

# NETLAKE toolbox for the analysis of high-frequency data from lakes



## Factsheet #9

### Determination of whole-column metabolism from profiling data

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#### *Objective*

Aquatic metabolism is a fundamental descriptor of ecosystem functioning in lakes. At an ecosystem scale, the metabolism represents the overall rates of production and consumption of organic matter, and is thus informative of the lake carbon balance (Staehr et al. 2012b). Rates of primary production and respiration in lakes are increasingly estimated from diel variations in free-water dissolved oxygen (DO) concentrations (Staehr et al. 2010). While most of the free-water approaches to lake metabolism rely on measurements from a single sonde placed in the epilimnion, increasingly common automated profiling systems allow the determination of metabolic rates along the whole water column (Obrador et al. 2014; Staehr et al. 2012a).

This technique allows determination of metabolic rates, gross primary production (GPP), ecosystem respiration (ER) and net ecosystem production (NEP) for different depth layers along the water column as well as areal, depth-integrated, rates (i.e. per unit area).

#### *Specific application*

We used this technique in Obrador et al. (2014) to quantify the relative contribution of the different depth layers to the total metabolism of the water column, and to assess the importance of mixing regime and light availability on the vertical patterns of metabolism in three stratified temperate lakes.

#### *Background*

This methodology requires previous knowledge on lake metabolism and on the basic procedures to determine metabolic rates from high-frequency oxygen data (Staehr et al. 2010, Hanson et al. 2008, see also Woolway 2016). Basic statistical knowledge, programming skills (R, SAS, Matlab), and some modelling experience are also required.

## Type of data and requirements

- High-frequency profiling data on:
  - Dissolved oxygen (DO)
  - Temperature (T)
- High-frequency data on:
  - Light attenuation ( $K_d$ ).
  - Wind speed
  - Incident Photosynthetically Active Radiation (PAR)

Data should be at least hourly frequency. The vertical resolution depends on the aim of the work, but at least one measurement in epilimnion, metalimnion and hypolimnion are required.

If high-frequency  $K_d$  values are not available, a simple light model from the optically active water components can be constructed, or  $K_d$  can be estimated from Secchi disk measurements.

## Basic procedures

### DATA ARRANGEMENT AND INITIAL CALCULATIONS

1. Align all input data with time so that all measurements of DO ( $DO_z$ ) and T ( $T_z$ ) at each depth  $z$  correspond in time. For slow profiling systems, it is possible to apply a temporal smoothing or to interpolate the data.
2. Calculate PAR for each time step and depth ( $PAR_z$ ) from incident PAR and  $K_d$  values.
3. Determine epilimnion, metalimnion and hypolimnion depths for each time step, using appropriate definitions, such as the bottom of the epilimnion ( $Z_{mix}$ ) being the shallowest depth at which the density gradient exceeds a certain threshold. These calculations can be easily done with Lake Analyzer (Read et al. 2011).
4. Create a table with  $DO_z$ ,  $T_z$  and  $PAR_z$  values, together with epi-, meta- and hypolimnion depths as well as the wind speed at each time step.
5. Calculate physical fluxes for each depth and time step. Calculate **diffusive air-water gas exchange** ( $D_s$ , only considered above  $Z_{mix}$ ) from the gas transfer velocity for oxygen, and the water-atmosphere oxygen gradient using a standard method (for example Crusius and Wanninkhof 2003, but see Bade 2009 and Woolway 2016 for more details). Calculate flux between adjacent depth layers due to **mixed-layer deepening** ( $D_z$ ) using changes in  $Z_{mix}$ . Calculate **vertical diffusive flux** ( $D_v$ ) using an estimated vertical diffusivity (for example, Hondzo and Stefan 1993).

### METABOLIC CALCULATIONS

7. Calculate the rates of change in DO ( $\frac{\Delta O_2(z)}{\Delta t}$ ). These are the rates of change in DO between two consecutive time steps for each depth layer  $z$ .
8. Calculate  $NEP_z$  for each time step and depth. Obtain high-frequency NEP rates at each depth from the model describing the dynamics in DO

$$\frac{\Delta O_2(z)}{\Delta t} = NEP_z + Dz_z - Dv_z - Ds_z \quad \text{Eq. (1)}$$

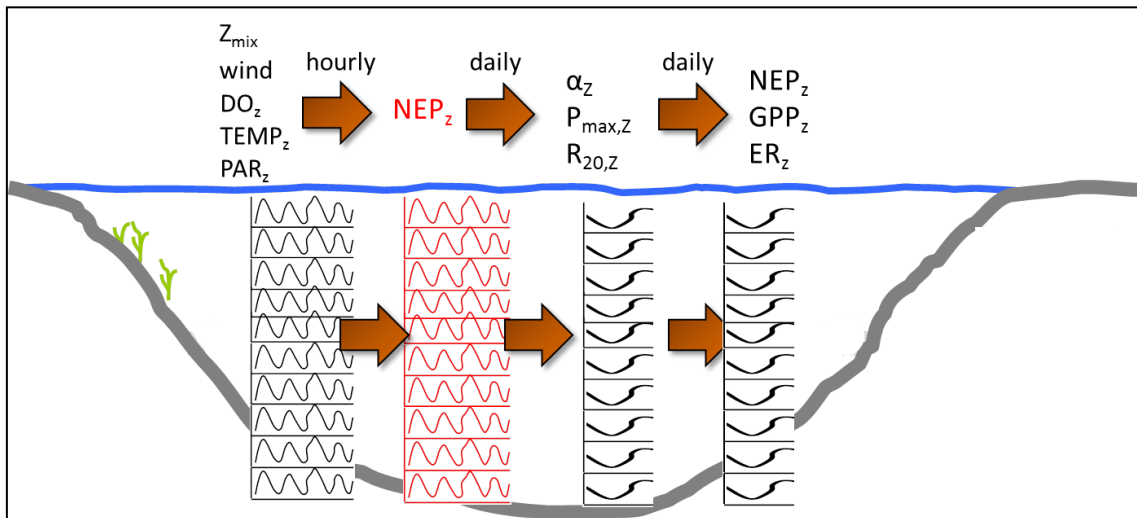
- Estimate daily physiological parameters for each depth layer. Use a light-dependent photosynthesis model combined with a temperature-dependent respiration model (Hanson *et al.* 2008).  $NEP_z$  equals photosynthesis ( $GPP_z$ ) minus respiration ( $ER_z$ ) at each depth layer  $z$ .

$$NEP_z = GPP_z - ER_z \quad \text{Eq. (2)}$$

Using, for example, the Jassby and Platt (1976) light saturating model of photosynthesis and a  $Q_{10}$  of 2 for respiration, the equation describing  $NEP_z$  from depth-specific light and temperature is:

$$NEP_z = P_{\max,z} \tanh\left(\frac{\alpha_z PAR_z}{P_{\max,z}}\right) - R_{20,z} 1.07^{(T_z - 20)} \quad \text{Eq. (3)}$$

where  $P_{\max,z}$ ,  $\alpha_z$ , and  $R_{20,z}$  are the maximum photosynthetic rate, the light use efficiency and the respiration rate at 20°C, respectively, at each depth  $z$ .



**Figure 1.** General approach to obtain daily metabolic rates by fitting mechanistic metabolic models to high-frequency profiling data.

- Apply non-linear fitting between modelled and observed DO data on a fitting window of 24 hours to estimate the parameters  $P_{\max}$ ,  $\alpha$ , and  $R_{20}$  at each depth for each day. The parameter estimation can be done by traditional least squares or maximum likelihood fitting methods or by implementing the model in a Bayesian framework (see Honti 2016 and Woolway 2016 in this booklet).
- Calculate hourly  $GPP_z$ ,  $R_z$  and  $NEP_z$  rates from Equations 2 and 3.
- Integrate the data over 24 hours to obtain the daily depth-specific  $GPP_z$ ,  $R_z$  and  $NEP_z$  rates.
- Integrate the depth-specific rates over the whole water column to obtain the daily areal rates.

## *Pitfalls and tips*

- This methodology is an improved version of the methods used in Staehr et al. (2012a) mainly in the use of a mechanistic modelling approach rather than the traditional book-keeping approach.
- A strict control of units is fundamental, particularly regarding the sign convention of fluxes.
- Changing the size of the smoothing window, or using variance control methods like Kalman filtering can help increase the signal-to-noise ratio in very noisy datasets (Batt and Carpenter 2012).
- The estimate of vertical diffusion can be improved with high-resolution profiles and more advanced mechanistic calculation methods (Imberger 1985).
- The technique can be modified to work with discrete depth data (i.e. from sondes placed at fixed depths along the water column).

## *Further reading*

### **Key References:**

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## **Code**

The code for this technique was written in Statistical Analysis System (SAS) and is available upon request.

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## **Suggested citation**

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