	0	0	0	0	0	1	0	0.42
Feeagh	0	0	0	0	0	0	0	0	3	0	0	0	1	0	3	0	0	0.36
Geneva03	1	0	0	0	0	0	0	3	3	3	3	3	3	0	0	0	3	1.17
Geneva05	1	0	0	0	0	0	0	3	3	3	3	3	3	0	0	0	3	1.17
GrosseDhuenn	3	3	3	3	3	3	3	1	3	1	1	1	3	1	0	1	3	2.03

Harp	1	0	0	0	0	0	0	3	3	3	3	3	3	0	0	1	3	1.33
Iseo	0	0	3	0	0	0	1	0	1	0	0	0	1	0	0	1	3	0.83
Kinneret03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0.33
Kinneret97	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0.33
Mendota	1	1	1	1	1	1	1	0	1	0	0	0	1	0	3	0	3	1.14
MtBold	0	3	3	2	2	3	1	3	3	3	3	3	3	0	0	0	3	1.39
Muggelsee	0	0	0	0	0	0	0	0	3	0	0	0	0	1	1	3	0	0.75
NamCo	0	1	1	1	1	1	1	3	3	3	3	3	3	3	3	0	1	1.33
Oneida	0	3	3	3	3	3	3	1	1	1	1	1	1	1	0	0	3	1.25
Pusiano	0	3	3	1	3	3	1	1	2	1	1	1	1	1	1	1	0	0.92
Rappbode	0	3	3	3	3	3	3	1	1	1	1	1	1	1	0	1	2	1.25
Rassnitzersee	0	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	3	1.83
Ravn	1	3	3	3	3	3	3	3	3	3	3	3	3	0	0	1	3	1.83
Rotorua	0	0	0	0	0	0	0	1	1	1	1	1	1	0	3	1	1	0.75
Stechlin	0	1	1	1	1	1	1	2	2	2	2	2	3	3	3	0	3	1.53
Tarawera	0	3	3	3	3	3	3	3	3	3	3	3	3	0	0	0	3	1.50
Toolik	0	0	0	0	0	0	0	1	1	1	1	1	1	0	1	0	0	0.25
Windermere	1	0	0	0	0	0	0	0	3	0	0	0	0	0	0	1	0	0.42
Woods	0	3	3	3	3	3	3	1	1	1	1	1	1	3	0	3	0	1.42
Zurich	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0.83

Table A3 – Input lake characteristics used for comparative analysis. Vales for lake depth, surface area and volume are averaged over the simulation period. Area: Depth Ratio, is the ratio be

Abbrv.	Lake Name	Depth (m)	Surface Area (m^2)	Area: Depth Ratio	Volume (m^3)	Length: Width Ratio	Inflow (m^3/day)	Res. Time (days)	Short Wave Radiation (W/m^2)	Air Temp. (˚C)	Wind Speed (m/s)	K_w (m^{-1})	Start Date
AL	Alexandrina	6.1	587,158,666	9.66E+07	1.11E+09	1.14	1.12E+07	98.96	186.98	14.88	3.81	0.30	1-Jul-10
AM	Ammersee	83.8	46,427,854	5.64E+05	1.81E+09	3.00	1.70E+06	1061.06	125.18	8.40	1.58	0.35	1-Jan-09
BL	Blelham	14.7	103,802	7.07E+03	5.78E+05	3.75	2.05E+04	28.14	100.78	9.41	1.46	0.67	1-Jan-08
BO	Bourget	140.5	40,379,890	3.03E+05	3.31E+09	5.83	5.48E+05	6035.65	117.27	11.48	2.08	0.40	1-Jan-09
CA	Cannonsville	49.7	18,014,685	3.83E+05	3.28E+08	27.40	2.80E+06	116.90	128.97	7.36	2.11	0.40	1-Jan-03
CO	Como	400.2	133,890,923	3.67E+05	2.21E+10	15.00	8.42E+06	2618.03	134.28	13.96	2.14	0.46	1-Jan-05
CN	Constance	253.4	465,703,202	1.87E+06	4.70E+10	4.00	3.26E+07	1443.46	126.05	10.26	2.51	0.23	1-Jan-94
EG	El Gergal	34.9	1,951,384	1.35E+05	2.47E+07	19.38	7.40E+05	33.43	189.57	18.14	1.64	0.79	1-Jan-01
EM	Emaiksoun	2.2	1,871,484	8.77E+05	2.89E+06	2.30	0.00E+00	N/A	93.80	-9.09	4.10	0.27	1-Jan-12
ES	Esthwaite	15.0	1,003,558	6.69E+04	6.38E+06	7.67	9.79E+04	65.16	94.79	9.50	2.09	1.07	1-Jan-08
FE	Feeagh	44.9	3,620,712	8.78E+04	6.49E+07	3.86	6.02E+05	107.72	115.20	10.11	5.87	0.30	1-Jan-11
G1	Geneva01	308.9	577,950,600	1.87E+06	9.12E+10	5.21	3.13E+07	2914.51	135.43	10.91	2.10	0.10	1-Jan-03
G3	Geneva03	308.8	577,404,068	1.87E+06	9.12E+10	5.21	2.77E+07	3292.98	148.04	10.95	2.14	0.10	1-Jan-01
GD	GrosseDhuenn	33.8	2,214,418	1.11E+05	3.26E+07	8.36	1.05E+05	309.21	108.20	9.51	2.50	0.60	1-Jan-96
HA	Harp	37.2	706,244	1.92E+04	9.31E+06	1.50	7.96E+03	1170.14	139.26	3.73	5.39	0.77	1-Jan-92
IS	Iseo	260.5	60,829,158	2.34E+05	7.91E+09	8.33	5.48E+06	1443.16	140.28	13.55	2.83	0.25	1-Jan-10
K3	Kinneret03	47.5	171,786,293	3.64E+06	4.96E+09	1.62	2.93E+06	1690.75	219.52	22.02	2.74	0.59	1-Jan-03
K7	Kinneret97	43.6	166,425,534	3.97E+06	4.29E+09	1.62	1.62E+06	2643.24	215.43	22.37	2.41	0.57	1-Jan-97
ME	Mendota	25.0	39,229,728	1.58E+06	4.96E+08	2.00	4.96E+05	1000.35	167.57	8.23	3.74	0.69	1-Jan-09
MB	MtBold	31.7	1,703,574	1.07E+05	1.99E+07	7.33	1.70E+05	116.81	195.67	16.36	5.55	0.98	1-Jul-03
MG	Muggelsee	7.8	7,173,756	9.43E+05	3.38E+07	1.69	3.65E+05	92.55	117.60	10.26	3.85	1.05	1-Jan-04
NM	NamCo	98.9	1,942,514,246	2.04E+07	1.00E+11	2.38	0.00E+00	N/A	244.03	-1.13	3.64	0.30	1-Jan-12
ON	Oneida	16.4	199,785,009	1.26E+07	1.35E+09	3.79	5.68E+06	236.69	131.55	10.96	3.73	0.60	1-Jan-11

PU	Pusiano	26.8	6,537,710	3.03E+05	7.72E+07	1.97	2.39E+05	322.45	131.21	13.91	1.62	0.66	1-Jan-02
RP	Rappbode	79.4	3,453,019	5.47E+04	8.60E+07	16.00	2.31E+05	371.77	118.44	7.82	2.77	0.40	1-Jan-08
RS	Rassnitzersee	34.8	2,714,136	8.71E+04	5.42E+07	1.24	5.14E+03	10551.99	107.95	9.66	7.26	0.44	1-Jan-01
RV	Ravn	32.3	1,748,402	6.00E+04	2.61E+07	1.33	3.57E+04	729.93	116.19	8.37	4.72	0.50	1-Jan-03
RO	Rotorua	21.8	78,779,626	3.66E+06	7.95E+08	1.17	1.23E+06	645.34	170.60	12.64	3.07	0.80	1-Jul-07
ST	Stechlin	69.5	4,230,060	6.11E+04	9.75E+07	0.76	4.00E+03	24364.00	104.49	8.93	2.02	0.25	1-Jan-01
TA	Tarawera	82.8	39,406,707	4.95E+05	2.18E+09	1.17	6.11E+05	3570.44	162.49	13.34	5.07	0.21	1-Jul-02
TO	Toolik	23.5	920,947	3.99E+04	6.18E+06	1.50	1.29E+04	479.13	117.31	-7.54	2.36	0.65	1-Jan-06
WI	Windermere	63.7	14,360,584	2.32E+05	5.15E+08	12.13	1.61E+06	319.72	104.08	9.44	2.60	0.60	1-Jan-08
WO	Woods	9.2	13,451,648	1.63E+06	5.55E+07	1.31	4.93E+04	1125.18	162.37	6.62	4.97	0.80	1-Jul-11
ZU	Zurich	136.0	66,593,085	4.90E+05	3.37E+09	11.20	6.20E+06	543.19	138.46	10.06	1.57	0.34	1-Jan-03

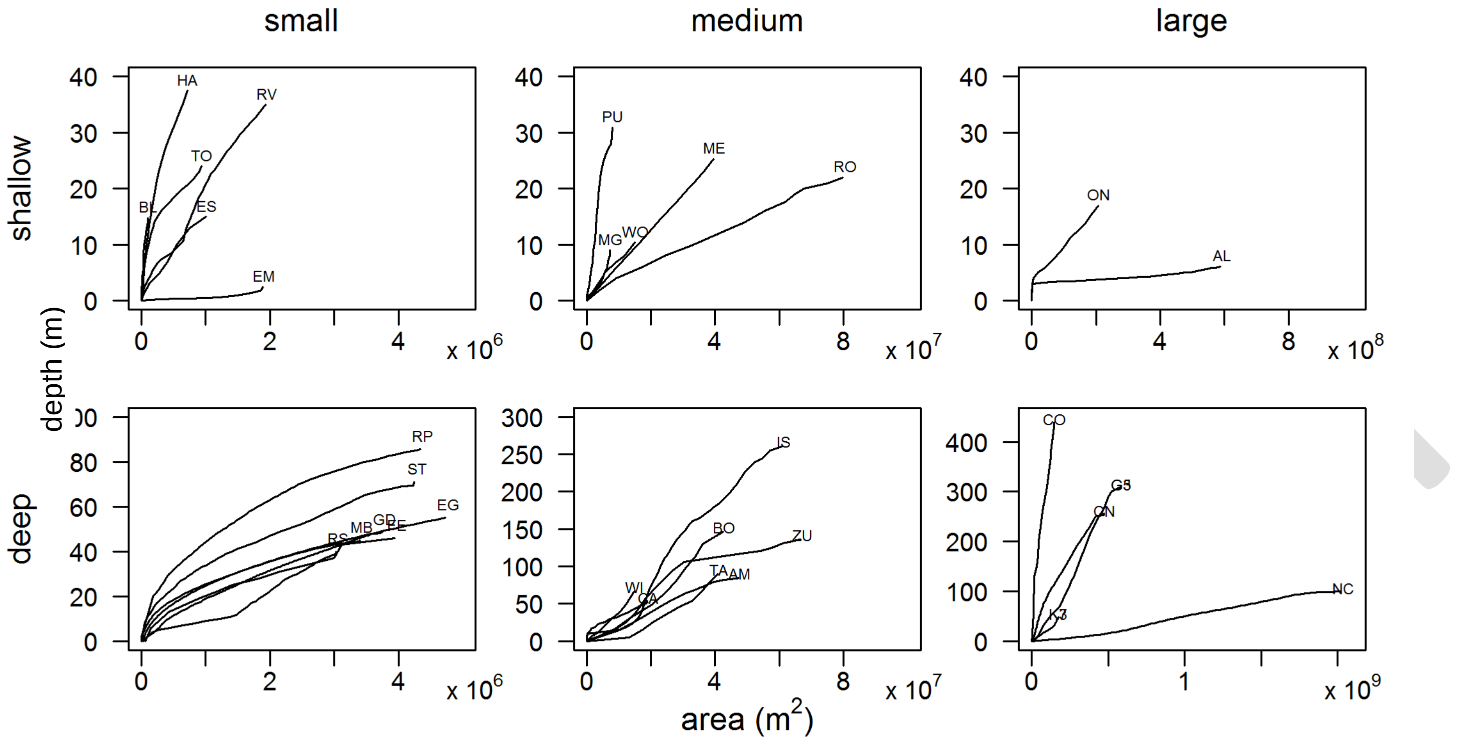


Figure A1 - Hypsographic curves for (a) small, shallow lakes, (b) medium, shallow lakes, (c) large, shallow lakes, (d) small, deep lakes, (e) medium, deep lakes, (f) large, deep lakes

6 Appendix B – Analysis of Model Performance

Table B1 – Model performance metrics for base simulations using standard parameter set. Note that for fully mixed lakes or for lakes where temperature profiles were shallower than the thermocline depth, *NMAE* values are listed as not applicable (N/A).

	All Temperature					Epilimnion Temperature					Hypolimnion Temperature					Thermocline Depth					Schmidt Number				
	RMSE	MEFF	r	PRE	NMAE	RMSE	MEFF	r	PRE	NMAE	RMSE	MEFF	r	PRE	NMAE	RMSE	MEFF	r	PRE	NMAE	RMSE	MEFF	r	PRE	NMAE
Alexandrina	1.43	0.86	0.98	-3.9	0.07	1.44	0.86	0.98	-4.0	0.07	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Ammersee	2.07	0.79	0.91	-6.0	0.19	2.78	0.84	0.99	14.8	0.20	0.78	0.30	0.59	-1.7	0.13	28.0	0.28	0.70	15.6	0.40	278	0.95	0.99	10.6	0.17
Blelham	1.32	0.89	0.97	-3.0	0.12	2.02	0.85	0.96	-12.0	0.13	3.24	-1.60	0.84	21.6	0.31	2.6	0.54	0.80	-0.2	0.18	24	0.65	0.96	27.0	0.45
Bourget	0.87	0.93	0.97	-4.5	0.08	2.01	0.91	0.97	0.1	0.11	0.53	-0.95	0.40	-4.9	0.07	36.4	0.56	0.79	3.9	0.32	823	0.98	0.99	0.9	0.09
Cannonsville	1.33	0.94	0.97	-1.0	0.10	1.06	0.97	0.99	-1.8	0.05	1.70	0.57	0.79	-5.3	0.15	11.6	0.32	0.62	-15.0	0.39	125	0.96	0.98	-5.7	0.12
Como	1.13	0.86	0.94	4.2	0.10	4.32	0.52	0.78	-10.0	0.17	0.57	-0.49	0.48	3.1	0.06	82.7	-0.43	0.67	26.6	0.64	5498	0.90	0.96	-10.1	0.19
Constance	1.08	0.95	0.98	2.8	0.08	1.49	0.95	0.98	4.4	0.09	0.44	0.25	0.74	2.8	0.07	31.0	0.92	0.96	6.7	0.11	1372	0.95	0.99	7.0	0.16
ElGergal	1.72	0.81	0.95	1.1	0.08	1.54	0.91	0.98	1.4	0.06	1.38	0.38	0.80	-5.6	0.07	8.5	0.55	0.79	16.8	0.30	328	0.74	0.97	24.1	0.27
Emaiksoun	0.80	0.95	0.99	8.0	0.08	0.80	0.95	0.99	8.0	0.08	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Esthwaite	1.49	0.89	0.98	1.4	0.13	1.50	0.93	0.98	-8.9	0.11	3.64	-0.66	0.92	21.4	0.35	2.7	0.40	0.71	10.3	0.15	12	0.93	0.97	-9.9	0.24
Feeagh	0.72	0.95	0.99	1.2	0.06	0.53	0.98	0.99	-0.9	0.04	1.30	0.80	0.97	5.8	0.09	9.7	0.41	0.67	6.3	0.14	34	0.90	0.95	11.6	0.30
Geneva01	1.18	0.92	0.96	-5.3	0.09	2.07	0.86	0.95	-7.0	0.11	0.36	-0.34	0.65	-2.6	0.04	94.4	0.46	0.80	36.3	0.41	3350	0.87	0.95	-14.0	0.22
Geneva03	1.16	0.93	0.97	-2.1	0.08	1.02	0.98	0.99	-1.0	0.05	0.34	-0.39	0.67	2.6	0.04	123.0	0.22	0.59	-15.6	0.52	3977	0.88	0.94	-3.6	0.20
GrosseDhuenn	0.81	0.97	0.99	-0.3	0.07	1.05	0.97	0.99	-3.1	0.05	1.02	0.78	0.90	-2.5	0.09	13.5	0.37	0.64	-4.1	0.37	69	0.98	0.99	0.7	0.09
Harp	1.54	0.92	0.96	-4.6	0.18	1.60	0.95	0.98	1.7	0.12	1.63	-0.79	0.70	-12.5	0.27	5.9	-0.48	0.38	34.3	0.68	60	0.94	0.98	-1.9	0.19
Iseo	1.07	0.96	0.98	-3.4	0.08	1.83	0.92	0.97	-8.0	0.10	0.55	0.03	0.56	-1.0	0.07	122.9	-0.33	0.39	19.3	0.76	2620	0.94	0.97	-0.5	0.16
Kinneret03	1.60	0.88	0.96	0.9	0.07	1.76	0.87	0.97	1.4	0.07	1.28	-3.04	0.28	-0.6	0.07	10.9	0.31	0.66	15.4	0.28	527	0.88	0.99	17.3	0.20

Kinneret97	1.49	0.87	0.97	3.1	0.05	1.65	0.89	0.99	4.6	0.06	1.10	-2.16	0.46	3.0	0.05	7.8	0.56	0.79	2.6	0.15	571	0.87	0.99	19.1	0.21
Mendota	1.60	0.92	0.97	5.9	0.11	1.94	0.94	0.98	7.9	0.10	1.42	0.84	0.95	7.8	0.11	7.8	0.15	0.56	5.3	0.30	96	0.88	0.99	20.0	0.23
MtBold	1.47	0.87	0.96	4.8	0.08	1.74	0.80	0.94	6.0	0.08	1.08	0.90	0.96	1.7	0.06	11.4	0.50	0.75	-9.3	0.25	146	0.57	0.94	28.7	0.43
Muggelsee	1.40	0.92	0.99	4.6	0.07	1.24	0.94	0.98	2.7	0.06	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
NamCo	1.13	0.85	0.95	17.6	0.23	1.04	0.93	0.98	11.1	0.17	0.85	0.70	0.93	19.1	0.22	29.6	0.16	0.58	13.4	0.28	304	0.81	0.98	25.7	0.35
Oneida	1.26	0.91	0.96	1.1	0.04	0.65	0.97	0.99	-1.0	0.03	1.83	0.79	0.91	2.8	0.06	3.0	-1.49	0.10	17.1	0.19	26	-0.48	0.63	-86.3	0.86
Pusiano	1.74	0.90	0.97	-3.8	0.14	2.38	0.90	0.98	1.2	0.11	2.81	-0.81	0.26	-19.3	0.26	5.3	0.69	0.84	6.4	0.24	146	0.88	0.98	13.3	0.19
Rappbode	1.15	0.91	0.97	-6.0	0.14	1.22	0.96	0.99	0.4	0.08	0.77	0.41	0.74	-5.3	0.12	13.3	0.67	0.84	3.6	0.23	254	0.92	0.99	11.5	0.16
Rassnitzersee	1.64	0.80	0.96	-15.3	0.17	1.82	0.90	0.99	-14.9	0.15	1.73	-1.00	0.77	-23.3	0.23	5.2	0.82	0.94	14.4	0.15	116	0.94	0.98	-14.9	0.17
Ravn	1.94	0.85	0.94	-9.3	0.19	1.81	0.91	0.99	-12.9	0.14	1.53	0.36	0.88	5.2	0.21	8.3	0.34	0.75	10.4	0.27	149	0.80	0.98	-33.1	0.34
Rotorua	1.33	0.91	0.99	3.8	0.07	1.33	0.91	0.99	3.9	0.08	1.38	0.89	0.99	3.9	0.08	3.9	0.04	0.36	4.9	0.09	11	0.74	0.88	-6.6	0.43
Stechlin	1.11	0.91	0.96	-7.3	0.13	1.73	0.93	0.99	2.5	0.11	0.77	0.04	0.80	-1.0	0.11	21.2	0.42	0.74	11.9	0.33	159	0.96	0.98	-3.9	0.14
Tarawera	0.77	0.86	0.95	-3.3	0.04	0.82	0.93	0.98	-1.4	0.04	0.47	-0.08	0.60	-2.4	0.03	21.4	0.46	0.76	-1.3	0.27	424	0.97	0.99	-6.6	0.10
Toolik	1.36	0.77	0.88	2.1	0.25	1.94	0.82	0.91	1.4	0.26	1.15	0.61	0.81	7.4	0.25	11.3	-0.89	0.29	52.3	0.61	17	0.74	0.86	-15.7	0.43
Windermere	1.61	0.82	0.95	12.4	0.14	3.21	0.54	0.81	-11.1	0.23	2.39	-0.82	0.85	25.2	0.26	10.2	0.20	0.79	15.8	0.22	271	0.90	0.98	16.2	0.21
Woods	2.14	0.82	0.99	-9.0	0.17	2.13	0.82	0.99	-9.1	0.17	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Zurich	1.24	0.94	0.98	7.6	0.12	1.48	0.96	0.99	5.3	0.09	1.11	-3.05	0.60	13.6	0.16	50.8	0.30	0.64	-7.6	0.42	816	0.94	1.00	16.2	0.17
Mean	**1.34**	**0.89**	**0.96**	**-0.16**	**0.11**	**1.67**	**0.89**	**0.97**	**-0.84**	**0.10**	**1.31**	**-0.25**	**0.73**	**1.97**	**0.14**	**26.5**	**0.23**	**0.66**	**9.89**	**0.32**	**753**	**0.83**	**0.96**	**1.23**	**0.25**
Median	**1.33**	**0.90**	**0.97**	**0.26**	**0.09**	**1.62**	**0.92**	**0.98**	**0.23**	**0.09**	**1.13**	**0.03**	**0.78**	**2.13**	**0.10**	**11.3**	**0.36**	**0.71**	**8.53**	**0.28**	**206**	**0.90**	**0.98**	**0.81**	**0.20**

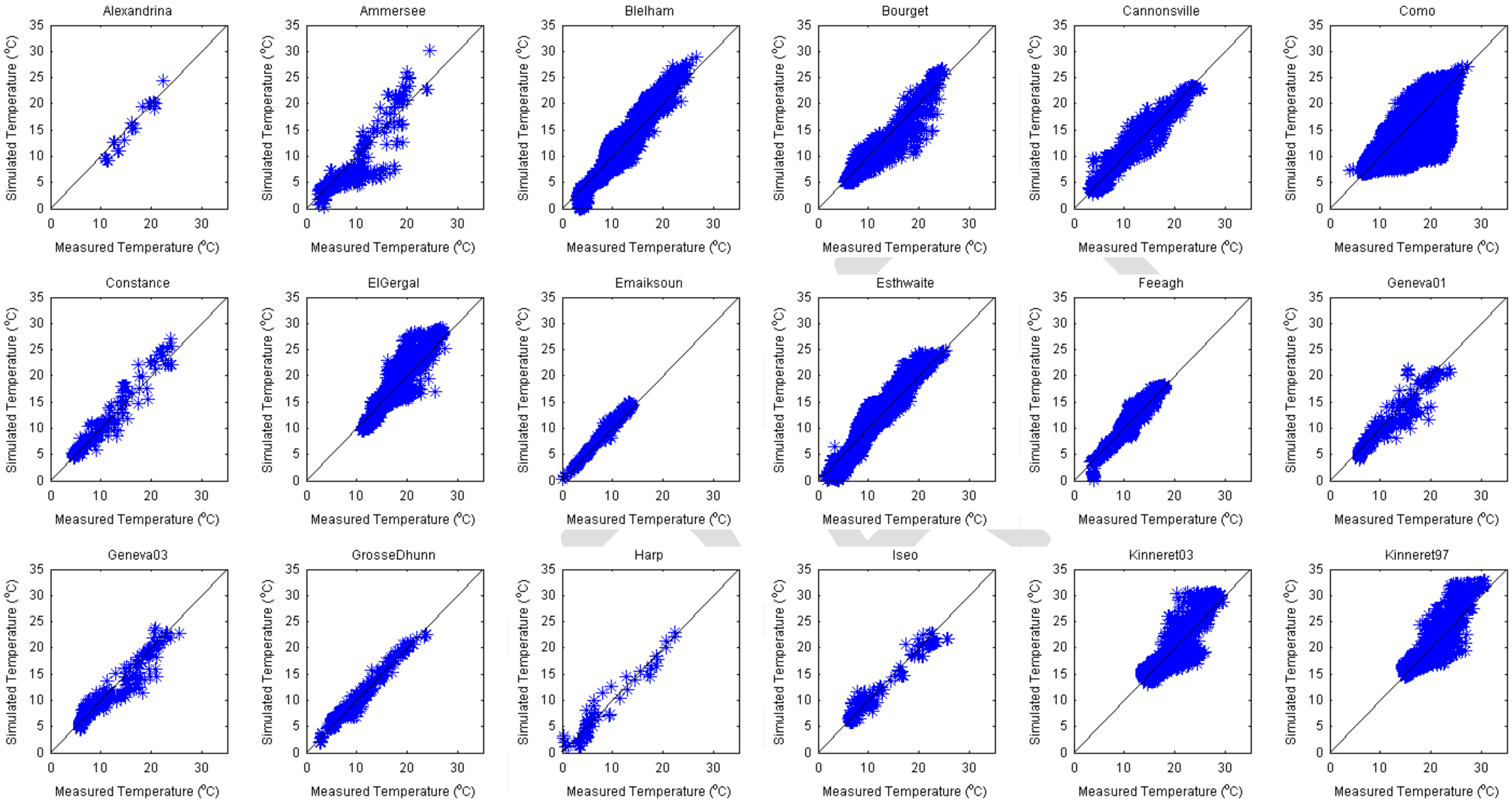
Table B2 – Significance and correlation between model performance metrics and input uncertainty.

		Full Profile Temperature					Epilimnion Temperature					Hypolimnion Temperature					Thermocline Depth					Schmidt Stability				
		RMSE	MEFF	r	*PRE*	*NMAE*	*RMSE*	MEFF	r	*PRE*	*NMAE*	*RMSE*	MEFF	*r*	*PRE*	*NMAE*	*RMSE*	NSE	r	*PRE*	*NMAE*	*RMSE*	MEFF	r	*PRE*	*NMAE*
	morph	0.05	0.26	0.03	-0.01	0.04	0.05	0.05	-0.10	-0.25	-0.02	0.09	0.12	0.22	0.22	0.14	-0.02	0.18	0.23	0.01	-0.01	-0.06	0.25	0.24	-0.09	-0.27
	distmet	0.27	-0.27	-0.16	-0.44	0.17	0.00	0.04	0.20	-0.18	0.00	0.14	-0.21	-0.22	-0.35	0.09	-0.18	0.09	0.07	-0.13	-0.14	-0.22	-0.15	-0.10	-0.38	0.04
	freqmet	0.11	-0.19	-0.27	-0.32	0.34	0.00	0.07	0.06	-0.01	0.11	-0.09	-0.11	-0.01	-0.35	0.11	0.24	-0.34	-0.18	0.32	0.50	-0.08	0.11	0.10	-0.21	-0.13
r	flow	-0.21	0.06	0.23	0.17	0.16	-0.24	0.18	0.24	0.29	0.09	-0.05	-0.01	0.07	0.00	0.05	-0.10	-0.19	-0.17	0.14	-0.01	-0.25	-0.08	-0.08	0.16	0.14
	Kw	0.30	-0.03	0.38	-0.16	0.03	0.15	-0.10	0.08	-0.27	0.06	0.33	-0.17	-0.19	-0.16	0.41	-0.17	0.42	0.40	-0.27	-0.29	0.02	0.24	0.26	0.03	-0.29
	obs	-0.03	0.21	-0.02	-0.31	-0.16	-0.17	0.30	0.31	0.13	-0.32	-0.33	-0.13	-0.09	-0.29	-0.32	0.34	-0.18	-0.07	0.25	0.40	-0.01	0.07	0.10	-0.31	-0.25
	mean	0.17	-0.02	0.01	-0.44	0.20	-0.10	0.22	0.32	-0.06	-0.05	-0.06	-0.18	-0.09	-0.37	0.05	0.10	-0.11	0.00	0.17	0.24	-0.20	0.08	0.11	-0.33	-0.21
	morph	0.80	0.14	0.88	0.94	0.83	0.77	0.78	0.57	0.15	0.93	0.65	0.51	0.24	0.25	0.47	0.93	0.33	0.22	0.95	0.97	0.76	0.19	0.20	0.64	0.15
	distmet	0.12	0.13	0.38	0.01	0.32	0.99	0.82	0.27	0.32	0.99	0.47	0.26	0.24	0.06	0.64	0.34	0.65	0.71	0.51	0.44	0.23	0.44	0.60	0.04	0.84
	freqmet	0.54	0.29	0.12	0.07	0.05	0.98	0.69	0.72	0.94	0.54	0.64	0.55	0.96	0.06	0.57	0.19	0.07	0.33	0.09	0.01	0.69	0.56	0.58	0.26	0.48
p	flow	0.24	0.72	0.19	0.34	0.35	0.17	0.31	0.17	0.09	0.62	0.79	0.94	0.72	0.99	0.79	0.59	0.31	0.36	0.46	0.94	0.18	0.69	0.67	0.41	0.46
	Kw	0.08	0.85	0.03	0.38	0.89	0.41	0.59	0.65	0.12	0.73	0.07	0.36	0.32	0.39	0.03	0.36	0.02	0.03	0.15	0.12	0.92	0.21	0.16	0.87	0.12
	obs	0.85	0.23	0.92	0.07	0.37	0.33	0.09	0.07	0.46	0.07	0.08	0.51	0.65	0.12	0.09	0.06	0.33	0.72	0.18	0.03	0.96	0.71	0.61	0.09	0.18
	mean	0.33	0.90	0.97	0.01	0.25	0.57	0.22	0.06	0.73	0.76	0.77	0.33	0.64	0.05	0.77	0.59	0.55	0.99	0.36	0.20	0.29	0.66	0.55	0.07	0.27

Table B3 – Significance (p) and correlation (r) between model performance metrics and mean values of lake volume (V), surface area (Area), depth (D), suface area divided by depth (A/D), length divided by width (L/W), inflow (Inf), residence time (RT), short wave radiation (sw), air temperature (T_{air}), wind speed (u_{wind}), light extinction coefficient (K_w), latitude (Lat) and Lake Number (LN). Significant correlations highlighted in red and corresponding *r* in yellow.

		All Temperature					Epilimnion Temperature					Hypolimnion Temperature					Thermocline Depth					Schmidt Stability				
		RMSE	MEFF	r	PRE	NMAE	RMSE	MEFF	r	PRE	NMAE	RMSE	MEFF	r	PRE	NMAE	RMSE	MEFF	r	PRE	NMAE	RMSE	MEFF	r	PRE	NMAE
r	V	-0.20	0.14	0.00	0.19	-0.22	0.12	-0.09	-0.13	0.18	-0.10	-0.65	-0.11	-0.37	0.02	-0.60	0.65	-0.03	-0.02	-0.05	0.16	0.63	0.07	0.02	-0.05	-0.20
	Area	-0.13	0.12	0.08	0.26	-0.26	0.01	-0.04	-0.03	0.26	-0.16	-0.56	-0.07	-0.30	0.06	-0.58	0.52	-0.10	-0.14	-0.06	0.05	0.50	-0.07	-0.11	-0.10	-0.05
	D	-0.25	0.14	-0.21	-0.03	-0.02	0.31	-0.17	-0.29	-0.04	0.07	-0.74	-0.12	-0.42	-0.08	-0.50	0.84	0.11	0.23	0.02	0.47	0.80	0.38	0.31	0.10	-0.50
	A/D	0.00	0.03	0.21	0.32	-0.30	-0.17	0.05	0.13	0.32	-0.25	-0.35	0.00	-0.15	0.09	-0.51	0.22	-0.15	-0.26	-0.11	-0.18	0.22	-0.29	-0.29	-0.14	0.20
	L/W	-0.09	0.12	0.02	0.14	-0.13	0.12	-0.16	-0.28	-0.14	-0.12	0.01	0.10	0.04	0.01	-0.09	0.12	0.06	0.11	-0.24	0.18	0.19	0.10	0.14	0.12	-0.21
	Inf	-0.23	0.21	0.02	0.46	-0.53	0.03	-0.14	-0.21	0.23	-0.25	-0.43	-0.02	-0.26	0.19	-0.59	0.57	-0.19	-0.18	-0.05	0.17	0.58	-0.14	-0.21	-0.05	0.06
	RT	-0.16	0.01	-0.19	-0.38	0.13	0.20	-0.02	-0.02	0.00	0.19	-0.58	-0.21	-0.43	-0.38	-0.33	0.38	0.03	0.09	0.23	0.26	0.36	0.32	0.18	-0.21	-0.44
	sw	0.18	-0.21	0.00	0.32	-0.12	-0.10	0.01	0.10	0.38	-0.18	-0.29	-0.09	-0.14	0.03	-0.38	0.01	0.01	-0.09	-0.09	-0.06	0.02	-0.08	0.04	0.36	0.12
	T_{air}	0.16	0.05	0.21	-0.18	-0.59	0.16	-0.12	-0.01	-0.16	-0.46	-0.04	-0.40	-0.43	-0.21	-0.52	0.08	0.34	0.29	-0.37	-0.28	0.19	-0.02	0.14	0.18	-0.13
	u_{wind}	0.03	-0.12	0.12	-0.19	0.05	-0.29	0.13	0.18	-0.15	-0.09	-0.04	0.24	0.35	-0.27	0.02	-0.26	-0.03	-0.05	0.03	-0.18	-0.25	-0.11	-0.10	-0.18	0.16
	K_w	0.47	-0.22	0.04	0.14	0.08	0.12	-0.14	-0.06	-0.05	0.08	0.67	0.02	0.27	0.15	0.43	-0.61	-0.14	-0.16	0.06	-0.23	-0.46	-0.26	-0.17	0.09	0.36
	Lat	-0.17	0.05	-0.16	-0.11	0.32	0.04	-0.03	-0.13	-0.22	0.35	0.24	0.12	0.23	0.13	0.48	-0.03	-0.13	0.02	0.32	0.16	-0.05	0.11	-0.05	-0.27	-0.01
	LN	-0.14	0.19	-0.04	0.01	-0.08	0.27	-0.16	-0.25	-0.08	0.04	0.07	-0.25	-0.26	-0.21	-0.06	0.08	0.21	0.28	0.02	0.17	0.19	0.34	0.31	0.25	-0.34
p	V	0.25	0.41	0.99	0.27	0.21	0.50	0.60	0.46	0.31	0.57	0.00	0.57	0.04	0.92	0.00	0.00	0.89	0.90	0.79	0.38	0.00	0.70	0.92	0.81	0.30
	Area	0.45	0.52	0.65	0.14	0.14	0.96	0.82	0.86	0.15	0.36	0.00	0.71	0.11	0.76	0.00	0.00	0.60	0.47	0.74	0.78	0.00	0.72	0.55	0.60	0.81
	D	0.15	0.42	0.23	0.87	0.90	0.08	0.35	0.09	0.84	0.68	0.00	0.54	0.02	0.66	0.00	0.00	0.55	0.23	0.91	0.01	0.00	0.04	0.10	0.62	0.01
	A/D	0.98	0.85	0.22	0.06	0.08	0.34	0.79	0.45	0.06	0.15	0.06	0.99	0.43	0.65	0.00	0.24	0.41	0.16	0.56	0.34	0.23	0.12	0.12	0.45	0.30
	L/W	0.61	0.49	0.92	0.42	0.48	0.50	0.36	0.11	0.43	0.51	0.94	0.62	0.83	0.94	0.63	0.51	0.74	0.56	0.19	0.33	0.32	0.60	0.47	0.53	0.25
	Inf	0.22	0.25	0.91	0.01	0.00	0.86	0.45	0.25	0.21	0.18	0.02	0.91	0.18	0.33	0.00	0.00	0.33	0.37	0.79	0.38	0.00	0.49	0.29	0.79	0.78
	RT	0.40	0.95	0.32	0.04	0.47	0.28	0.92	0.94	1.00	0.31	0.00	0.29	0.02	0.05	0.09	0.05	0.90	0.64	0.24	0.18	0.06	0.10	0.35	0.29	0.02

	sw	0.30	0.24	1.00	0.06	0.49	0.59	0.98	0.57	0.02	0.30	0.12	0.63	0.45	0.88	0.04	0.96	0.94	0.62	0.63	0.75	0.93	0.66	0.82	0.05	0.54
	T_{air}	0.37	0.78	0.23	0.32	0.00	0.37	0.52	0.98	0.38	0.01	0.85	0.03	0.02	0.26	0.00	0.69	0.07	0.12	0.04	0.14	0.31	0.91	0.47	0.35	0.49
	u_{wind}	0.86	0.51	0.49	0.27	0.80	0.09	0.48	0.32	0.39	0.63	0.83	0.20	0.06	0.15	0.91	0.16	0.88	0.79	0.89	0.35	0.17	0.57	0.62	0.35	0.40
	K_w	0.00	0.20	0.84	0.42	0.66	0.52	0.44	0.72	0.77	0.67	0.00	0.90	0.14	0.42	0.02	0.00	0.47	0.39	0.74	0.22	0.01	0.17	0.38	0.64	0.05
	Lat	0.33	0.79	0.36	0.53	0.07	0.82	0.89	0.46	0.22	0.04	0.20	0.52	0.22	0.49	0.01	0.88	0.50	0.93	0.08	0.39	0.77	0.57	0.80	0.16	0.96
	LN	0.41	0.29	0.83	0.95	0.66	0.13	0.37	0.15	0.65	0.82	0.70	0.19	0.17	0.27	0.74	0.66	0.26	0.14	0.92	0.37	0.30	0.06	0.09	0.18	0.06


Alexandrina
Ammersee
Blelham
Bourget
Cannonsville
Como
Constance
ElGergal
Emaiksoun
Esthwaite
Feeagh
Geneva01
Geneva03
GrosseDhunn
Harp
Iseo
Kinneret03
Kinneret97
Simulated Temperature (°C)
Measured Temperature (°C)

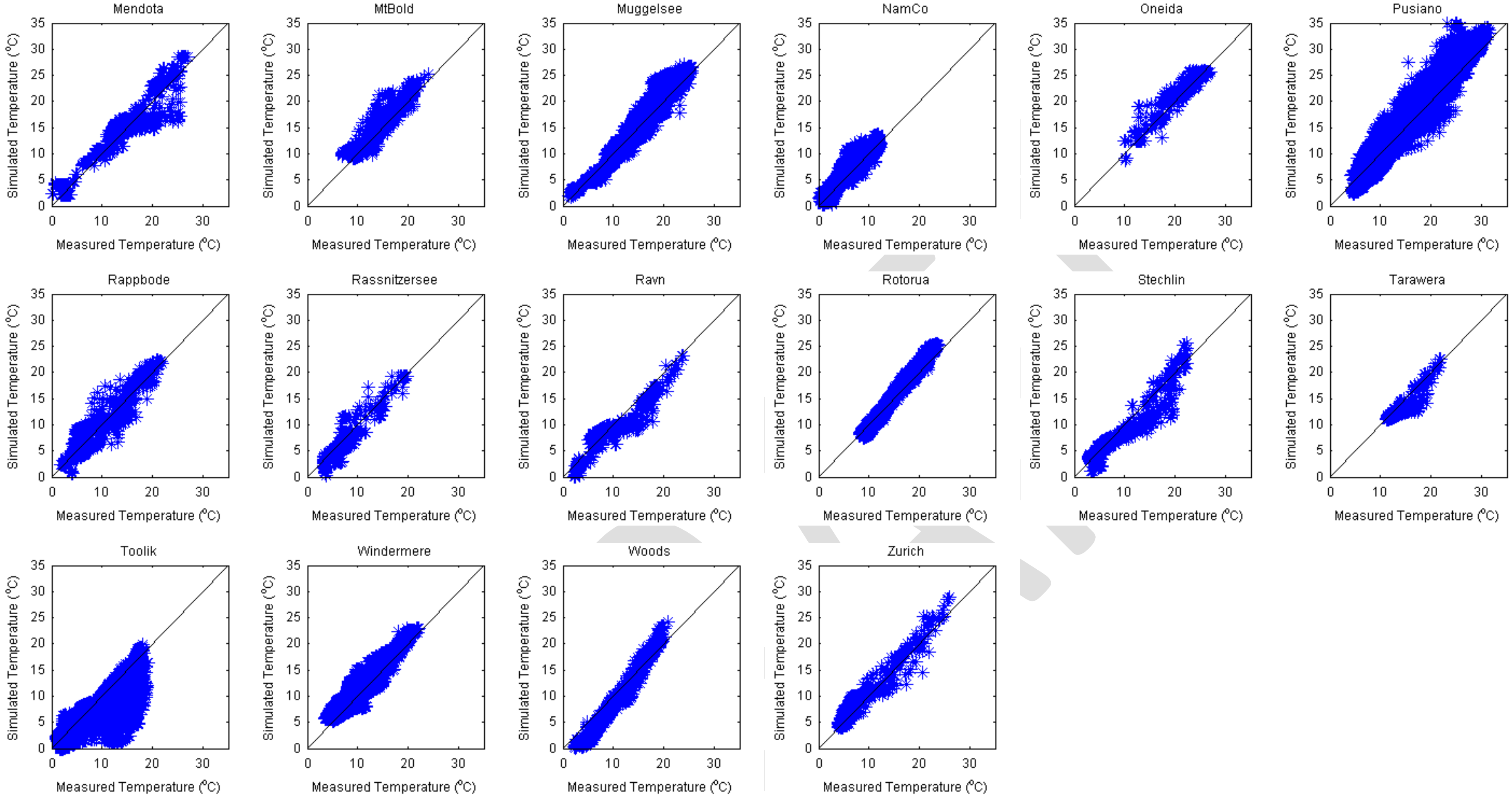


Figure B1 – Plot of modelled vs observed temperature data for each of the MLCP lakes.

7 Appendix C – Sensitivity Analysis

Table C1 - Significance (p) and correlation (r) between sensitivity indices for full profile temperature and mean values of lake volume (V), surface area (Area), depth (D), suface area divided by depth (A/D), length divided by width (L/W), inflow (Inf), residence time (RT), short wave radiation (sw), air temperature (T_{air}), wind speed (u_{wind}), light extinction coefficient (K_w), latitude (Lat) and Lake Number (LN). Significant correlations highlighted in red and corresponding *r* in yellow.

	Attribute	C_c	C_w	C_s	C_t	C_{KH}	C_{hyp}	C_e	C_h	C_d
r	V	0.08	0.04	-0.09	-0.10	0.47	0.04	-0.07	-0.20	0.02
	Area	0.15	0.09	0.02	0.09	0.33	0.16	-0.43	-0.18	-0.06
	D	0.06	0.03	-0.12	-0.13	0.49	0.02	0.06	-0.16	0.03
	A/D	-0.02	-0.03	-0.16	-0.22	0.43	-0.08	0.30	-0.13	0.05
	L/W	-0.08	0.14	-0.10	0.15	-0.05	0.21	-0.15	-0.08	-0.40
	Inf	0.01	0.06	0.00	-0.24	0.43	0.07	-0.08	-0.41	-0.32
	RT	0.21	0.04	-0.01	0.18	0.18	0.06	-0.24	0.09	0.26
	sw	-0.10	-0.11	-0.18	-0.14	0.39	-0.12	0.41	0.12	0.18
	T_{air}	-0.23	-0.24	-0.26	-0.22	-0.40	-0.30	0.34	-0.67	0.03
	u_{wind}	-0.30	-0.32	-0.19	-0.15	-0.14	-0.30	0.33	0.09	0.22
	K_w	-0.25	-0.16	-0.04	-0.16	-0.30	-0.14	0.42	0.12	0.11
	Lat	0.22	0.16	0.24	0.18	-0.24	0.20	-0.49	0.19	-0.06
p	V	0.68	0.85	0.64	0.60	0.01	0.84	0.73	0.30	0.91
	Area	0.42	0.65	0.90	0.65	0.08	0.40	0.02	0.34	0.75
	D	0.75	0.89	0.54	0.48	0.01	0.92	0.77	0.39	0.90
	A/D	0.90	0.87	0.39	0.24	0.02	0.67	0.11	0.49	0.79
	L/W	0.68	0.47	0.60	0.44	0.80	0.27	0.44	0.66	0.03
	Inf	0.95	0.74	0.98	0.23	0.02	0.72	0.68	0.03	0.10
	RT	0.29	0.83	0.97	0.36	0.37	0.76	0.21	0.67	0.18
	sw	0.61	0.56	0.35	0.47	0.04	0.52	0.02	0.54	0.35
	T_{air}	0.22	0.21	0.17	0.25	0.03	0.11	0.07	0.00	0.88
	u_{wind}	0.11	0.08	0.31	0.43	0.48	0.10	0.08	0.65	0.25

	K_w	0.18	0.39	0.84	0.39	0.11	0.45	0.02	0.53	0.57
	Lat	0.25	0.41	0.20	0.35	0.20	0.28	0.01	0.31	0.76

Table C2 - - Significance (p) and correlation (r) between sensitivity indices for epilimnion temperature and mean values of lake volume (V), surface area (Area), depth (D), suface area divided by depth (A/D), length divided by width (L/W), inflow (Inf), residence time (RT), short wave radiation (sw), air temperature (T_{air}), wind speed (u_{wind}), light extinction coefficient (K_w), latitude (Lat) and Lake Number (LN). Significant correlations highlighted in red and corresponding *r* in yellow.

	Attribute	C_c	C_w	C_s	C_t	C_{KH}	C_{hyp}	C_e	C_h	C_d
r	V	0.24	0.19	0.31	0.25	0.56	-0.10	-0.20	0.21	0.31
	Area	0.40	0.29	0.27	0.30	0.63	0.09	-0.25	0.21	0.33
	D	0.18	0.14	0.31	0.22	0.49	-0.13	-0.17	0.20	0.28
	A/D	0.00	0.01	0.24	0.12	0.30	-0.21	-0.05	0.13	0.17
	L/W	-0.07	0.10	-0.13	0.20	0.25	0.41	-0.18	0.14	-0.22
	Inf	0.13	0.09	0.07	0.14	0.51	-0.05	-0.31	-0.16	-0.09
	RT	0.44	0.29	0.40	0.09	0.22	-0.06	0.09	0.21	0.60
	sw	-0.13	-0.13	0.27	0.10	0.03	-0.20	0.09	0.19	0.08
	T_{air}	-0.21	-0.50	-0.54	-0.40	-0.10	-0.34	0.43	-0.46	-0.61
	u_{wind}	-0.18	0.08	-0.11	-0.05	-0.26	-0.10	0.35	0.08	-0.02
	K_w	-0.43	-0.37	-0.33	-0.37	-0.58	-0.14	0.32	-0.31	-0.36
	Lat	0.26	0.23	-0.06	0.03	-0.05	0.26	-0.16	-0.15	0.12
p	V	0.19	0.31	0.10	0.19	0.00	0.62	0.30	0.27	0.10
	Area	0.03	0.12	0.15	0.10	0.00	0.63	0.18	0.26	0.08
	D	0.35	0.45	0.10	0.24	0.01	0.50	0.38	0.29	0.13
	A/D	0.99	0.94	0.20	0.51	0.11	0.27	0.79	0.50	0.37
	L/W	0.71	0.60	0.49	0.28	0.18	0.02	0.34	0.45	0.24
	Inf	0.50	0.64	0.73	0.48	0.01	0.80	0.11	0.40	0.66
	RT	0.02	0.14	0.03	0.67	0.25	0.75	0.66	0.28	0.00
	sw	0.50	0.49	0.14	0.62	0.86	0.30	0.65	0.31	0.67
	T_{air}	0.27	0.00	0.00	0.03	0.58	0.06	0.02	0.01	0.00
	u_{wind}	0.33	0.68	0.56	0.78	0.17	0.61	0.06	0.68	0.94
	K_w	0.02	0.04	0.07	0.05	0.00	0.45	0.09	0.10	0.05
	Lat	0.17	0.22	0.77	0.88	0.80	0.16	0.39	0.43	0.51

Table C3 - - Significance (p) and correlation (r) between sensitivity indices for hypolimnion temperature and mean values of lake volume (V), surface area (Area), depth (D), suface area divided by depth (A/D), length divided by width (L/W), inflow (Inf), residence time (RT), short wave radiation (sw), air temperature (T_{air}), wind speed (u_{wind}), light extinction coefficient (K_w), latitude (Lat) and Lake Number (LN). Significant correlations highlighted in red and corresponding *r* in yellow.

	Attribute	C_c	C_w	C_s	C_t	C_{KH}	C_{hyp}	C_e	C_h	C_d
r	V	-0.11	-0.37	-0.33	-0.26	-0.07	-0.22	0.08	-0.27	-0.26
	Area	-0.03	-0.34	-0.29	-0.21	-0.14	-0.20	-0.23	-0.22	-0.32
	D	-0.11	-0.34	-0.31	-0.24	-0.02	-0.18	0.16	-0.25	-0.22
	A/D	-0.14	-0.29	-0.26	-0.19	0.02	-0.14	0.31	-0.22	-0.12
	L/W	-0.10	0.19	0.20	0.17	0.14	0.22	-0.39	-0.15	-0.09
	Inf	-0.39	-0.39	-0.20	-0.25	-0.08	-0.19	-0.02	-0.68	-0.38
	RT	0.18	-0.29	-0.39	-0.13	-0.34	-0.36	-0.03	0.17	-0.24
	sw	-0.14	-0.22	0.01	-0.05	0.03	-0.08	0.59	0.11	-0.22
	T_{air}	-0.22	-0.23	0.01	-0.11	-0.64	-0.22	0.32	-0.50	-0.20
	u_{wind}	-0.29	-0.21	-0.35	-0.17	-0.21	-0.22	0.01	0.27	0.04
	K_w	-0.14	0.15	0.27	0.17	0.13	0.25	0.16	0.07	0.27
	Lat	0.11	0.14	-0.03	0.09	0.15	0.00	-0.48	0.03	0.21
p	V	0.55	0.04	0.07	0.16	0.71	0.25	0.69	0.15	0.17
	Area	0.88	0.07	0.12	0.27	0.46	0.28	0.22	0.24	0.09
	D	0.55	0.06	0.10	0.20	0.92	0.34	0.40	0.19	0.25
	A/D	0.46	0.12	0.17	0.30	0.93	0.46	0.10	0.24	0.52
	L/W	0.61	0.32	0.29	0.36	0.46	0.25	0.04	0.42	0.65
	Inf	0.04	0.04	0.30	0.21	0.68	0.34	0.93	0.00	0.05
	RT	0.37	0.14	0.04	0.50	0.08	0.06	0.88	0.40	0.22
	sw	0.47	0.24	0.96	0.78	0.87	0.66	0.00	0.56	0.25
	T_{air}	0.25	0.22	0.94	0.57	0.00	0.25	0.09	0.01	0.30
	u_{wind}	0.12	0.26	0.06	0.36	0.27	0.25	0.96	0.15	0.85
	K_w	0.46	0.42	0.15	0.38	0.48	0.18	0.38	0.71	0.16
	Lat	0.55	0.46	0.87	0.63	0.44	0.99	0.01	0.86	0.28

Table C4 - - Significance (p) and correlation (r) between sensitivity indices for thermocline depth and mean values of lake volume (V), surface area (Area), depth (D), suface area divided by depth (A/D), length divided by width (L/W), inflow (Inf), residence time (RT), short wave radiation (sw), air temperature (T_{air}), wind speed (u_{wind}), light extinction coefficient (K_w), latitude (Lat) and Lake Number (LN). Significant correlations highlighted in red and corresponding *r* in yellow.

	Attribute	C_c	C_w	C_s	C_t	C_{KH}	C_{hyp}	C_e	C_h	C_d
r	V	0.48	0.43	0.30	0.35	0.58	0.29	0.23	0.31	0.25
	Area	0.57	0.54	0.29	0.42	0.61	0.27	0.40	0.36	0.17
	D	0.41	0.36	0.27	0.31	0.51	0.28	0.14	0.27	0.25
	A/D	0.22	0.19	0.22	0.18	0.33	0.20	0.02	0.15	0.25
	L/W	0.01	0.16	-0.01	0.04	0.04	0.06	0.06	0.15	-0.04
	Inf	0.50	0.43	0.34	0.38	0.53	0.33	0.23	0.40	0.23
	RT	0.25	0.13	-0.06	0.10	0.28	0.08	0.16	0.07	0.10
	sw	0.03	0.08	0.31	-0.06	0.10	0.17	0.05	0.03	0.38
	T_{air}	0.11	0.13	0.19	0.06	0.09	0.34	0.19	0.18	0.44
	u_{wind}	-0.19	-0.13	0.06	-0.18	-0.22	-0.19	0.00	-0.33	0.06
	K_w	-0.42	-0.24	-0.27	-0.26	-0.46	0.03	-0.23	-0.04	0.08
	Lat	-0.01	-0.11	-0.34	0.01	-0.09	-0.19	-0.06	-0.05	-0.32
p	V	0.01	0.02	0.11	0.06	0.00	0.12	0.21	0.10	0.17
	Area	0.00	0.00	0.12	0.02	0.00	0.15	0.03	0.05	0.38
	D	0.03	0.05	0.15	0.10	0.00	0.14	0.45	0.15	0.18
	A/D	0.24	0.31	0.24	0.35	0.08	0.29	0.93	0.42	0.18
	L/W	0.94	0.39	0.94	0.83	0.83	0.74	0.77	0.43	0.84
	Inf	0.01	0.02	0.07	0.04	0.00	0.09	0.25	0.04	0.24
	RT	0.21	0.50	0.77	0.61	0.15	0.70	0.40	0.71	0.60
	sw	0.86	0.68	0.10	0.75	0.60	0.37	0.79	0.88	0.04
	T_{air}	0.55	0.49	0.31	0.75	0.63	0.07	0.30	0.34	0.02
	u_{wind}	0.31	0.49	0.74	0.34	0.25	0.31	1.00	0.07	0.76
	K_w	0.02	0.20	0.14	0.16	0.01	0.89	0.22	0.83	0.68
	Lat	0.95	0.58	0.07	0.96	0.64	0.30	0.77	0.81	0.08

Table C5 - - Significance (p) and correlation (r) between sensitivity indices for Schmidt number and mean values of lake volume (V), surface area (Area), depth (D), suface area divided by depth (A/D), length divided by width (L/W), inflow (Inf), residence time (RT), short wave radiation (sw), air temperature (T_{air}), wind speed (u_{wind}), light extinction coefficient (K_w), latitude (Lat) and Lake Number (LN). Significant correlations highlighted in red and corresponding *r* in yellow.

	Attribute	C_c	C_w	C_s	C_t	C_{KH}	C_{hyp}	C_e	C_h	C_d
r	V	0.02	0.13	0.27	0.15	-0.08	-0.06	-0.16	-0.07	0.00
	Area	0.00	0.07	0.10	-0.06	-0.30	-0.28	-0.25	-0.15	-0.31
	D	0.04	0.14	0.31	0.22	0.02	0.04	-0.09	-0.01	0.13
	A/D	0.05	0.12	0.33	0.30	0.15	0.17	0.07	0.03	0.30
	L/W	-0.15	-0.16	-0.21	-0.17	-0.06	-0.08	0.03	-0.12	-0.21
	Inf	0.02	0.17	0.31	0.16	0.13	0.07	-0.16	0.07	0.13
	RT	0.01	0.07	-0.05	0.00	-0.25	-0.14	-0.20	0.02	-0.13
	sw	-0.10	-0.14	0.04	0.16	-0.22	0.00	0.17	-0.04	0.00
	T_{air}	0.00	-0.05	-0.01	0.00	-0.08	0.03	-0.15	-0.29	0.00
	u_{wind}	0.04	-0.18	0.03	-0.21	0.00	-0.15	0.43	-0.05	0.14
	K_w	-0.11	-0.11	-0.25	0.15	0.31	0.32	0.32	0.24	0.26
	Lat	0.06	0.08	-0.07	-0.16	0.16	-0.05	-0.13	0.17	-0.05
p	V	0.93	0.48	0.14	0.43	0.67	0.77	0.41	0.73	0.98
	Area	0.99	0.70	0.62	0.74	0.10	0.13	0.19	0.44	0.10
	D	0.83	0.45	0.09	0.24	0.91	0.85	0.62	0.95	0.49
	A/D	0.80	0.53	0.08	0.11	0.44	0.37	0.70	0.87	0.11
	L/W	0.43	0.40	0.26	0.36	0.77	0.67	0.86	0.54	0.27
	Inf	0.92	0.40	0.11	0.43	0.52	0.74	0.42	0.72	0.52
	RT	0.95	0.72	0.78	0.98	0.20	0.48	0.31	0.94	0.50
	sw	0.60	0.45	0.84	0.40	0.24	1.00	0.38	0.85	0.98
	T_{air}	0.98	0.80	0.95	0.98	0.66	0.88	0.44	0.11	0.99
	u_{wind}	0.85	0.33	0.87	0.26	0.99	0.42	0.02	0.77	0.46
	K_w	0.57	0.55	0.19	0.41	0.09	0.08	0.08	0.20	0.17
	Lat	0.77	0.68	0.70	0.39	0.39	0.80	0.50	0.36	0.79

8 Appendix D – Acknowledgements

Table D1 – Acknowledgements by individual lake. Note other includes technical staff/students who helped set up the GLM.

Lake Name	Morphometry	Meteorology	Flow	Field Data	Institutions	Funding	People
Alexandrina	Department of Environment, Water and Natural Resources	Natural Resources SA Murray-Darling Basin	Murray-Darling Basin Authority (MDBA)	Natural Resources SA Murray-Darling Basin	The University of Western Australia	ARC Discovery Grant DP130104078	Alex Perry
Ammersee	Bavarian Environment Agency	German Weather Service,Wielenbach; Bavarian Agency of Agriculture, Rothenfeld + Westerschondorf	Water Agency Weilheim	Water Agency Weilheim		Bavarian Environment Agency; Bavarian State Ministry of the Environment and Consumer Protection	Otfried Baume
Blelham	Ramsbottom, A.E. 1976. Depth charts of the Cumbrian Lakes. Freshwater Biological Association	Centre for Ecology and Hydrology	Environment Agency	Centre for Ecology and Hydrology	University of Reading; Centre for Ecology and Hydrology	UKLEON (NE/I007407/1)	Bernard Tebay
Bourget	Delebecque, 1898 and IFREMER 1992	Météo France	DREAL Rhône-Alpes	© SOERE OLA-IS, INRA Thonon-les-Bains, CISALB, [2012], developed by INRA's ORE Eco-Information system	INRA Thonon les Bains	CISALB, Agence de l'eau Rhône-Méditerranée-Corse, SOERE OLA, Ecole des Ponts ParisTech, INRA	Orlane Anneville
Cannonsville	New York City Department of Environmental Protection	Cannonsville Dam Station	Trout Creek and West Branch Delaware River	New York City Department of Environmental Protection, Kingston, NY	New York City Department of Environmental Protection	New York City Department of Environmental Protection	Karen E.B. Moore
Como	Lombardy Region	Water Research Institute - National Research Council of Italy (IRSA-CNR); Bergamo-Orio al Serio Aiport; Regional Authority for Environmental Protection (ARPA Lombardia)	Consorzio dell'Adda	Water Research Institute - National Research Council of Italy (IRSA-CNR)	Centro Volta Como ; Istituto Nazionale della Montagna	Simulake Project; WAAESs Project	Gianni Tartari (Water Research Institute - National Research Council of Italy (IRSA-CNR)

Constance	IGKB (Internationale Gewässerschutzkommission für den Bodensee	German meteorological service (DWD)	IGKB (Internationale Gewässerschutzkommission für den Bodensee	IGKB (Internationale Gewässerschutzkommission für den Bodensee	LUBW Landesanstalt für Umwelt, Messungen und Naturschutz Baden-Württemberg; Limnological Institute, University of Konstanz	DFG, grant Ri 2040/1-1	Thomas Wolf
El Gergal	Empresa Metropolitana de Abastecimiento y Saneamiento de Aguas de Sevilla, S.A.	Empresa Metropolitana de Abastecimiento y Saneamiento de Aguas de Sevilla, S.A.	Empresa Metropolitana de Abastecimiento y Saneamiento de Aguas de Sevilla, S.A.	Empresa Metropolitana de Abastecimiento y Saneamiento de Aguas de Sevilla, S.A.	University of Granada	CGL2005-04070/HID	Carmelo Escot
Emaiksoun	Kenneth M. Hinkel, University of Cincinnati	Brittany L. Potter, University of Nebraska-Lincoln		Brittany L. Potter, University of Nebraska-Lincoln; Kenneth M. Hinkel, University of Cincinnati	LimnoTech; University of Nebraska-Lincoln; University of Cincinnati	NSF ARC-1107792	Brittany L. Potter, Kenneth M. Hinkel
Esthwaite	Ramsbottom, A.E. 1976. Depth charts of the Cumbrian Lakes. Freshwater Biological Association	Centre for Ecology and Hydrology	Environment Agency	Centre for Ecology and Hydrology	University of Reading; Centre for Ecology and Hydrology	UKLEON (NE/I007407/1)	Bernard Tebay
Feeagh	Marine Institute	Met Eireann; Marine Institute	Marine Institute	Marine Institute	Marine Institute	Marine Institute	Eleanor Jennings; Elizabeth Ryder; Mary Dillane; Russell Poole; Burrishoole field staff
Geneva03	SOERE OLA-IS, INRA Thonon-les-Bains, CIPEL	SOERE OLA-IS, INRA Thonon-les-Bains, CIPEL	SOERE OLA-IS, INRA Thonon-les-Bains, CIPEL	SOERE OLA-IS, INRA Thonon-les-Bains, CIPEL			Orlane Anneville
Geneva05	As Above	As Above	As Above	As Above	As Above	As Above	As Above
GrosseDhuenn	Wupperverband (reservoir manager)	German Weather Service stations Luedenscheid, Cologne-Bonn	Wupperverband (reservoir manager)	Wupperverband (reservoir manager), Helmholtz Centre for Environmental Research UFZ	Helmholtz Centre for Environmental Research UFZ	District Council Cologne and Ministry of Environment North Rhine-Westphalia	Karsten Rahn, Martin Wieprecht, Wilfried Scharf
Harp		Dorset Environmental Science Centre; Environment Canada	Dorset Environmental Science Centre				

Iseo	Regione Lombardia	Università degli Studi di Brescia; Bergamo-Orio al Serio Aiport; Regional Authority for Environmental Protection (ARPA Lombardia)	Consorzio dell'Oglio	Università degli Studi di Brescia; Prof. Letizia Garibaldi (Università degli Studi di Milano-Bicocca)			
Kinneret03	Kinneret Limnological Laboratory	Isr. Meeorl. Service; Kinneret Limnological Laboratory	Isr. Hydrological Service	Kinneret Limnological Laboratory, IOLR	Israel Water Authority	Israel Water Authority	
Kinneret97	As Above	As Above	As Above	As Above	As Above	As Above	As Above
Mendota	Wisconsin Departement of Natural Resources	SSEC-GAMIS-RIG UW-Madison; US National Climatic Data Center	U.S. Geological Survey	University of Wisconsin - Madison LTER program	University of Wisconsin, Madison	NSF grant DEB-0822700 (North Temperate Lakes Long-Term Ecological Research)	
MtBold	South Australian Water Corporation	Burea of Meteorology; South Australian Water Corporation, Happy Valley Reservoir	Department of Water and Natural Resources; SA Water Major Systems	South Australian Water Corporation	University of Adelaide, Adelaide, South Australia	Water Research Foundation, Boulder, CO, USA; South Australian Water Corporation	Mike Burch; Rob Daly;
Muggelsee	Leibniz Institute of Freshwater Ecology and Inland Fisheries (IGB)	Leibniz Institute of Freshwater Ecology and Inland Fisheries (IGB)	Senatsverwaltung für Stadtentwicklung und Umwelt Berlin	Leibniz Institute of Freshwater Ecology and Inland Fisheries (IGB)	Leibniz Institute of Freshwater Ecology and Inland Fisheries (IGB)	Leibniz Institute of Freshwater Ecology and Inland Fisheries (IGB)	Thomas Hintze (IGB) for operating the Müggelsee Lake Station.
NamCo	Institute of Tibetan Plateau Research, Chinese Academy of Sciences	Institute of Tibetan Plateau Research, Chinese Academy of Sciences			Institute of Tibetan Plateau Research, Chinese Academy of Sciences;Institut für Geographie, Friedrich-Schiller-Universität	the National Basic Research Program of China (2012CB956100), National Natural Science Foundation of China (41071123) and CADY project (TP2:03G0813F) from BMBF, Germany	
Oneida	National Oceanic and Atmospheric Administration; Cornell Biological Field Station	Northeast Regional Climate Center	United States Geological Survey	Cornell Biological Field Station	Cornell University	Cornell University Brown Endowment; New York State Department of Environmental Conservation; United States Department of Agriculture 0226747	Lars Rudstam

Pusiano	Water Research Institute - National Research Council of Italy (IRSA-CNR)	Regional Authority for Environmental Protection (ARPA Lombardia); National Oceanic and Atmospheric Administration	Water Research Institute - National Research Council of Italy (IRSA-CNR)	Water Research Institute - National Research Council of Italy (IRSA-CNR)	Parco Valle Lambro; Fondazione CARIPLO	Progetto PIROGA	Gianni Tartari and Franco Salerno (Water Research Institute - National Research Council of Italy (IRSA-CNR)
Rappbode	Reservoir authority of the state of Saxony-Anhalt (Talsperrenbetrieb Sachsen-Anhalt)	German Meteorological Service (DWD)	Rappbode Reservoir Authority (Talsperrenbetrieb Sachsen-Anhalt)	Fernwasserversorgung Elbaue Ostharz; Helmholtz Centre for Environmental Research - UFZ; Talsperrenbetrieb Sachsen-Anhalt	Helmholtz Centre for Environmental Research - UFZ		Karsten Rahn (UFZ, SEEFO); Martin Wieprecht (UFZ, SEEFO); Maren Dietze (Talsperrenbetrieb Sachsen-Anhalt); Dieter Noga (DWD); Marco Matthes (Fernwasserversorgung Elbaue Ostharz).
Rassnitzersee	Helmholtz Centre for Environmental Research - UFZ	German Meteorological Service (DWD)	Lausitzer and Mitteldeutsche Braunkohle Verwaltungsgesellschaft - LMBV	Uwe Kiwel(UFZ) and Karsten Rahn (UFZ)	Helmholtz Centre for Environmental Research - UFZ	Helmholtz Centre for Environmental Research - UFZ	Uwe Kiwel(UFZ) and Karsten Rahn (UFZ)
Ravn	National Monitoring Program for Water and Nature. Data hosted by Aarhus University.	Danish Meteorological Institute (DMI). Data made available for analyses relating to the National Monitoring Program for Water and Nature.	National Monitoring Program for Water and Nature. Data hosted by Aarhus University.	National Monitoring Program for Water and Nature. Data hosted by Aarhus University.	Aarhus University	CLEAR centre of excellence (Villum-Kann Rasmussen Foundation)	
Rotorua	Digitised bathymetry held by University of Waikato, Bay of Plenty Regional Council	Meteorological Service of New Zealand Limited. Data obtained via 'cliflo' database (National Institute of Water and Atmospheric Research (NIWA), New Zealand).	National Institute of Water and Atmospheric Research.	Bay of Plenty Regional Council	University of Waikato-Environmental Research Institute	Bay of Plenty Regional Council Chair in Lake Restoration at University of Waikato	

Stechlin		German Meteorological Service (DWD), Umwelt Bundesamt (UBA), Energiewerke Nord GmbH (Betriebsteil Kernkraftwerk Rheinsberg)		Leibniz-Institute of Freshwater Ecology and Inland Fisheries	Leibniz-Institute of Freshwater Ecology and Inland Fisheries	German Federal Ministry of Research and Education (BMBF Project KLIMZUG-INKABB TP22)	Peter Kasprzak
Tarawera	Digitised bathymetry held by University of Waikato, Bay of Plenty Regional Council	National Institute of Water and Atmospheric Research	Bay of Plenty Regional Council	Bay of Plenty Regional Council	University of Waikato-Environmental Research Institute	Bay of Plenty Regional Council Chair in Lake Restoration at University of Waikato	Andy Bruere
Toolik	Toolik Field Station - Environmental Data Center (TFS EDC). Jason J. Stuckey (TFS GIS Manager) performed a bathymetrical study of the lake in 2008 using a Garmin GPSMAP 188 Sounder	Meteorological datasets provided by the Toolik Field Station Environmental Data Center are based upon work supported by the U. S. National Science Foundation (NSF) under grants #455541 and #1048361	Arctic Long Term Ecological Research (ARC LTER), funded by NSF, Division of Environmental Biology (DEB) 0423385	(a) Arctic Long Term Ecological Research (ARC LTER); (b) Toolik Field Station - Environmental Data Center (TFS EDC), University of Alaska Fairbanks (UAF)	(a) Department of Ecology, Evolution, and Marine Biology, University of California, Santa Barbara, California; (b) Marine Science Institute, University of California, Santa Barbara, California	NFS Support, from two different grants of Arctic Natural Sciences (ANS) to Sally MacIntyre: #0714085 and #1204267	Adam Crowe
Windermere	Ramsbottom, A.E. 1976. Depth charts of the Cumbrian Lakes. Freshwater Biological Association	Centre for Ecology and Hydrology	Environment Agency	Centre for Ecology and Hydrology	University of Reading; Centre for Ecology and Hydrology	UKLEON (NE/I007407/1)	Bernard Tebay
Woods	Hydro Tasmania	Australian Bureau of Meteorology	Hydro Tasmania	Hydro Tasmania	University of Tasmania	ARC Linkage Grant LP130100756	Carolyn Maxwell, Leon Barmuta, Abhijeet Kulkarni, Aditya Singh
Zurich	David M. Livingstone	MeteoSwiss	Federal Office for the Environment (FOEN)	Wasserversorgung der Stadt Zürich (Zurich Water Supply)	Eawag: Swiss Federal Institute of Aquatic Science and Technology	Amt für Abfall, Wasser, Energie und Luft (AWEL) of the Canton of Zurich (Lake Monitoring)	