Collaborative Project (large-scale integrating project)
Grant Agreement 226273
Theme 6: Environment (including Climate Change)
Duration: March 1st, 2009 – February 29th, 2012

SEVENTH FRAMEWORK PROGRAMME

WISER

Water bodies in Europe: Integrative Systems to assess Ecological status and Recovery

DELIVERABLE

Deliverable D5.2-4: Internet tool (model to assess target loads) for lake managers

Lead contractor: **Finnish Environment Institute (SYKE)**

Contributors: **Olli Malve, Niina Kotamäki, Timo Huttula, Anita Pätynen, Antti Taskinen, Kai Rasmus**

Due date of deliverable: **Month 36**

Actual submission date: **Month 36**

Project co-funded by the European Commission within the Seventh Framework Programme (2007-2013)		
Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

Content

Non-technical summary

As the Water Framework Directive requires water bodies to be in good ecological status in the future, it is essential to be able to develop and apply tools that can be used for estimating the required pressure levels to achieve good status.

The eutrophication of European lakes was studied using a linear mixed effects chlorophyll a model which was fitted to 461 European lakes. The effect of total phosphorus, total nitrogen and water temperature on chlorophyll a concentrations varied within WFD affiliated lake types. The data structure was three-way nested as in every lake type there were several lakes and from every lake multiple chlorophyll *a* samples were taken. By using the linear mixed effects model for nested data we could substantially decrease the variation of this kind of data by selecting both the fixed effects and variance structure properly to get more reliable estimates. The statistical inference was based on Bayesian approach thus giving a more realistic assessment of the effect of model uncertainty.

Based on the data analysis of the European data set, the effect of climate warming on eutrophication proved to be positive. Thus, in warmer climatic conditions, a bigger reduction of nutrients is needed to achieve good ecological condition in a lake. For predicting phytoplankton response to the reduction of nutrient load and climate change, a chlorophyll *a* model was developed. This model was then included in the LakeLoadResponse (LLR) internet tool.

LLR tool delivers predictions on water quality status with statistical confidence intervals to give more insight for the management actions to be taken. The LakeLoadResponse (LLR) model tool has been developed in Finnish Environment Institute (SYKE) originally for Finnish river basin managers to ease the use of the models in lake management planning. During the WISER project the LLR tool has been further developed to answer the problems caused by the climate warming. Therefore the LLR user interface has been translated from Finnish to English and the data used in the modelling is from the large European database (WISER data). Open access internet tool LLR makes it easy to estimate needed reduction of nutrient load in a variety of climatic conditions. With LLR tool it is possible to test how the changes in water temperature and different risk levels affect the nutrient reduction needed. LLR produces water quality predictions with statistical confidence intervals to give more insight for the management actions to be taken.

LLR tool has been successfully used in Finland for river basin management. At the moment the beta version of European wide LLR tool has been tested. Although the preliminary results seem to be quite encouraging, the model has to be improved for some points and the LLR interface further updated.

Introduction

The Lake Load Response (LLR) internet tool has been developed for estimating required loading reduction to achieve good water quality, expressed as phosphorus, nitrogen and chlorophyll *a* concentrations or phytoplankton biomass. The predictions are based on the LakeState (LS) model, which consists of three components: 1) Chapra's (1975) model for retention of total phosphorus and nitrogen, 2) the hierarchical, linear regression model for chlorophyll *a* (Malve 2007) and 3) the logistic regression model for phytoplankton biomass (Kauppila P., Lepistö L., Malve O. & Raateland A. Unpublished). In LS, mechanistic and statistic models are combined using the Bayesian inference with the Markov Chain Monte Carlo (MCMC) simulation methods for obtaining water quality predictions with error estimations. This kind of approach is useful for experts in river basin management since uncertainties in the predictions can be taken into account and scaling of the treatments performed. In Figure 1 the mass balance and causal linkages in LLR tool have been demonstrated.

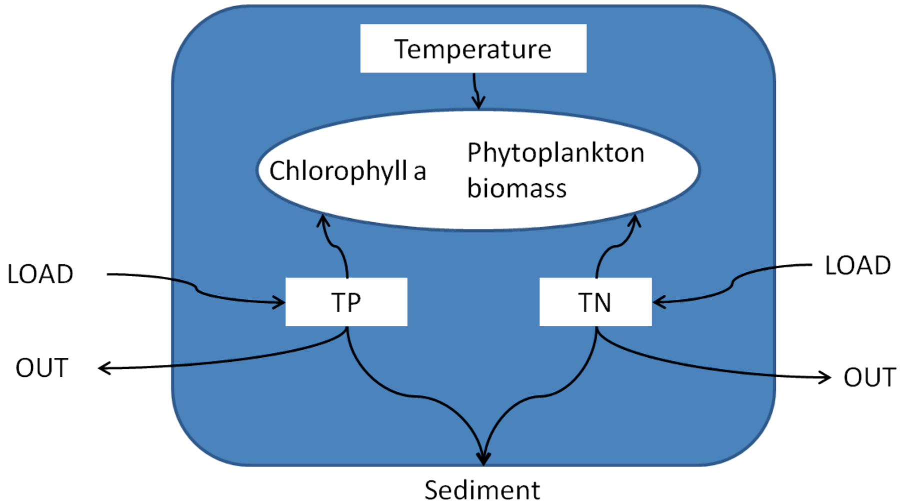


Figure 1.Mass balance and causal linkages in LLR model tool.

The hierarchical linear regression model based on relationship of nutrients and chlorophyll *a* concentrations has been further developed in the WISER project. A model with water temperature effect added was fitted to the data. The lake type effect was taken into account, as it has been shown that the chlorophyll-nutrients relationship is different in different lake types (Carvalho, 2008).

Material and Methods

Data

The main requirement in data sampling from the WISER data base was that there is a coexistence with total phosphorus (totP), total nitrogen (totN), water surface temperature (t) and chlorophyll *a* (Chla) observations. Most of the samples of the data set have been taken in the summer time, but there are also some observations from the winter time and quite many from early spring and late autumn (Table 1). In order to get as comprehensive picture as possible from the water temperature effects to chlorophyll *a*, we examined the data from two different temporal points of views. The whole data set (referred as "All data") has observations from all year round. In addition to analysis of the whole data set we also examined data that had values only from July and August (referred as "Jul-Aug").

Table 1: Number of Chla, totP, totN and temperature observations per month.

Jan	Feb	Mar	Apr	May	Jun	**Jul**	**Aug**	Sep	Oct	Nov	Dec
4	9	5	118	181	218	484	927	182	115	15	7

The two data sets have data from 21 intercalibrated lake types (more detailed description of lake types is found from EC (2008)). Group of lakes that have not been given a certain type has been pooled to two groups (LNX and LNU). The number of samples and lakes per country are shown in Table 2 and same information per lake type in Table 3.

Table 2: Overview of contents of the LLR model data per country: number of lakes and samples for chlorophyll a for the whole data set and for July-August data.

Country	All data Number of samples	July-August Number of samples	All data Number of lakes	July-August Number of lakes
BE (Belgium)	29	11	7	6
DE (Germany)	130	32	35	25
DK (Denmark)	24	6	1	1
FR (France)	7	2	2	2
LV (Latvia)	77	38	38	26
NL (Netherlands)	74	22	20	15
PL (Poland)	2	2	2	2
HU (Hungary)	28	7	11	5
FI (Finland)	636	467	141	140
IT (Italy)	32	2	1	1
NO (Norway)	2	2	1	1
SE (Sweden)	1224	820	202	202
Sum	**2265**	**1411**	**461**	**426**

Table 3: Overview of contents of the LLR model data per lake type: number of lakes and samples for chlorophyll a for the whole data set and for July-August data.

Lake type	All data Number of samples	July-August Number of samples	All data Number of lakes	July-August Number of lakes
LAL3	32	2	1	1
LCB1	198	67	62	48
LCB2	108	35	36	23
LCB3	37	11	7	6
LEC1	21	5	9	3
LEC2	7	2	2	2
LN1	34	25	12	11
LN11	21	19	7	7

LN2a	263	151	42	42
LN2b	2	2	2	2
LN3a	304	211	61	61
LN3b	175	107	30	30
LN5	74	61	16	16
LN6a	309	207	57	57
LN6b	25	25	7	7
LN7	23	17	5	5
LN8a	286	181	22	22
LN8b	13	13	4	4
LN9	14	13	4	4
LNU	10	10	3	3
LNX	309	247	72	72
Sum	**2265**	1411	461	426

The whole data set characterizes more of the dynamic variation of species and phytoplankton production annually, whereas the July-August situation is about the summer primary production maximum and variation of phytoplankton abundance there. Obviously water temperature does have an effect to plankton abundance. The effect in late summer is more straightforward, as for the whole data set the temperature effect is mixed with inter annual dynamic variation of the phytoplankton. The variation in the temperature in summer time is smaller and the possibility to get the effect of changing temperature is thus harder. Thus, the analysis of the whole data may give more insight to the effects of the water temperature than July-August data alone.

Histograms, scatter plots and correlations between the variables are shown in Figure 2. Prior to analysis nutrients and chlorophyll *a* were logarithmically transformed (base 10) to meet the assumptions of regression analysis: to ensure that variables are normally distributed and their variances are homogeneous. The correlations between log-scaled chlorophyll *a* and the predictors are relatively strong (Fig. 2). The correlation between log(Chla) and log(totP) is 0.72 and between log(Chla) and log(totN) is 0.60. The correlation between surface water temperature and log(Chla) is lower (0.23) but it can roughly be assumed that when the water gets warmer the concentration of chlorophyll *a* grows somewhat linearly. The correlation between the predictor variables TotN and TotP is 0.77. High correlation between the main nutrients is usually the case in this kind of observational data. We tested the variance inflation factor (VIF) which was under 5 for all the possible predictor variables. This means that the predictor variables are not strongly related and does not hinder the reliability of the analysis.

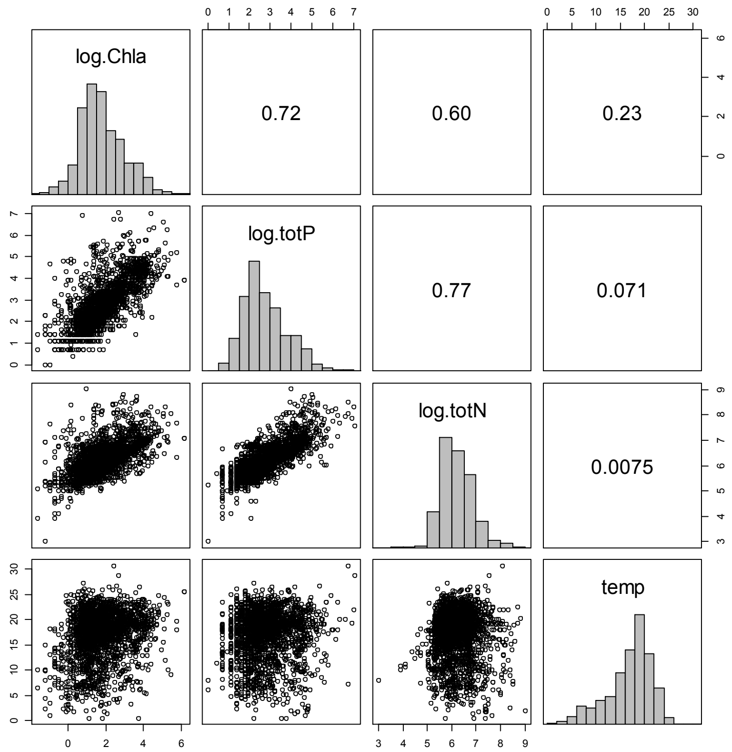


Figure 2 Histograms, scatter plots and correlations between the variables for the whole data set.

It is known that the trophic status of different lake types varies. The substantial variation in chlorophyll *a* concentrations between the lake types is clearly demonstrated in Figure 3 that shows box plots of chlorophyll *a* conditional on lake type. The lowest medians are in Northern GIG type LN7 and the highest is in Central European and Baltic GIG types (LEC, LCB). There are some differences of chlorophyll *a* concentrations between the data sets. E.g. LEC lake types that are in Hungary the differences are obvious, although there are not many observations from there. Also for Central Europe and Baltic countries' types (LCB) the median concentrations and variations are somewhat different in late summer and in the whole data set.

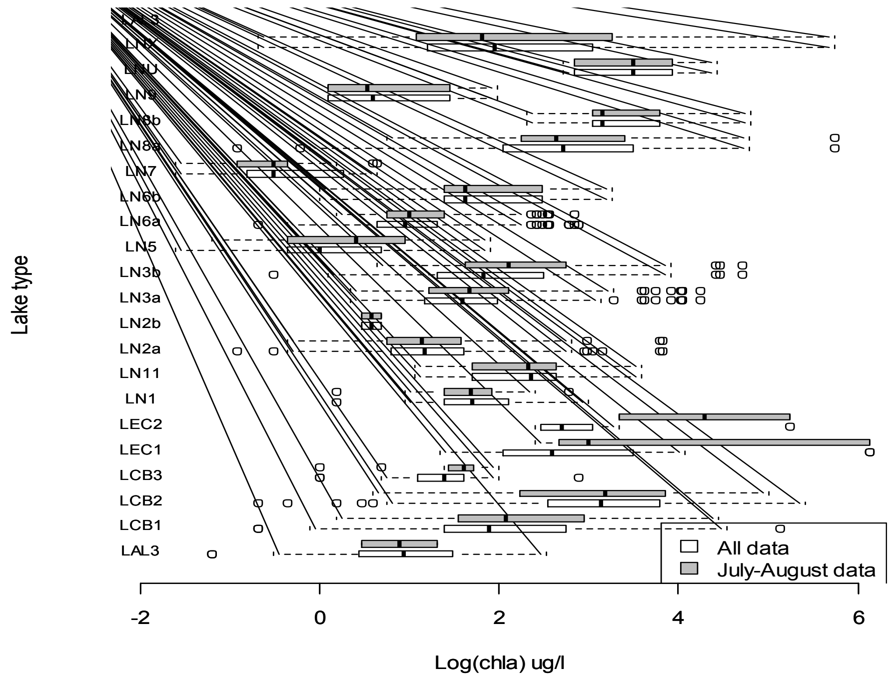


Figure 3 Box plots of of log(Chla) [µg/l] concentrations in each lake type for the whole data set (white boxes) and for July-August data (grey boxes).

The variation of surface water temperatures for lake types are shown in Figure 4. The differences between the lake types is due to the fact that the types are grouped by geographical location (i.e. GIGs). Naturally there is also substantial variation between the two data sets. The variation in the whole data set for some lake types is bigger that in the data set oft he late summer. Especially this is the case for Northern European lake types (NGIG, types LN).

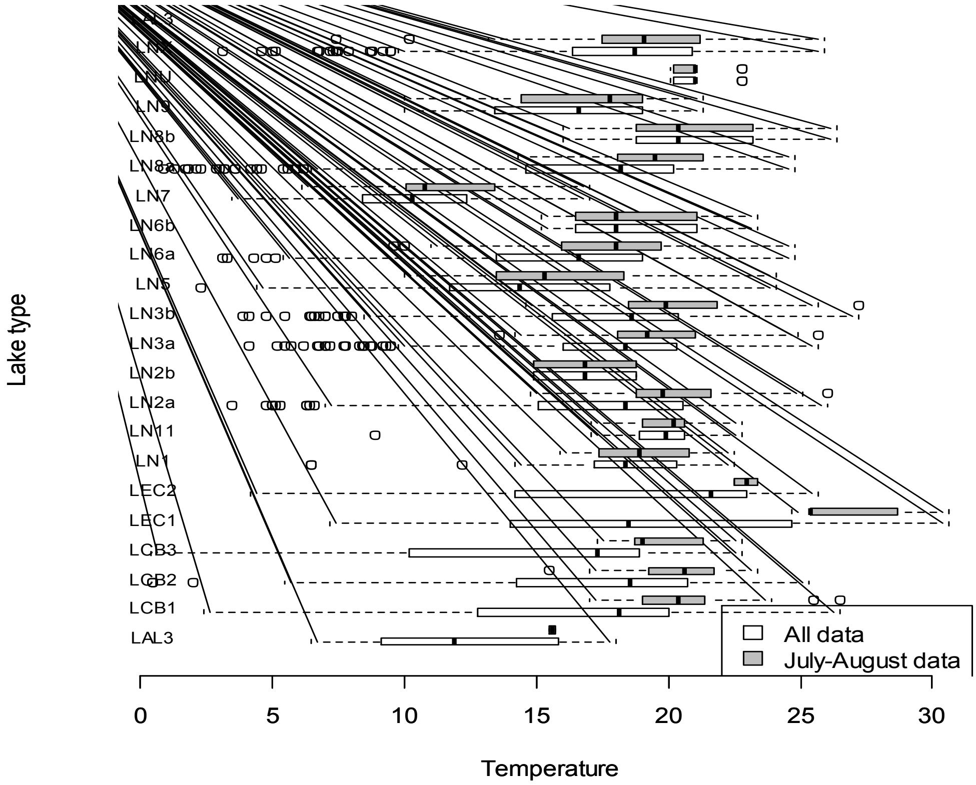


Figure 4 Box plots of surface water temperature in each lake type for both the whole data set (white boxes) and for July-August data (grey boxes).

A regression tree for the whole data set of the possible model parameters is shown in Figure 5. The most influential predictor of chlorophyll *a* concentration is TotP concentration. When TotP is more than 37.75 µg/l, the surface water temperature also plays a role. TotN concentration seems to be important predictor of chlorophyll *a* concentration when totP is under 57.5 µg/l and the water temperature is under 24.25 °C. When temperature is higher than this, nitrogen is no longer important predictor of chlorophyll *a*.

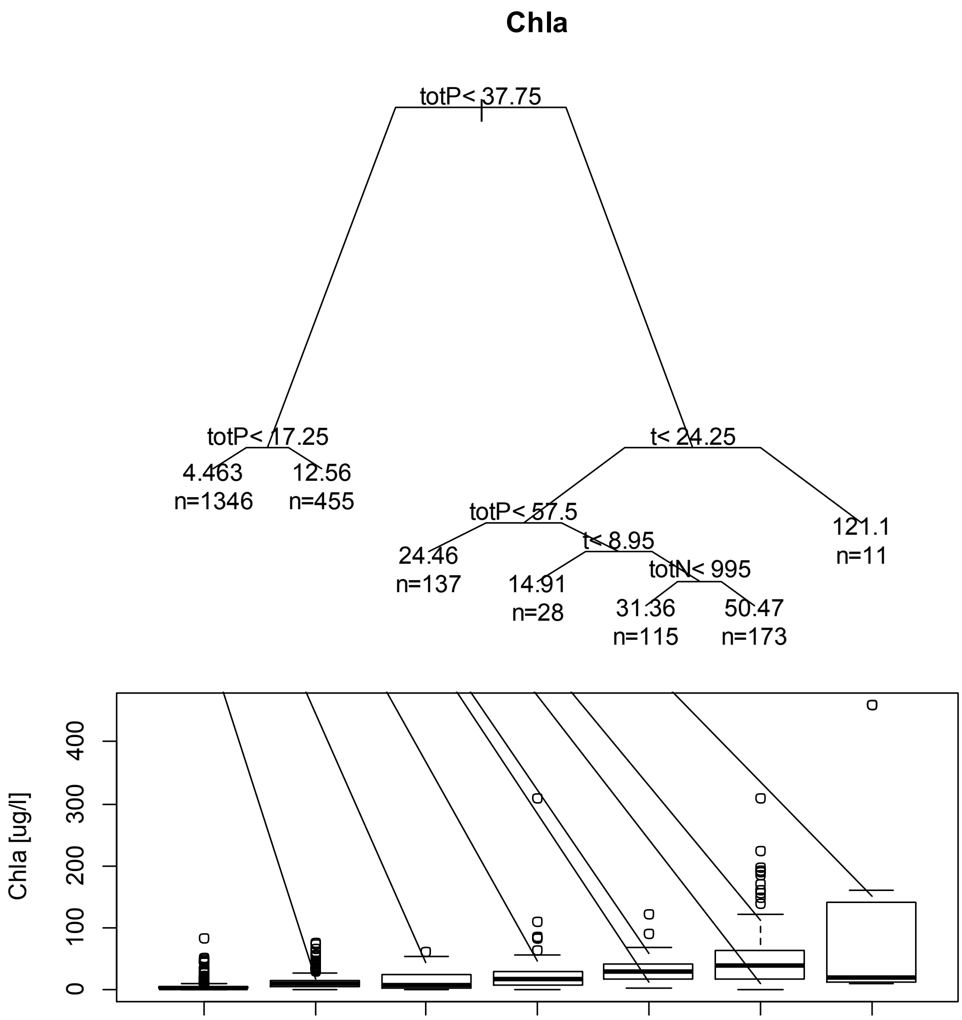
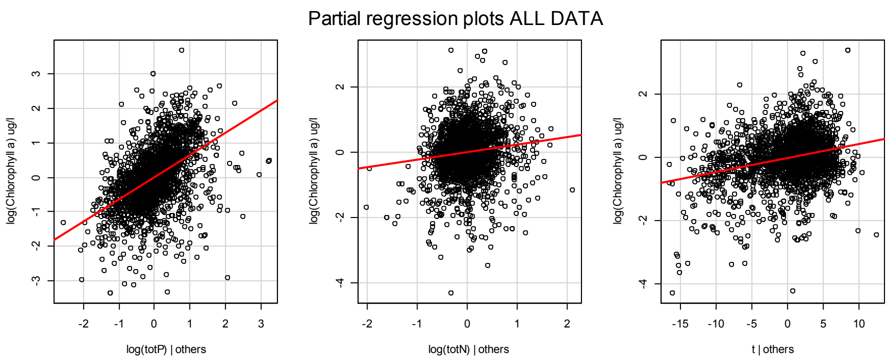


Figure 5 Regression tree for WISER data with the distribution of the Chla [µg/l] in each leaf depicted by a box plot. The terminal nodes oft he tree are chlorophyll-a mean values and the values oft he box plot are medians of Chlorophyll a.

The regression tree and the partial regression plots (Figure 6) are shown to illustrate the structure of the data set and the relationships between log(Chla) and the predictor variables. In partial regression plot it can be seen that in the late summer data (July-August) the temperature effect is clearly weaker than in the whole data set (the right most plots).



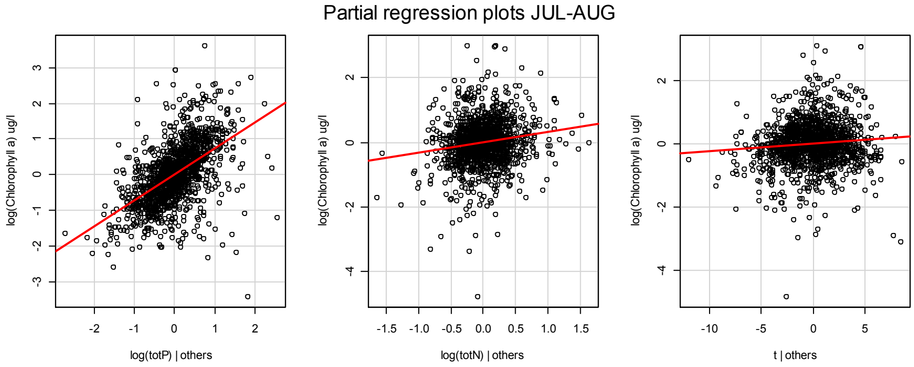


Figure 6 Partial regression plots for the whole data set and for late summer data.

Temperature effects to chlorophyll *a* concentrations for different lake types can be seen in Figure 7. For July-August it seems that for LEC types the effect is very strong. But as there are only few data points we can not say anything about this relationship. Nevertheless there seem to be some kind of linear relationship between chlorophyll *a* and water temperature for some lake types. And the relationships seem to be stronger fort he whole data set than fort he late summer data. In Figures 8 and 9 the scatter plots and linear regression lines are drawn for chlorophyll *a* and the total nutrients (Fig. 8 for totP and Fig 9 for totN). It is clear that phosphorus affects the chlorophyll most, and this is the case for most of the lake types in both data sets. Same stands for totN. Some negative relationships are due tot he fact that there are not enough data points.

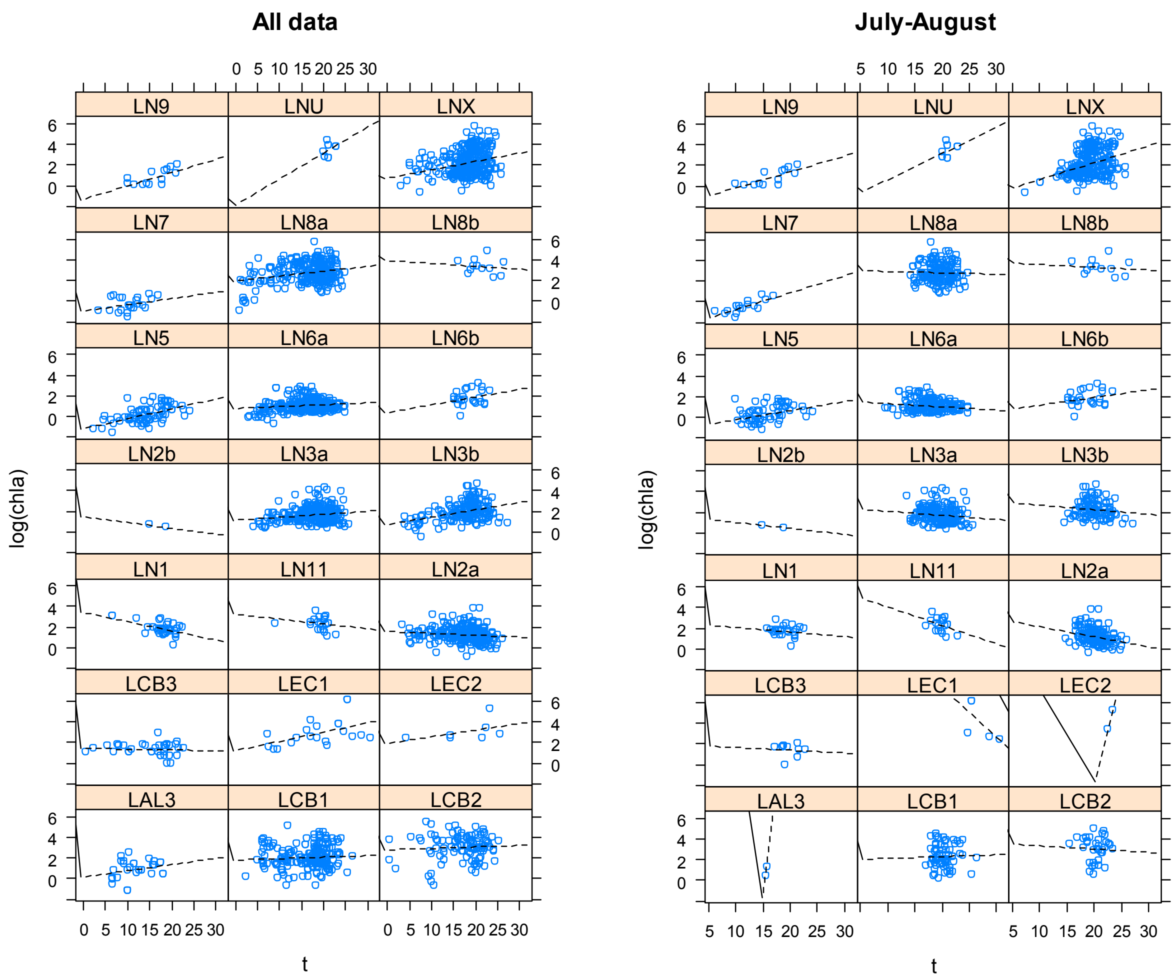


Figure 7 Scatter plots and linear regression lines (dashed line) of log(Chla) [µg/l] and temperature [°C] for lake types in both data sets.

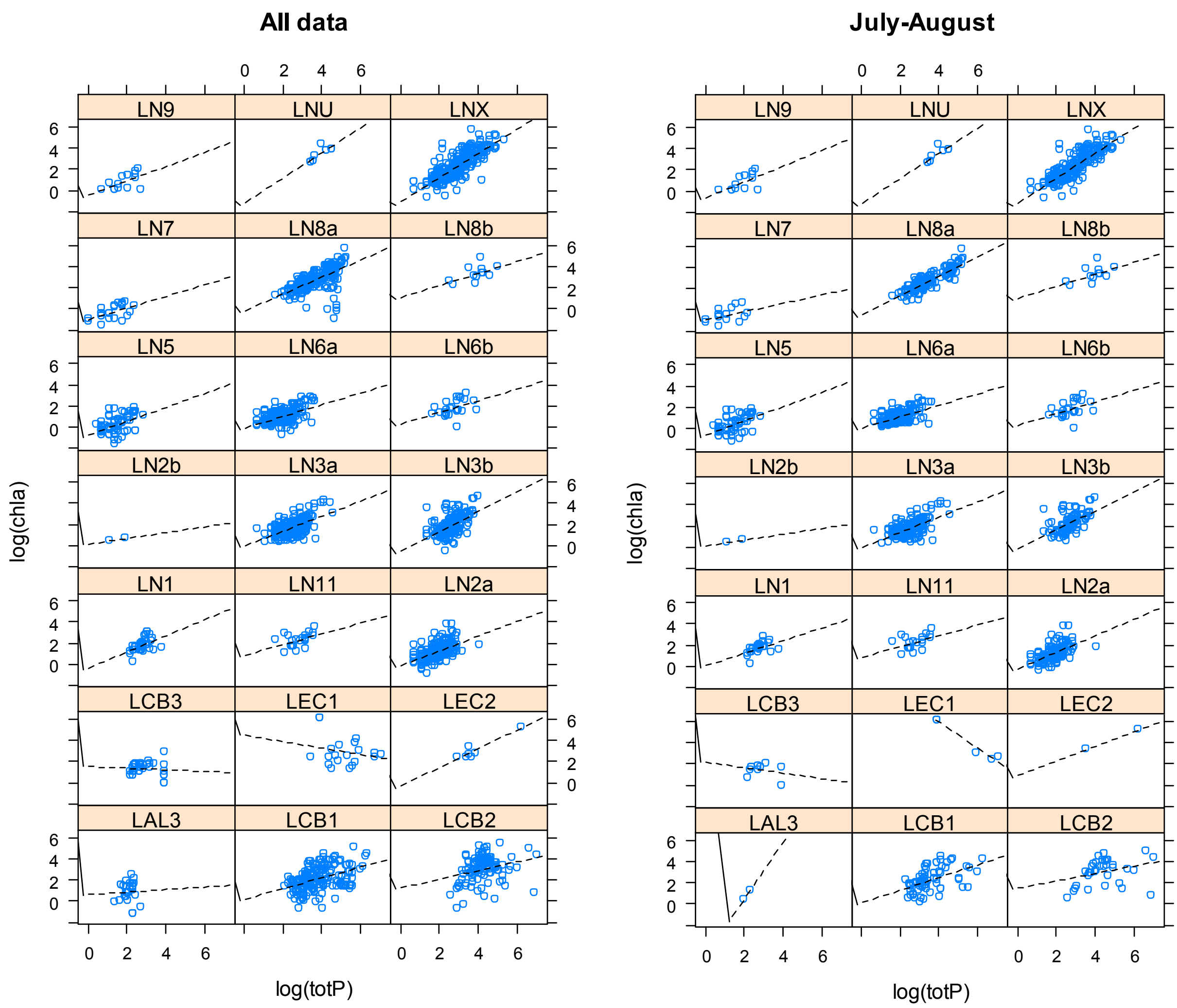


Figure 8 Scatter plots and linear regression lines (dashed line) of log(Chla) [µg/l] and log(totP) [µg/l] for lake types in both data sets.

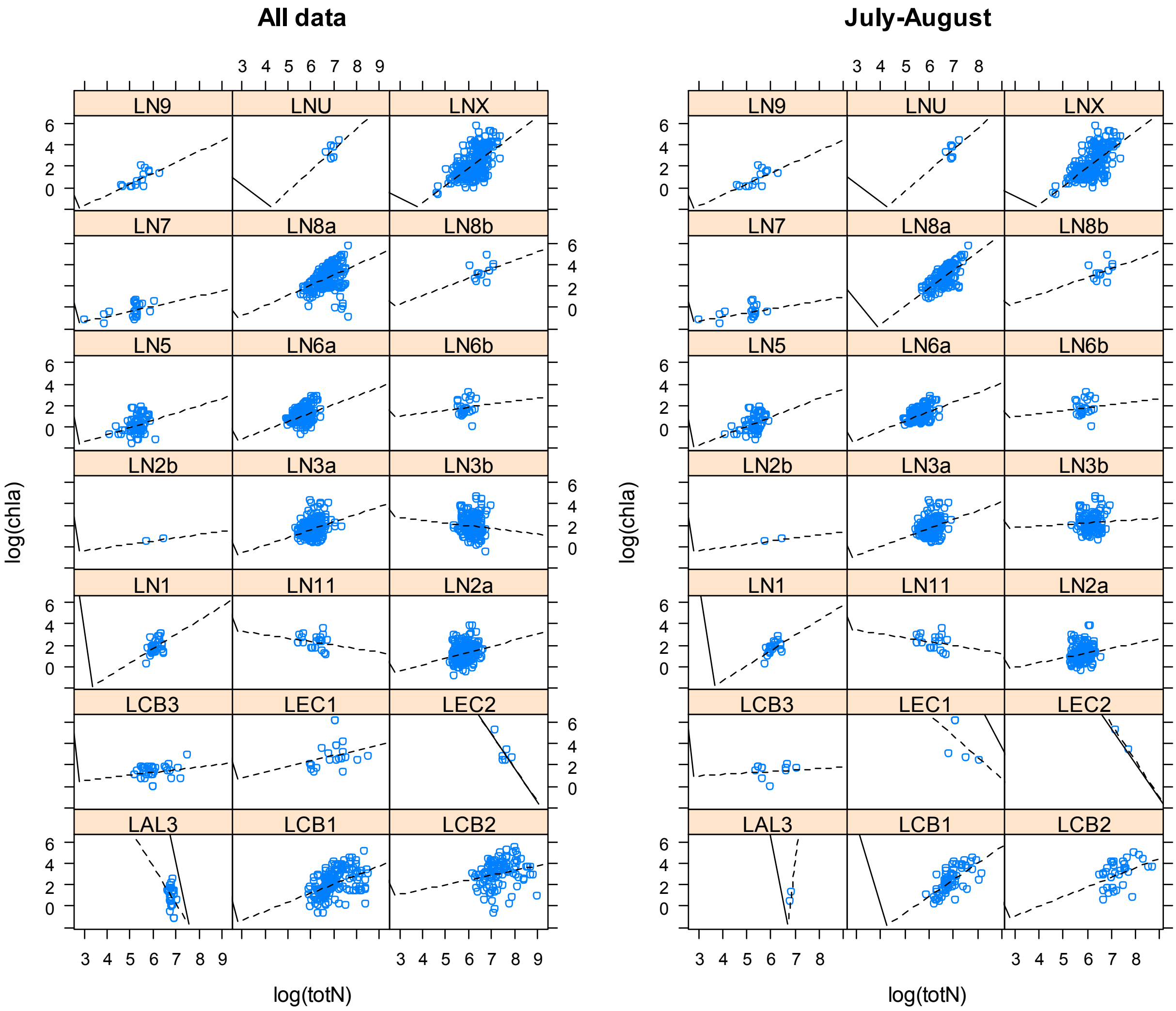


Figure 9 Scatter plots and linear regression lines (dashed line) of log(Chla) [µg/l] and log(totN) [µg/l] for lake types in both data sets.

Methods

As we could see the chlorophyll *a* response to nutrients and water temperature can be assumed to be linear. Although using linear regression models requires several assumptions concerning the normality and homoscedasticity of the variables, independence of observations and deterministic nature of variables. In natural sciences, violating these assumptions is usually the case. There were differences in the responses of the nutrients and temperature to chlorophyll *a* in several lake types. These differences have to be taken into account. One approach would be to fit a linear regression model for all lake types separately. This kind of approach is used widely, but it doesn't conduct sufficiently the whole information of the data. This heteroscedasticity and different responses in the lake types can be dealt with by using (hierarchical) mixed effects models. Mixed effects models allow different lake types to have different variation. Also the observations from the same lake within the lake type may correlate and this violates the assumptions of the traditional regression analysis. With mixed effects models this correlation can be considered properly.

There is plenty of literature available from the mixed effects models. One good book for ecologists is Zuur 2009. This is how linear mixed model is described e.g. in SPSS Technical report: "In a linear mixed-effects model, responses from a subject are thought to be the sum (linear) of so-called fixed and random effects. If an effect affects the population mean, it is fixed. If an effect is associated with a sampling procedure (e.g., subject effect), it is random. In a mixed-effects model, random effects contribute only to the covariance structure of the data. The presence of random effects, however, often introduces correlations between cases as well. Though the fixed effect is the primary interest in most studies or experiments, it is necessary to adjust for the covariance structure of the data."

Linear mixed effects models simply model the fixed and random effects as having a linear form. The basic notation of linear mixed effects model in matrix form is

$$Y_i = X_i\beta + Z_i b_i + \varepsilon_i,$$

$$b_i \sim N(0, D),$$

$$\varepsilon_i \sim N(0, \Sigma_i),$$

where

Y_i is the $n_i \times 1$ response vector for observations in group i.
X_i is the $n_i \times p$ model matrix for the fixed effects for observations in group i.
β is the $p \times 1$ vector of fixed-effect coefficients.
Z_i is the $n_i \times q$ model matrix for the random effects for observations in group i.
b_i is the $q \times 1$ vector of random-effect coefficients for group i.
ε_i is the $n_i \times 1$ vector of errors for observations in group i.
D is the $q \times q$ covariance matrix for the random effects.
Σ_i is the $n_i \times n_i$ covariance matrix for the errors in group i.

To find a proper model that deal with both fixed and random part of the model properly, we tested several linear mixed models and compared them. All the models had the same fixed variables (the main effects of the nutrients and temperature) as we know that they do have a linear relationship with chlorophyll *a* concentration. This was also proven with a generalized linear model with only the model error term in the random part (M_gls). This model doesn't take into account the nested structure of the data. We then added a random type intercept to the model (M_type). This model seemed to be more sufficient although it didn't deal with the fact that also the lakes within the type are correlated and the observations are not independent. So we added a random intercept term for all lakes (M_lake). As we could see from the previous figures (Fig 7, 8 and 9), the slopes of the linear regression lines of different lake types seemed to be somewhat different. That is why we added a random slope term for lake type (M_type_slope).

These three models were fitted by restricted maximum likelihood method (REML). Because of the same estimation method and the fact that the models have exactly the same fixed effects form, the models can be compared with so called Akaike's information criterion (AIC) and likelihood ratio test. The homogeneity of the model residuals was also examined. (Model comparison and validation will be presented in more detail in forthcoming publication.)

	Df	AIC	Chisq	p-value
M_type	6	4966.876	NA	NA
M_lake	7	4573.9	394.9755	6.83E-88
M_type_slope	16	4478.483	113.4167	2.96E-20

The AIC value for the model that has random intercept and slope for type and random intercept for lake (M_type_slope) is smallest (AIC=4478), indicating that this is the best model of these three. Also the likelihood ratio test indicates that the model with the random type intercept and slope (M_lake) is considerably better than the model without random slope (M_type_slope) (Chisq=113.4, p<<0.001). For this model the residuals are nicely around the zero line indicating that there is no heterogeneity in the residuals.

Therefore the best model according to AIC, likelihood ratio tests and residual analysis is the model that has random intercept and slopes for types and random intercept for lakes.

The final chlorophyll *a* model is of the form:

$$chla_{ijk} = \underbrace{totP_{ijk} + totN_{ijk} + temp_{ijk}}_{fixedeffects} + \underbrace{u_k + u1_{j|k} + u2_{j|k} + u3_{j|k}}_{randomeffectsoftypes} + \underbrace{v_{j|k}}_{Rrandomeffectsoflakes} + \underbrace{\varepsilon_{ijk}}_{errorterm}$$

where

$chla_{ijk}$	is the log scale chlorophyll *a* concentration from sample *i* from lake *j* of lake type *k*
$Ltotp_{ijk}$	is the log scale total phosphorus concentration from sample *i* from lake *j* of lake type *k*
$totn_{ijk}$	is the log scale total nitrogen concentration from sample *i* from lake *j* of lake type *k*
$temp_{ijk}$	is the temperature from sample *i* from lake *j* of lake type *k*
u_k	is the random intercept of type *k*, allows for variation between the lake types, normally distributed with mean 0 and variance σ_{type}^2
$u1_{j\|k}$,$u2_{j\|k}$,$u3_{j\|k}$	is the type specific random slopes for totP, totN and temp
$v_{j\|k}$,	is the a random intercept of lake *j* of type *k*, allows for variation between the lakes, normally distributed with mean 0 and variance σ_{lake}^2
ε_{ijk}	is the model error term.

This model was then used in MCMC model runs, so the posterior distributions of the model parameters could be simulated. This way the uncertainties of the model results can be properly taken into account. As we can estimate the uncertainty of the model results, we get more precise loading reductions by reducing the model uncertainty. By doing this we can focus on to the right nutrient reduction methods and thus save money from doing e.g. too drastic and expensive reductions.

All the data analysis and model runs were done by using R software (R Development Core Team, 2011). Mixed models were fitted with `lmer`-package (Bates et. al, 2011) and the MCMC runs were done by `MCMCglmm`-package (Hadfield, 2010).

Results

The mixed effects models with random intercept and slope for lake types and random intercept for lakes were fitted to the whole data set and to July-August data in a Bayesian framework using Markov Chain Monte Carlo (MCMC) methods. The box plots of the posterior distributions of MCMC runs separately for both data sets are shown in Figure 10. The fixed effects differ in the way that in the whole data the phosphorus effect is stronger than in the late summer data. Also the fixed global temperature effect is slightly clearer in the whole data than in the July-August data. Temperature effect in different lake types in July-August is not significant as could be anticipated. Although for the whole data set there are lake types that have significant temperature effect on chlorophyll *a*. E.g. for Northern GIG lake types (LN3a, LN3b and LN8a) the temperature effect is significant and positive.

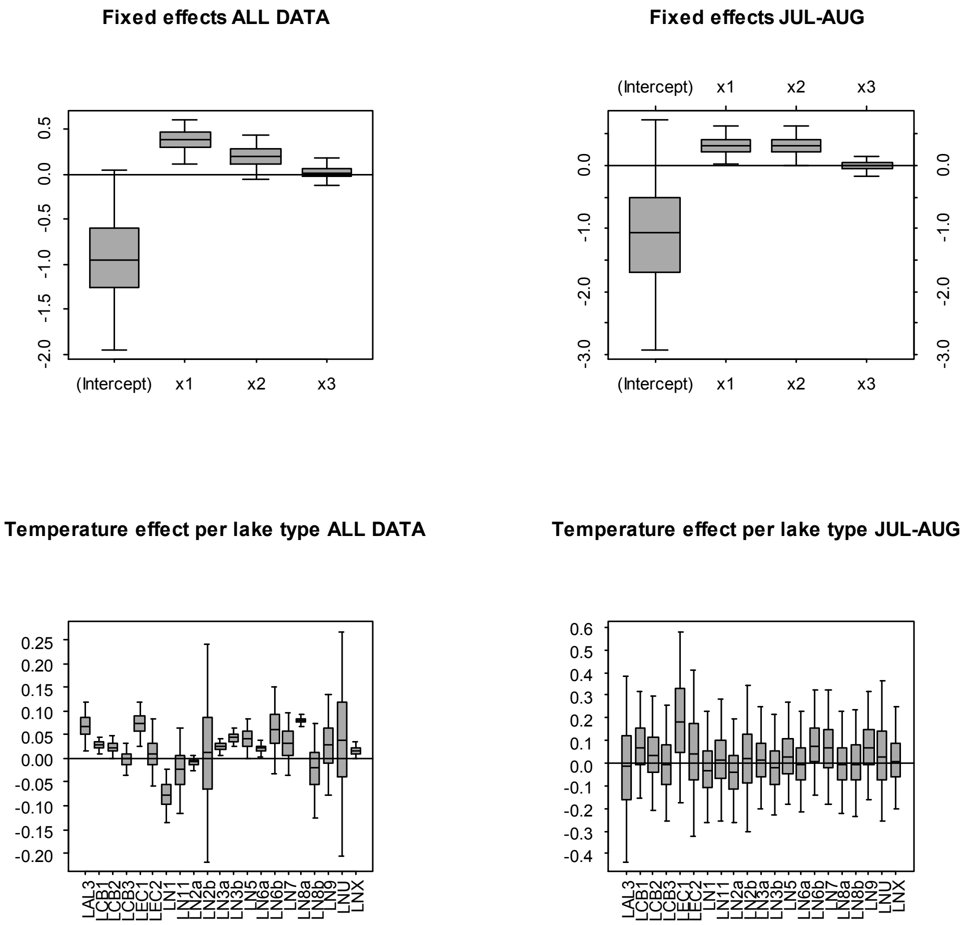


Figure 10 Box plots of fixed effects (Intercept=constant, x1=log(totP), x2=log/totN9, x3=temp) and temperature effect in lake types for the whole data set and for July-August data.

Although the temperature effect is not very strong globally, it can clearly be identified for some lake types. In Figure 11 the effect of temperature to chlorophyll *a* is simulated for all lake types. For most of the types the effect is modest but for previously mentioned types it can clearly be seen that increase of lake temperature increases also the chlorophyll *a* concentration.

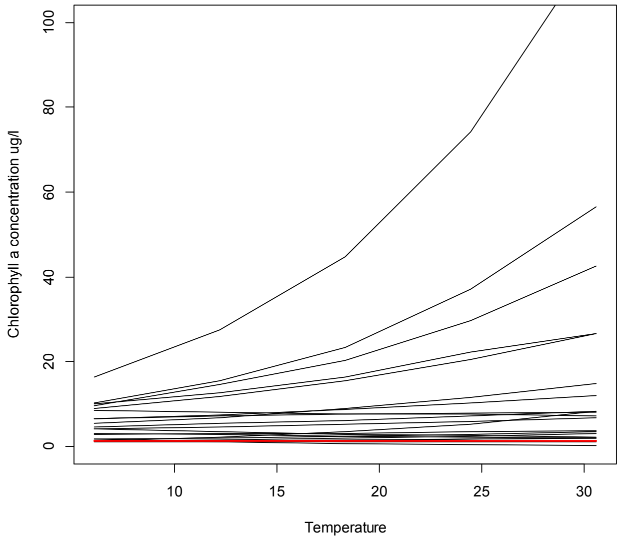


Figure 11 Chlorophyll a and temperature relationship within different types. Red line denotes the general model. Temperature is varied within the observational range and nutrients are kept constant (median).

The hierarchical chlorophyll *a* model with temperature effect was implemented in the LakeLoadRespose (LLR) tool. LLR is open access, web based tool (http://lakestate.vyh.fi/). It is relatively easy to use and the user interface has help pages that shortly guides how to use the tool. In Figure 12 there is a view of the LLR tool's front page and input form. First the user chooses which variable he wishes the loading reductions to be estimated with. The phytoplankton (chlorophyll *a*) model can be used to estimate the effects of the nutrient loading and climate change scenarios.

In the web pages there is more information about the projects which have funded the development of the tool, basic information about the LLR tool and the models and help pages that shortly guides how to use the tool.

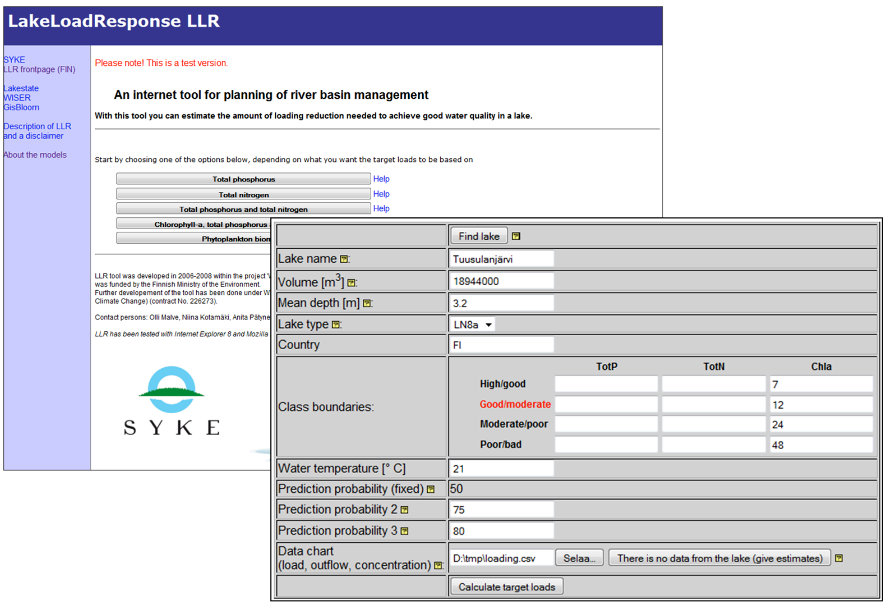
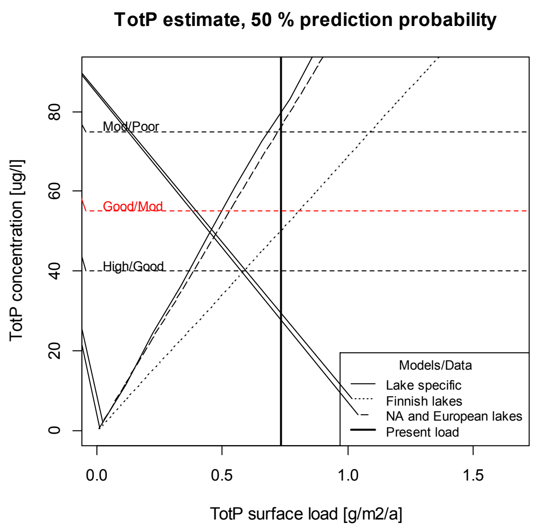


Figure 12 A view of the LLR user interface: the front page and the input form.

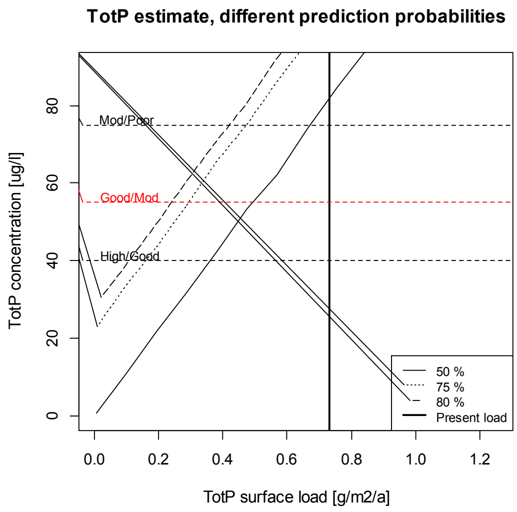
As a result, LLR gives several figures that show the nutrient loading reduction with different risk levels and with different variables. The information of the loading reductions is also shown in table format.

The results of LLR tool and the hierarchical chlorophyll *a* model are demonstrated here shortly for Lake Tuusulanjärvi in Southwest Finland. Lake Tuusulanjärvi is quite shallow, mean depth is only 3.2 m, and maximum depth is 9.8 m. Surface area is 6 km^2 and volume $19x10^6$ m^3. Theoretical retention time of the lake is 250 days. Lake Tuusulanjärvi is quite eutrophied lake and it has been classified to lake type LN8a (= lowland, shallow, moderate alkalinity, mesohumic.)

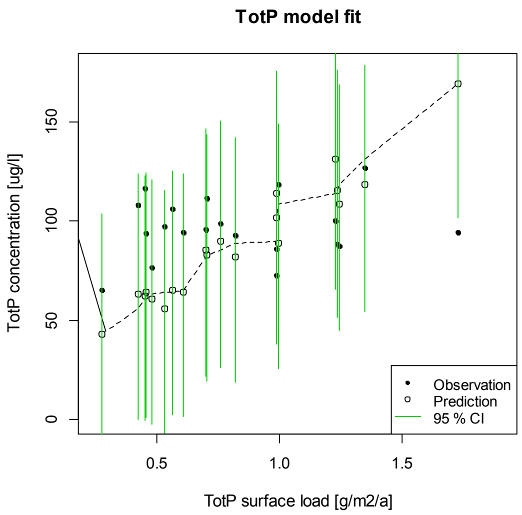
The first three figures show the results of the nutrient models.



Estimates of three models for total phosphorus concentration as a function of phosphorus loading. The horizontal lines indicate the lake type specific class boundaries of total phosphorus concentration, of which the most important is the Good/Moderate status class limit. The amount of loading reduction for reaching a certain boundary can be estimated.



Effect of different prediction probabilities on the estimate of the lake specific model. Reaching good water quality with higher probability means bigger reduction to loading.



From the graph you see how well the model predictions (solid line) fit the observations (circles). The verticals represent the 95 % confidence intervals.

The interesting part of the model results are the results of the chlorophyll *a* model. The results are shown with the model fitted to the whole data set. In Figure 13 is the main result of chlorophyll *a* model. From the set of level curves it can be seen the phosphorus - nitrogen loading combinations with which the chlorophyll *a* concentration stays below the good/moderate status class limit. The arrows indicate the model estimate of the chlorophyll-a concentration with present loading. The black solid lines denote the present water temperature situation (observed median for the lake) and the red dashed curves are in the situation of climate warming in the sense of +5°C warmer temperature. As can be seen the loading reduction must be bigger in the warmer lake water temperature.

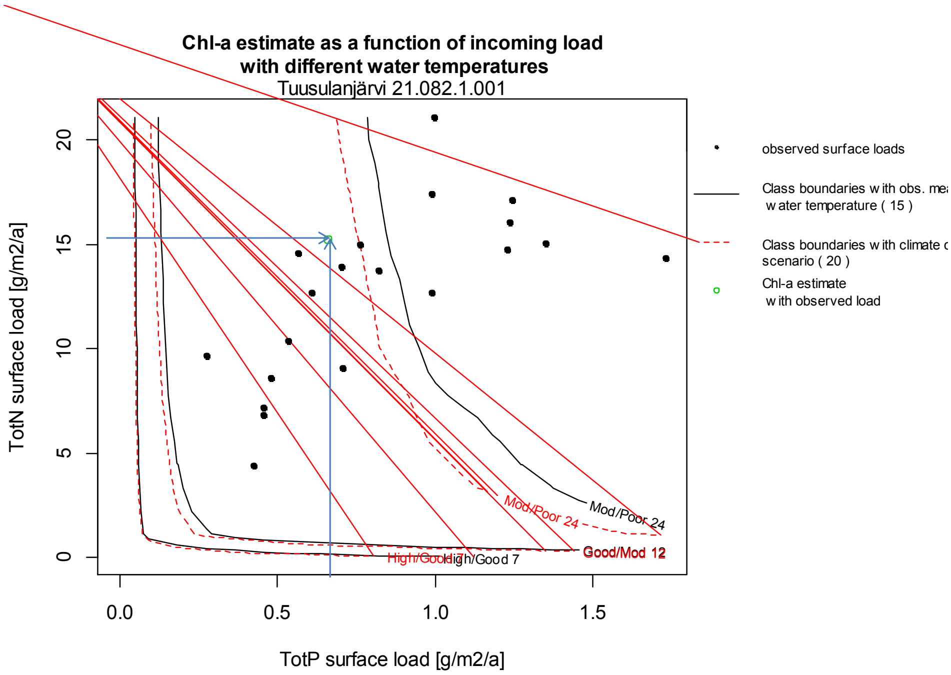


Figure 13 LLR result of chlorophyll a model: Estimate for chlorophyll-a concentration in Lake Tuusulanjärvi as a function of phosphorus and nitrogen loading (g/m^2/a) to the lake for present temperature situation (black solid line) and for 5°C warmer water (red dashed line).

Summary and Discussion

The eutrophication of European lakes was studied using a linear mixed effects chlorophyll a model which was fitted to 461 European lakes. The effect of total phosphorus, total nitrogen and water temperature on chlorophyll a concentrations varied within WFD affiliated lake types. The data structure was three-way nested as in every lake type there were several lakes and from every lake multiple chlorophyll a samples were taken. By using the linear mixed effects model for nested data we could substantially decrease the variation of this kind of data by selecting both the fixed effects and variance structure properly to get more reliable estimates. The statistical inference was based on Bayesian approach thus giving a more realistic assessment of the effect of model uncertainty.

Based on the data analysis of the European data set, the effect of climate warming on eutrophication proved to be positive. Thus, in warmer climatic conditions, a bigger reduction of nutrients is needed to achieve good ecological condition in a lake. For predicting phytoplankton response to the reduction of nutrient load and climate change, a chlorophyll *a* model was developed and included in the LLR tool.

The LLR tool is easy to use and it is freely accessible through internet. Low data requirements makes it helpful tool for less studied lakes. As LLR produces water quality predictions with statistical confidence intervals it gives more insight for the management actions to be taken. The advanced statistical methods used in the modelling makes the results more confident and the uncertainty is also estimated properly. Nevertheless LLR tool is a beta version and it will to be further developed. Also for lakes that have substantial internal loading the nutrient models are not sufficient at the moment.

LLR tool will be developed further in many perspectives. However the idea is still to keep the models relatively simple and the data requirements modest. In Finland the LLR tool is planned to be used as a classification tool for the lakes that has not been classified yet.

In GisBloom project (Life+ 2010-2013), LLR will be demonstrated to Finnish river basin and lake managers using a web based map service which integrates all the necessary data and a set of related models www.environment.fi/syke/gisbloom. If combined with a map-based web service, the model can help water managers illustrate the forecasted effects in maps. For instance, the effect of fisheries management and interaction with other plankton indicators will be analyzed using extensive data from Finnish lakes in the GisBloom project (Life+ 2010–2013).

References

Bates, D., Maechler, M. and Bolker, B. 2011. lme4: Linear mixed-effects models using S4 classes. R package version 0.999375-42. http://CRAN.R-project.org/package=lme4

Carvalho, L.; Solimini, A.; Phillips, G.; van den Berg, M.; Pietilainen, O.-P.; Lyche Solheim, A.; Poikane, S.; Mischke, U.. 2008 Chlorophyll Reference Conditions for European Lake Types used for

Intercalibration of Ecological Status. Aquatic Ecology, 42 (2). 203-211. doi:10.1007/s10452-008-9189-4

Chapra S. 1975. Comment on "An empirical method of estimating the retention of phosphorus in lakes" by W. B. Kirchner and P. J. Dillon. Water Resour. Res. 11: 1033-1034.

EC, 2008. COMMISSION DECISION of 30 October 2008 establishing, pursuant to Directive 2000/60/EC of the European Parliament and of the Council, the values of the Member State monitoring system classifications as a result of the intercalibration exercise.

Hadfield, J. D. 2010. MCMC Methods for Multi-Response Generalized Linear Mixed Models: The MCMCglmm R Package. Journal of Statistical Software, 33(2): 1-22.

URL http://www.jstatsoft.org/v33/i02/.

Kauppila, P., Lepistö, L., Malve, O., Raateland, A. Predicting phytoplankton blooms and their species dominance relationships in Nordic clear-water and humic lakes. UNPUBLISHED

Malve, O. 2007. Water quality prediction for river basin management. PhD. thesis, Helsinki University of Technology. 126 pp.

R Development Core Team. 2011. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.)

Technical Report: Linear mixed effects modeling in SPSS® An Introduction to the MIXED Procedure. http://www.spss.ch/upload/1107355943_LinearMixedEffectsModelling.pdf