

# LAKE SURFACE WATER TEMPERATURE AUTOCORRELATION FUNCTION

Margarita Choulga, LEGMC

Ekaterina Kurzeneva, FMI

Laura Rontu, FMI

Kalle Eerola, FMI

Homa Kheyrollah Pour, UW, EC

# Contents:

- ▶ Background
- ▶ Introduction into the objective analysis
- ▶ Main objective of the study
- ▶ LSWT observations
- ▶ Estimation of the autocorrelation function
- ▶ Sensitivity experiments with the HIRLAM NWP system
- ▶ Conclusions & Future plans

# Background

- ▶ Lakes occupy about 1,8% of the land surface, and are distributed very unevenly.
- ▶ Lakes influence local weather conditions and local climate. Especially in Canada, Scandinavian peninsula, Finland, northern Russia including Siberia, etc.
- ▶ Lakes can influence global climate through carbon cycle in lakes (Tranvik et al. 2009), thermokarst lakes (Walter et al. 2007, Stepanenko et al. 2011).

surface heat,  
moisture and  
momentum fluxes

atmospheric  
conditions

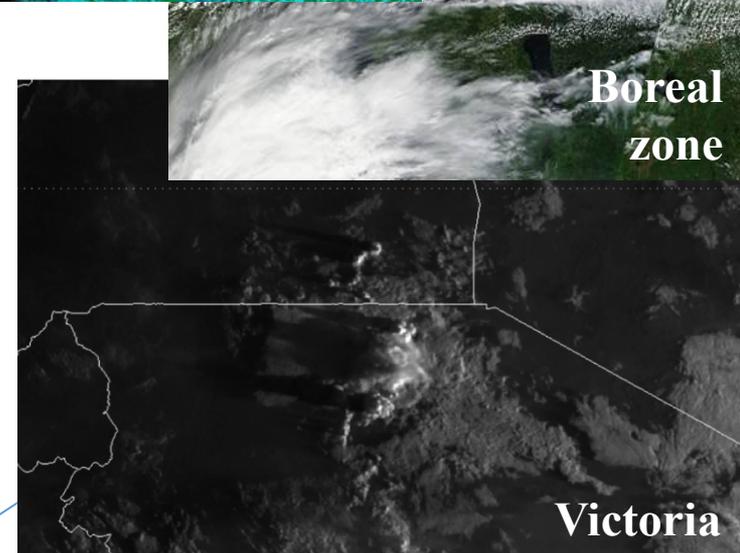
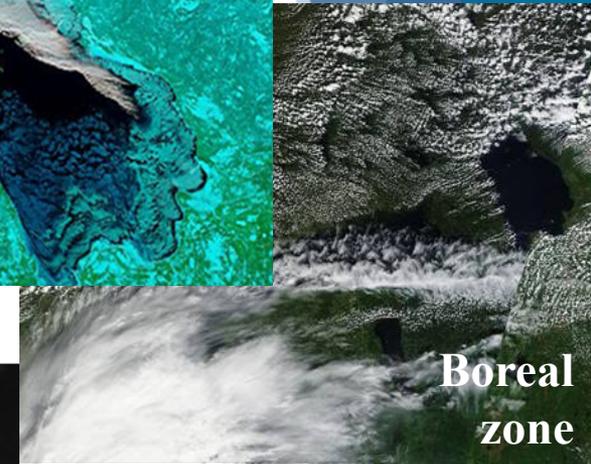
properties of the  
land cover

largely determined  
by inland water  
bodies  
(in lake-rich areas)

# Background: examples of the lake influence ...

Lake influence the local weather conditions and local climate in various ways.

- *Great lakes (USA)*: intensive winter snowstorms;
- *Lake Ladoga (Russia)*: low clouds, increase of surface temperature;
- *Boreal zone*: decrease of summer precipitation;
- *Lake Victoria (Africa)*: night convection, intensive thunderstorms → death of thousands fisherman every year.



## Surface fluxes

surface energy balance  
(during lake freezing and melting)

lake surface radiative and conductive properties

latent and sensible heat released from lakes to the atmosphere

Structure of the atmospheric boundary layer

# Objective analysis

- ▶ Lake Surface Water Temperature (LSWT) → lake heat fluxes → critical to measure, assimilate and predict in NWP!
- ▶ **Objective analysis** (minimizes errors of the analysis) → observation-based description of the lake surface state (uses weighting factors based on statistical properties of the analyzed field)
- ▶ **Optimal interpolation** (OI) → the best possible initial value of a prognostic variable at each grid-point by using all available information (observations + model state)
- ▶ OI univariate setup → weight of a certain observation depends on the distance between the observation and the grid-point and the distance between this and the other observations (Gandin, 1965)
- ▶ **Autocorrelation functions** incorporate information about the statistical structure of the field of the considered variable
- ▶ Often an exponential representation is used, where the influence radius  $L$  becomes a tuning value (~~density of observations~~ → real statistical properties of the fields!)
- ▶ Currently in the operational analysis of LSWT the autocorrelation function is borrowed from the SST analysis,  $L = 80 \text{ km}$

$$\mu(\rho) = e^{-\frac{\rho^2}{2L^2}}$$

Error of each observation type + background error are taken into account!

No reason why statistical properties of LSWT and SST should be similar!

# Main objective of the study:

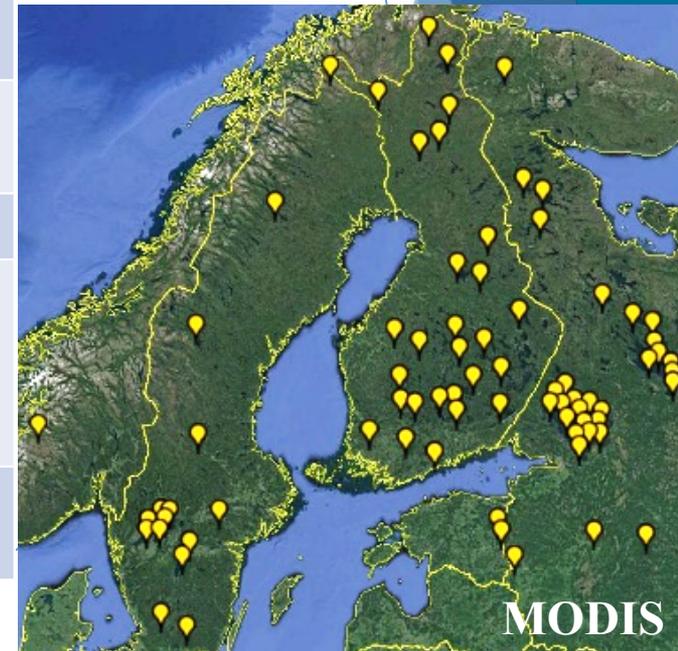
- ▶ to study the LSWT autocorrelation function (ACF) as an internal property of the LSWT field
- ▶ to obtain improved ACF formulation for use in the objective analysis in NWP models.
  - calculate observation statistics depending on the distance between the observation points as well as on the lake depth differences for:
    - local in-situ – provided by SYKE\* for different lakes in Finland;
    - satellite-based – consist of MODIS\*\* data over Fennoscandia and North-Western Russia;
  - estimate the observation error for these two types of measurements;
  - calculate new autocorrelation functions.

\* SYKE – Finnish Environment Institute

\*\* MODIS – Moderate Resolution Imaging Spectroradiometer

# LSWT observations

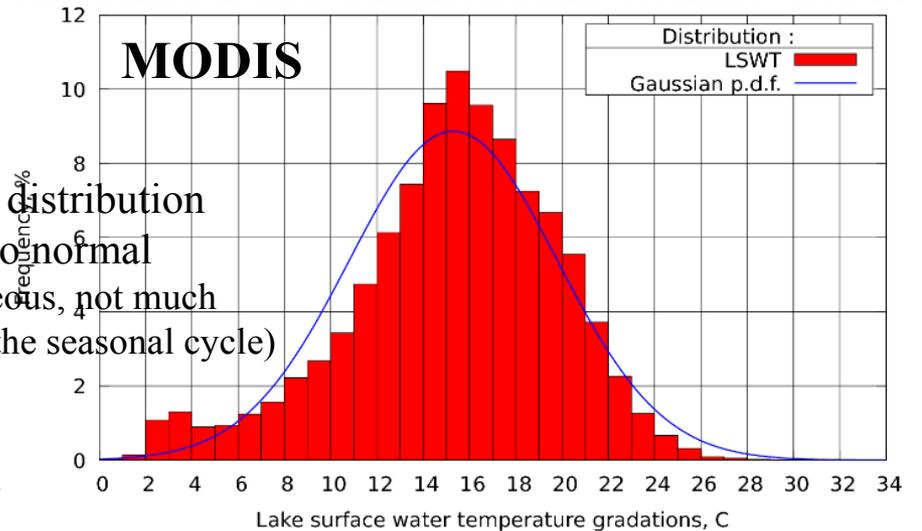
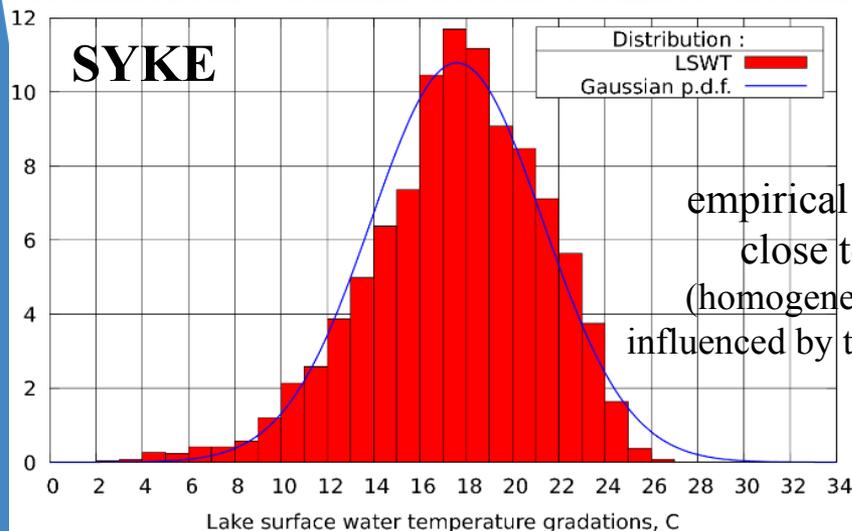
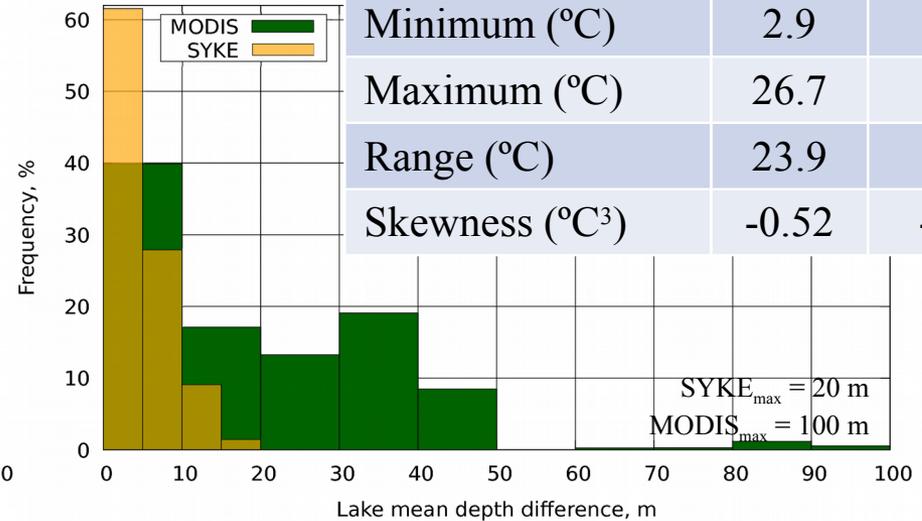
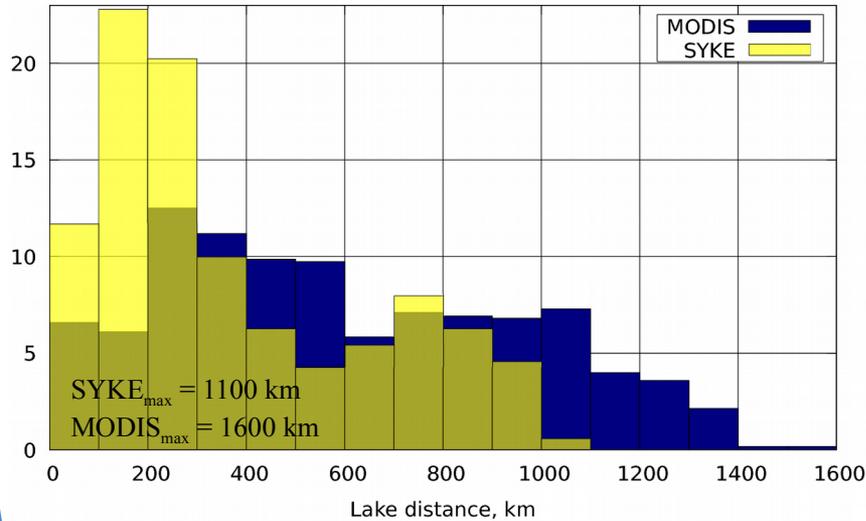
| Data  | SYKE   | MODIS   |
|---|--|---|
| Period  | 5 summers (JJA) of 2010–2014                             |   |
| Type  | regular in-situ  | satellite derived   |
| Measurements  | once a day<br>(8.00 local time)                          | daily averages (day- and<br>night-time obs.)                |
| Place   | 20 cm below the<br>water surface,<br>close to lake shore | close to SYKE location,<br>but far enough from the<br>shore |
| Represent<br>temperature                                      | daily minimum  | thin uppermost layer of<br>water (skin)                     |
| Restrictions  | only during the<br>ice-free season                       | cloud cover,<br>ice cover                                   |
| Amount of lakes   | 27   | 44 (71 pixel)   |
| Amount of daily<br>measurements<br>(% of maximum<br>possible) | 12 227<br>(98.6 %)                                       | 20 694<br>(63.4 %, due to clouds)                           |
| Pre-processing<br>applied                                     | no   | moving averages $\pm 24$ h,<br>threshold $\pm 3$ degrees    |



# LSWT observations: statistics

MODIS data are more uniformly distributed than SYKE

| Statistics                  | SYKE  | MODIS |
|-----------------------------|-------|-------|
| Mean (°C)                   | 17.6  | 15.3  |
| Median (°C)                 | 17.5  | 15.5  |
| Variance (°C <sup>2</sup> ) | 13.7  | 20.3  |
| Std. deviation (°C)         | 3.7   | 4.5   |
| Minimum (°C)                | 2.9   | 0.6   |
| Maximum (°C)                | 26.7  | 31.0  |
| Range (°C)                  | 23.9  | 30.4  |
| Skewness (°C <sup>3</sup> ) | -0.52 | -0.55 |



# Obtaining the autocorrelation function

Determination of the autocorrelation function for LSWT with dependency on the horizontal distance and the depth difference between lakes requires a reliable and homogeneous observational network (Gandim, 1965).

▶ time average  $\bar{f}(r)$

▶ deviation from this time average  $f'(r) = f(r) - \bar{f}(r)$

▶ distance categories 0-100, 100-200, ..., till 600 km, depth categories 0-5, 5-10 m or 0-10, 10-20 cm, etc.

▶ structure function  $b(r_1, r_2) = \overline{[f'(r_1) - f'(r_2)]^2}$

▶ autocorrelation function  $m(r_1, r_2) = \overline{f'(r_1)f'(r_2)}$

▶ observation error variance  $\sigma^2$

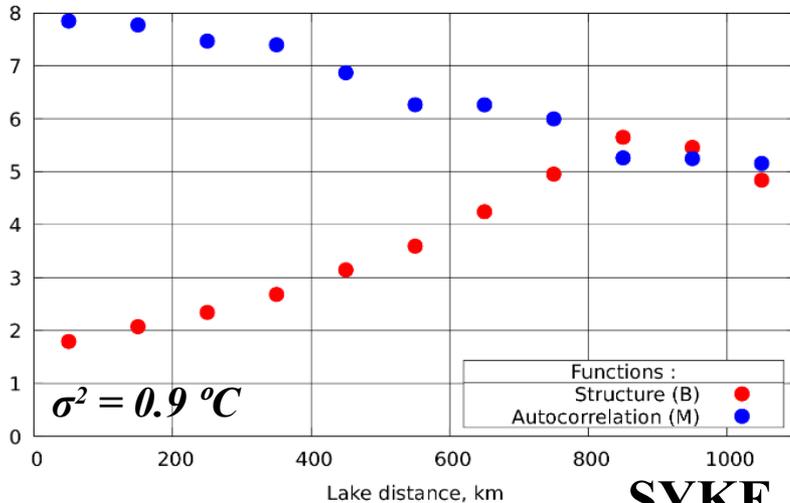
▶ total variance of LSWT observations within each category

▶ normalized autocorrelation function  $\mu(\rho) = \frac{m(\rho)}{f'^2}$

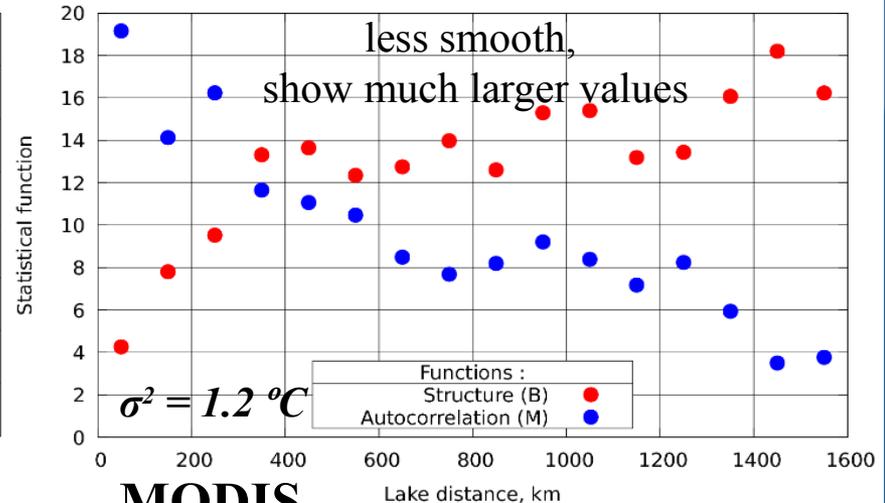
influence of observation errors was taken into account

# Estimation of the autocorrelation function: 2D

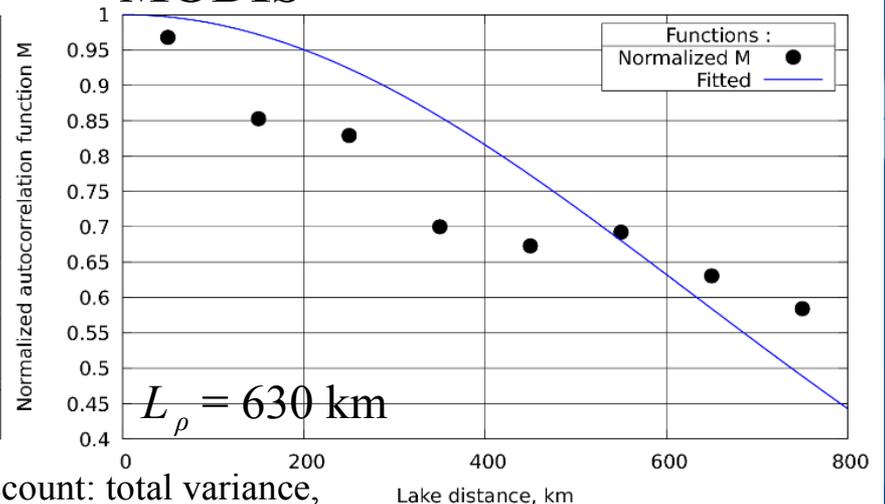
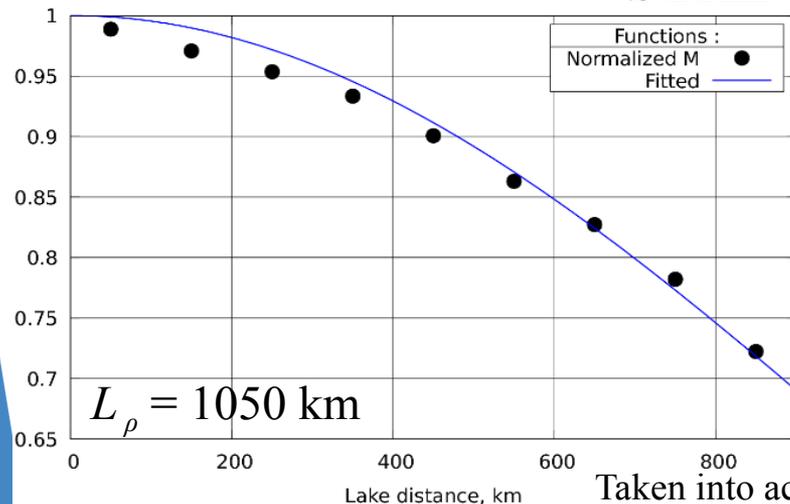
$$\mu(\rho) = e^{-\frac{\rho^2}{2L^2}}$$



**SYKE**

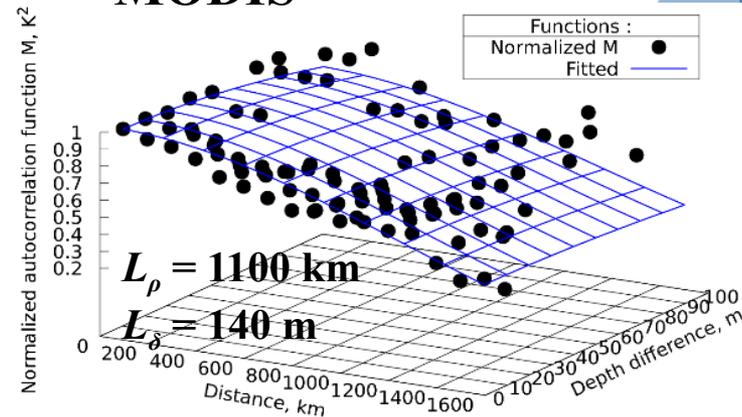
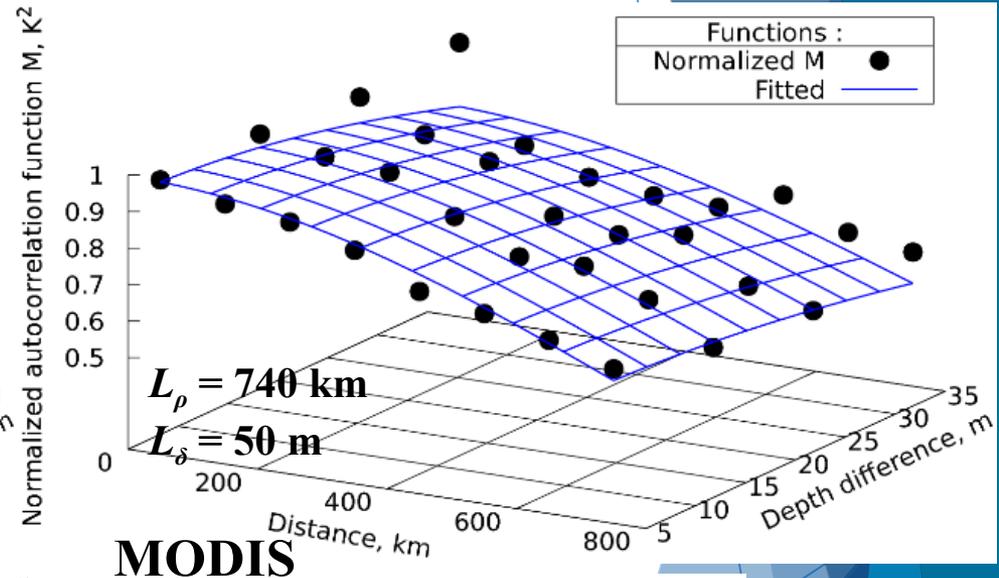
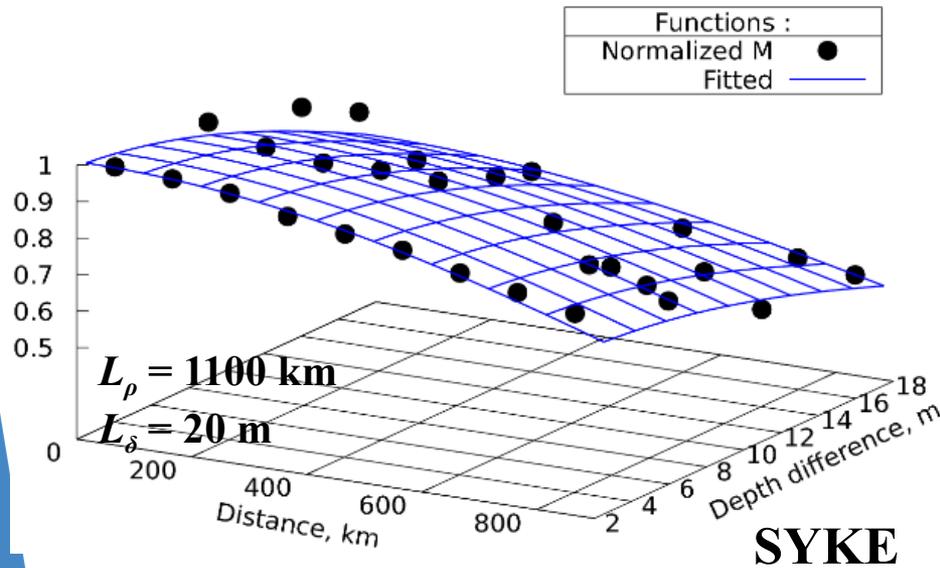


**MODIS**



Taken into account: total variance,  
observation error variance!

# Estimation of the autocorrelation function: 3D



$$\mu(\rho, \delta) = e^{-\left(\frac{\rho^2}{2L_\rho^2} + \frac{\delta^2}{2L_\delta^2}\right)}$$

In central part of the plot: approximation errors are very large, the fit is quite poor

example of  
Lake Valday  
mean depth 14 m  
33.3E 58.0N

# Sensitivity experiments with the HIRLAM v7.4 NWP system

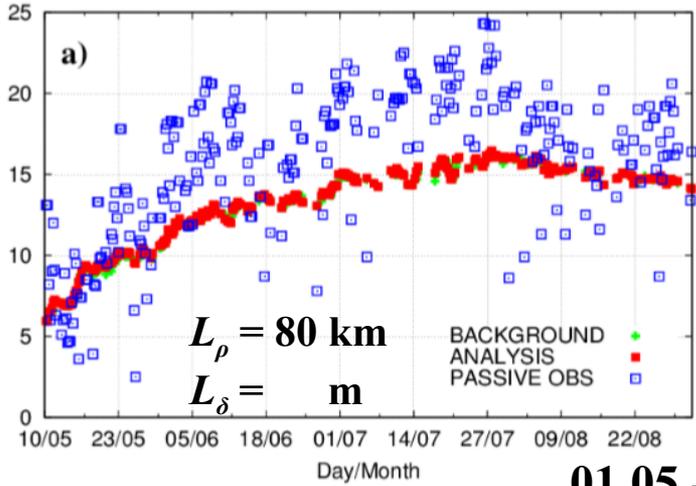
validating the objective analysis against independent observations

only short (+6h) HIRLAM forecasts to provide back-ground for the next analysis-forecast cycle

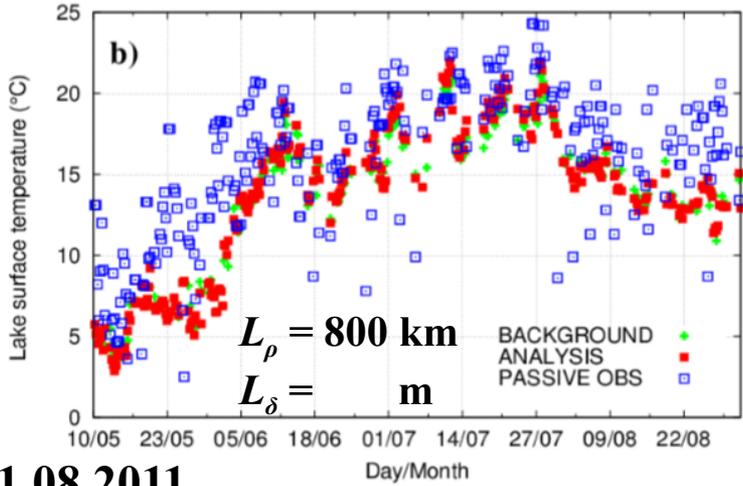
observation error standard deviation in the LSWT analysis was kept at 1.5 °C

background error standard deviation of 1.0 °C was retained

EXP: LH80LVNO Valday ( 33.3E 58.0N) Depth: 14.

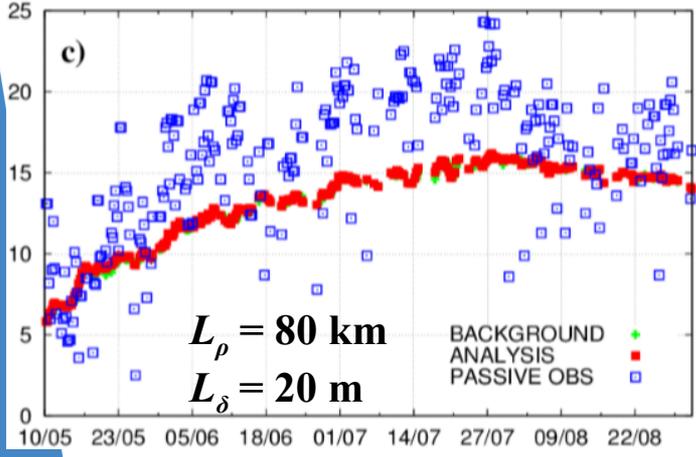


EXP: LH800LVNO Valday ( 33.3E 58.0N) Depth: 14.

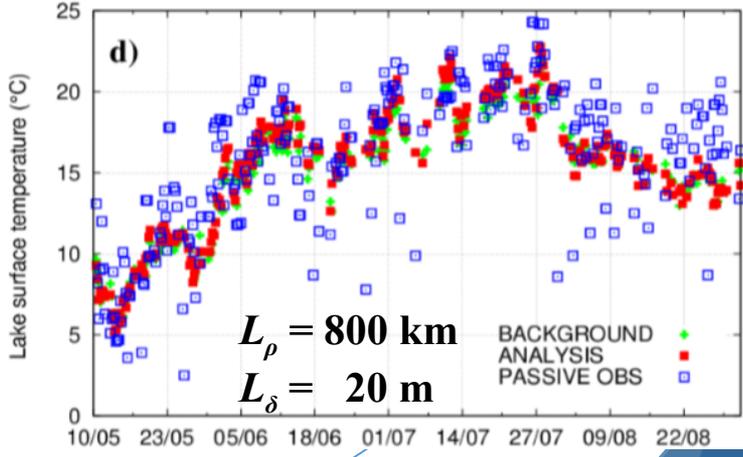


01.05.-31.08.2011.

EXP: LH80LV20 Valday ( 33.3E 58.0N) Depth: 14.



EXP: LH800LV20 Valday ( 33.3E 58.0N) Depth: 14.



# Sensitivity experiments with the HIRLAM v7.4 NWP system

- ▶ Results from the 800 km and 80 km length scale experiments were of comparable quality.
  - Largest differences between the resulting analyses – in spring and early summer when lakes are warming up or cooling differently depending on their location, size and depth.

**NB!** When there were no or only few observations available close to the lake:

- large influence radius brings in distant measurements → more data improves the analysis;
- distant observations represent different conditions + may dominate in the analysis → deterioration of the result;
- accounting for the depth difference in addition to the distance was useful:
  - ✓ when lakes of different depth are close to each other;
  - ✓ with deep and shallow parts of the same large lake.

# Sensitivity experiments with the HIRLAM v7.4 NWP system

- ▶ In-situ LSWT measurements from SYKE (over Finland) played a stabilizing role in the objective analysis of LSWT, while MODIS observations brought more variability.
  - When the background LSWT field comes from the previous analysis, relaxation towards the LSWT climate is needed to avoid drift of the analysis from the reality.
  - Observation quality control within the HIRLAM system worked well, removing obviously erroneous observations by testing observations against the background.

**NB!** OI check (comparison to the neighboring observations) played a minor role, presumably because observation and background errors were not optimal.

**NB!** It is very important to prevent the influence of ocean observations on LSWT analysis.

# Conclusions & Future plans

- ▶ studying the LSWT autocorrelation function for other seasons (spring, autumn)
- ▶ application of OI for spatialization of lake ice in NWP

H. KheyrollahPour, M. Choulga, K. Eerola, E. Kourzeneva, L. Rontu, F. Pan, C.R. Duguay. **Towards improved objective analysis of lake surface water temperature in a NWP model: preliminary assessment of statistical properties.** *Tellus A*, ZELA 1313025. DOI: 10.1080/16000870.2017.1313025.

Link: <http://dx.doi.org/10.1080/16000870.2017.1313025>.



**Thank you for your attention!**