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Using the NOAA Advanced Very High Resolution Radiometer to characterise temporal and spatial trends in water temperature of large European lakes

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ABSTRACT

Lakes are major repositories of biodiversity, provide multiple ecosystem services and are widely recognised as key indicators of environmental change. However, studies of lake response to drivers of change at a pan-European scale are exceptionally rare. The need for such studies has been given renewed impetus by concerns over environmental change and because of international policies, such as the EU Water Framework Directive (WFD), which impose legal obligations to monitor the condition of European lakes towards sustainable systems with good ecological status. This has highlighted the need for methods that can be widely applied across large spatial and temporal scales and produce comparable results. Remote sensing promises much in terms of information provision, but the spatial transferability and temporal repeatability of methods and relationships observed at individual or regional case studies remains unproven at the continental scale. This study demonstrates that NOAA Advanced Very High Resolution Radiometer (AVHRR) thermal data are capable of producing highly accurate ($R^2 > 0.9$) lake surface temperature (LST) estimates in lakes with variable hydromorphological characteristics and contrasting thermal regimes. Validation of the approach using archived AVHRR thermal data for Lake Geneva produced observations that were consistent with field data for equivalent time periods. This approach provides the basis for generalizing temporal and spatial trends in European lake surface temperature over several decades and confirms the potential of the full 30 year NOAA AVHRR archive to can provide AVHRR-derived LST estimates to help inform European policies on lake water quality.

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1. Introduction

Lakes are dynamic ecosystems with characteristics that vary according to landscape setting and the environmental history of the water body and its associated catchment (Horne & Goldman, 1994; Moss, 1998). The trajectory of change depends on the mode of basin formation, rate of natural processes such as sedimentation and wetland succession, as well as anthropogenic factors such as shoreline development (Maitland, 1990; Welch, 1935). Natural evolution in lakes occurs over hundreds to tens of thousands of years (Hickling, 1975), while change due to human activities (e.g. pollution from industry, urban waste and agriculture, lakeshore constructions etc.) may occur more rapidly and depends on the intensity of pressures and the specific sensitivities of the system (Foley et al., 2005; ILEC, 2011).

A major driver of change in lakes is climate variability with several studies suggesting that lakes are sensitive indicators of changes to climate at local to larger spatial scales (e.g. De Stasio et al., 1996;

Williamson et al., 2010). For example, European lake ecosystems are influenced by variations in the North Atlantic Oscillation (e.g. Gerten & Adrian, 2000, 2001; Livingstone & Dokulil, 2001; Straile, 2000; Straile & Adrian, 2000; Weynhenmeyer et al., 1999, 2002). In addition, lakes have the potential to reveal changes and homogeneous trends even at relatively short (i.e. decadal) temporal scales (e.g. Arhonditsis et al., 2004; Livingstone, 2003). Climatic changes are predicted to occur non-uniformly across the globe (Hardy, 2003) and have different effects on lakes depending on geographic location (Adrian et al., 2009). This is likely to lead to complex response patterns requiring comprehensive surveillance monitoring programmes to identify rates of change and the greatest sensitivity within individual systems in terms of water resource and ecological response. Factors complicating the linkages between water quality parameters and climate include catchment land management changes, linked agricultural policies, point and diffuse pollution, habitat destruction and the impacts of invasive alien species (EUROPA WFD, 2011; UNEP, 2000). Nevertheless, the surface water temperatures of lakes respond directly to meteorological fluctuations in air temperature, cloud cover, water vapour pressure (relative humidity) and wind speed (Livingstone & Dokulil, 2001). Even though the responsiveness of different systems owes much to site-specific characteristics such as lake size, shape and catchment characteristics (Gerten & Adrian, 2001), lakes located many kilometres apart

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and in different hydroclimatic regions have been shown to exhibit similar response to synoptic-scale meteorological forcing (Livingstone & Padisák, 2007). The latter suggests a coherent response to the same regional-scale climatic phenomena.

In Europe there are approximately 500 000 lakes with a surface area greater than 0.01 km² (EEA, 2010). Due to the dynamic and variable character of lake ecosystems and the range of pressures on lake function, repeated monitoring of these ecosystems is vital to prevent degradation and promote system recovery where necessary. This has led to the implementation of various policy-related programmes and schema at both national and international levels, most notably the EC Water Framework Directive (WFD) introduced in 2000 (EUROPA WFD, 2011). According to this surface water bodies (including lakes) require biophysical condition monitoring every six years. The international character of the WFD has introduced the need for methods that can be widely applied over large spatial and temporal scales and produce comparable results. The ability to study multiple sites, despite the large distance separating them and the extreme differences in their ecological characteristics, could offer an insight into the inter-regional drivers of thermal change in European lakes.

Monitoring lakes across multiple spatial and temporal scales can often be challenging, as it depends on an understanding of the underlying drivers of change, the direct and/or indirect response of individual lakes to the latter and the reliability of methods used for lake monitoring. Because of that, recent advances in lake water mapping techniques, such as the incorporation of estimates of water quality from remote sensing instruments, have revolutionised the monitoring of lacustrine systems (Kondratyev & Filatov, 1999). Remote sensing has been employed at local and regional scales for lake studies due to its ability to estimate lake properties covering large spatial scales (e.g. George, 1997; Gitelson et al., 1993; Pulliainen et al., 2001). However, transferring methods and relationships observed over continental scales and multiple sites has proved problematic and no European study has to date overcome the challenges of reconciling transferable regionalised algorithms capable of accommodating different ecoregions, lake morphometries and thermal regimes. In addition, issues like the skin effect, when remotely sensed temperature estimates from the uppermost layer of the water surface (i.e. skin temperatures) are compared to bulk temperatures measured *in situ* at depths ranging from a few centimetres to a few metres (e.g. buoys and ship measurements), introduce uncertainty in the accuracy assessment of LST estimation algorithms (Donlon et al., 2002; Minnett, 2003). In fact, the difference between skin and bulk temperature can be between 0.1 and 0.5 °C and it is a highly recognised limitation in LST estimations with remote sensing (Crosman & Horel, 2009). As a result, reliable, transparent and transferable methodologies are needed.

The use of NOAA AVHRR thermal data over large lakes has been demonstrated in the past for individual sites or sites within the same geographic region and for limited time periods (e.g. Oesch et al., 2005; Wooster et al., 1994, 2001). For example, Bussi eres and Schertzer (2003) used AVHRR LST estimates to produce seasonal time series for a 6 month period and study temperature trends within a group of boreal lakes. In this paper, the aim is to demonstrate the reliability of the NOAA AVHRR in concurrently estimating LST across multiple lakes within different settings across Europe using a universal algorithm. The remote sensing-based approach produces LST time-series across multiple hitherto unmonitored sites; thus allowing for synoptic scale characterisation of trends unachievable with conventional ground-based monitoring.

2. Data and methodology

2.1. Approach

The first stage was to evaluate the performance of remote sensing-derived temperate estimates (using NOAA AVHRR) against conventional

field measurements. Data were sourced from 23 lakes across Europe wherein government and research agencies had established long-term and systematic field data collection programmes. The sites spanned a range of latitudes and longitudes and are situated across the European mainland and Great Britain. Four lakes from this larger dataset are reported in the current investigation as exemplars of the approach. They also represent four major WFD ecoregions (Alps, Hungarian lowlands, Central plains and Fenno-Scandian shield) and encompass a range of mixing regimes (cf. Hutchinson & Loffler, 1956; Kolada et al., 2005).

Many lake classification schemes (typologies) are available, usually based upon specific chemical, biological and/or thermal properties. For consistency with CEN Guidance Standards, this study employed the 'System A' lake typology of the WFD (CEN, 2010; EC Guidance Document No 10, 2003). This scheme employs the idea of ecoregions and categorises lakes according to four natural abiotic lake characteristics (Table 1), including altitude, mean depth, surface area and geology (EC Guidance Document No 10, 2003; Kolada et al., 2005). We also used the mixing-regime based scheme of Hutchinson and Loffler (1956) (as cited in Kondratyev & Filatov, 1999) that distinguishes lakes into amictic, cold monomictic, dimictic, warm monomictic and oligomictic, taking into consideration their thermal properties, altitude, geographical location (with respect to latitude) and the depth of the basin.

2.2. Study sites

Lake Geneva or L eman (Alps) is a deep and very large glacial trough located in an Alpine setting between Switzerland and France. The climatic regime is temperate maritime and due to its great depth (Table 2) full mixing does not happen in all years (Livingstone, 1993). Thermal stratification is usually established between April and October, while in the rest of the year the lake (partially) mixes responding to meteorological forcing (Livingstone, 1993). The River Rh one is the main inflow into the eastern part of the lake and discharges at the southwestern end (ILEC, 2011). There are no islands.

Lake Balaton (Hungarian lowlands) is the largest lake in Hungary and is a tectonic basin (Padis ak, 1992). Due to its size, shallow depth and absence of islands it is strongly influenced by wind action that causes frequent mixing (ILEC, 2011). As a result, Lake Balaton is polymictic and generally isothermal, so the temperature measured at the surface is considered representative of the column as a whole (Livingstone & Padis ak, 2007). It has a freezing period of two months in winter. The main inflow is the River Zala located in the south-west (ILEC, 2011).

Lake V attern (Central plains) is a deep, very large lake situated in a low lying shield setting in southern Sweden. The deepest water is located in the southern sub-basin, while the lake is shallower in the central and northern parts. There are numerous small islands within

Table 1
WFD lakes typology; obligatory parameters used in System A (CEN, 2010; EC Guidance Document No. 10, 2003).

Parameter	Description
Altitude	Lowland: <200 m a.s.l Mid-altitude: 200–800 m a.s.l High: > 800 m a.s.l
Mean depth	Very shallow: <3 m Shallow: 3–15 m Deep: > 15 m
Surface area	Small: 0.5–1 km ² Medium: 1–10 km ² Large: 10–100 km ² Very large: > 100 km ²
Geology	Organic Siliceous Calcareous

Table 2
Morphological properties of the lakes covered in this study.

Lake	Altitude (m a.s.l.)	Max depth (m)	Mean depth (m)	Volume (km ³)	Surface area (km ²)	Shoreline length (km)	Catchment size (km ²)
Geneva	372	310	153	88.9	584	167	7975
Balaton	105	12	3.2	1.9	593	236	5775
Vättern	89	128	40	74	1856	642	4503
Oulujärvi	122	38	7	6.2	887	(n/a)	(n/a)

the lake, mostly situated close to the lakeshore. Lake Vättern is dimictic and freezes partially in winter (ILEC, 2011).

Lake Oulujärvi (Fenno-Scandian shield) in Finland contains three distinct sub-basins. It is a shallow and very large dimictic lake. There are numerous islands within Lake Oulujärvi and a few enclosed bays (ILEC, 2011).

2.3. Field measurements

Any remotely sensed estimates of LST require independent validation using field data and so a number of organisations were contacted and archived field LST measurements were requested. Previous remote sensing-based studies have relied on measurements made during the night to avoid discrepancies between field measurements and satellite estimations due to the skin effect induced by solar insolation. For example, Oesch et al. (2005) found that data collected at night generally showed more reliable results, as the day-time algorithms overestimated surface temperature especially in warm summer months due to solar warming of the surface. However, the majority of field measurements are generally acquired during the day and from different depths (Table 3). As this work relied upon field measurements previously acquired, day-time satellite data that matched the timings of the field LST measurements were used.

Table 3 summarises the sampling period, frequency, sampling depth and the field data supplier in the four study sites. The location of the study sites and the sampling stations within each site are shown in Fig. 1.

2.4. Study periods

The study periods were determined after the field data acquisition was completed and remote sensing data were acquired to coincide with periods of field data richness. A large number of frequent field sampling dates increased the possibility of coinciding cloud-free satellite overpasses, despite the frequent cloud cover in Europe. To determine which periods would be suitable, a field data quantity and quality assessment took place. The periods for which field and remote sensing data coincided most frequently were the four-year periods of 1993–96 and 2001–04. Both these observation periods featured significant air-temperature related weather phenomena across Europe

Table 3
Data suppliers and sampling period, frequency and depth of lake surface temperature in the four study sites.

Lake	Data supplier	Temperature	Sampling depth (m)
Vättern	Swedish Environmental Protection Agency	1969–2003 monthly; Apr–Oct	0.5
Geneva	International Commission for the Protection of Lake Geneva (CIPEL)	1984–2004 biweekly–monthly; all months	0
Balaton	Hungarian Ministry of Environmental Protection and Water Management; Ministry of Health	2000–2006 weekly; mid May–mid Sep	0.3–0.5
Oulujärvi	Finnish Environment Institute (SYKE)	1960–2005 biweekly, monthly, seasonally	1

linked to the winter North Atlantic Oscillation (NAO) index inter-annual variability (CRU, 2011; Hurrell, 1995; Livingstone, 1997). The decade 1998–2007 has been the warmest since 1850, and especially the years 2002, 2003 and 2004 were among the top five warmest years since 1890 (WMO, 2011).

2.5. Satellite data acquisition

The data acquired included all five wavebands of the AVHRR/2 (NOAA 9, 11, 12 and 14) and six wavebands of the AVHRR/3 (NOAA 16 and 17) instrument onboard the NOAA polar satellites. The reflected radiance in AVHRR/2 and AVHRR/3 bands 1 (0.58–0.68 μm) and 2 (0.725–1.1 μm) and AVHRR/3 band 3a (1.58–1.64 μm), and the emitted radiance in AVHRR/2 band 3 (3.55–3.93 μm) and AVHRR/3 3b (3.55–3.93 μm) were acquired to facilitate the development of a cloud mask model. The brightness temperatures of bands 4 (10.3–11.3 μm) and 5 (11.5–12.5 μm) were used for the LST estimation. The spatial resolution of the instrument at the satellite nadir is approximately 1.1 km.

The data consisted of the full swath of NOAA-9, -11, -12, -14, -16, -17 AVHRR scenes and hence each included more than one study site. A total of 87 NOAA AVHRR cloud-free (or almost cloud-free) images were used for the validation of the MCSST and NLSST algorithms and 16 NOAA AVHRR cloud-free images were used for the algorithm calibration for lake waters. Table 4 shows the number of cloud-free NOAA AVHRR images available for each site and the number of pairs of field data and satellite estimations that were consequently available for the algorithm validation process.

Satellite images were typically acquired within the same 12 hour daytime period from the time of field measurements, whenever that was known. The exception being in Lake Vättern for which only five cloud-free images were available on dates that coincided with field measurements. In order to increase the sample size for that site, seven more scenes acquired ± 2 days of the field sampling date were also included. For the latter the assumption was made that the variability in temperature was not significant within a period of 1–2 days.

2.6. Data pre-processing

The NOAA AVHRR visible and near-infrared data were atmospherically corrected for Rayleigh scattering and the NOAA AVHRR thermal data were atmospherically corrected for water vapour absorption by the Natural Environment Research Council (NERC) Earth Observation Data Acquisition and Analysis Service (NEODAAS) Plymouth Marine Laboratory (PML) Remote Sensing Group (RSG). Geometric corrections were not applied. Instead, a geolocation file was appended to each dataset to facilitate the comparison of satellite data pixel values to field data from sampling stations of known coordinates.

The cloud pixel information provided by the NEODAAS PML RSG was developed for marine applications and thus its accuracy over inland waters was uncertain (NEODAAS PML RSG, Personal communication, 2007). To check the validity of the cloud mask, a visual analysis of the AVHRR/2 and AVHRR/3 bands was undertaken to exclude non-water and mixed pixels within the images. In addition, the adjacency effect, a phenomenon that occurs within pixels close to land-water boundaries (or any bright/dark boundary), where effectively the signal from pure water pixels is affected by scattered radiation from neighbouring land (Odermatt et al., 2008), was also addressed. The adjacency effect occurs in the visible and nIR spectral regions and is greatly influenced by the amount and vertical distribution of aerosol particles in the atmosphere (Minomura et al., 2001). It causes an overestimation of atmospheric radiance over the affected pixels and a subsequent underestimation of water leaving radiance (Ruiz-Verdú et al., 2008). In lakes, the adjacency effect is uncertain and so whilst the removal of near-shore pixels from further analysis should address the problem (cf. Lavender et al., 2004), and thus applied here, its real impact requires further investigation.

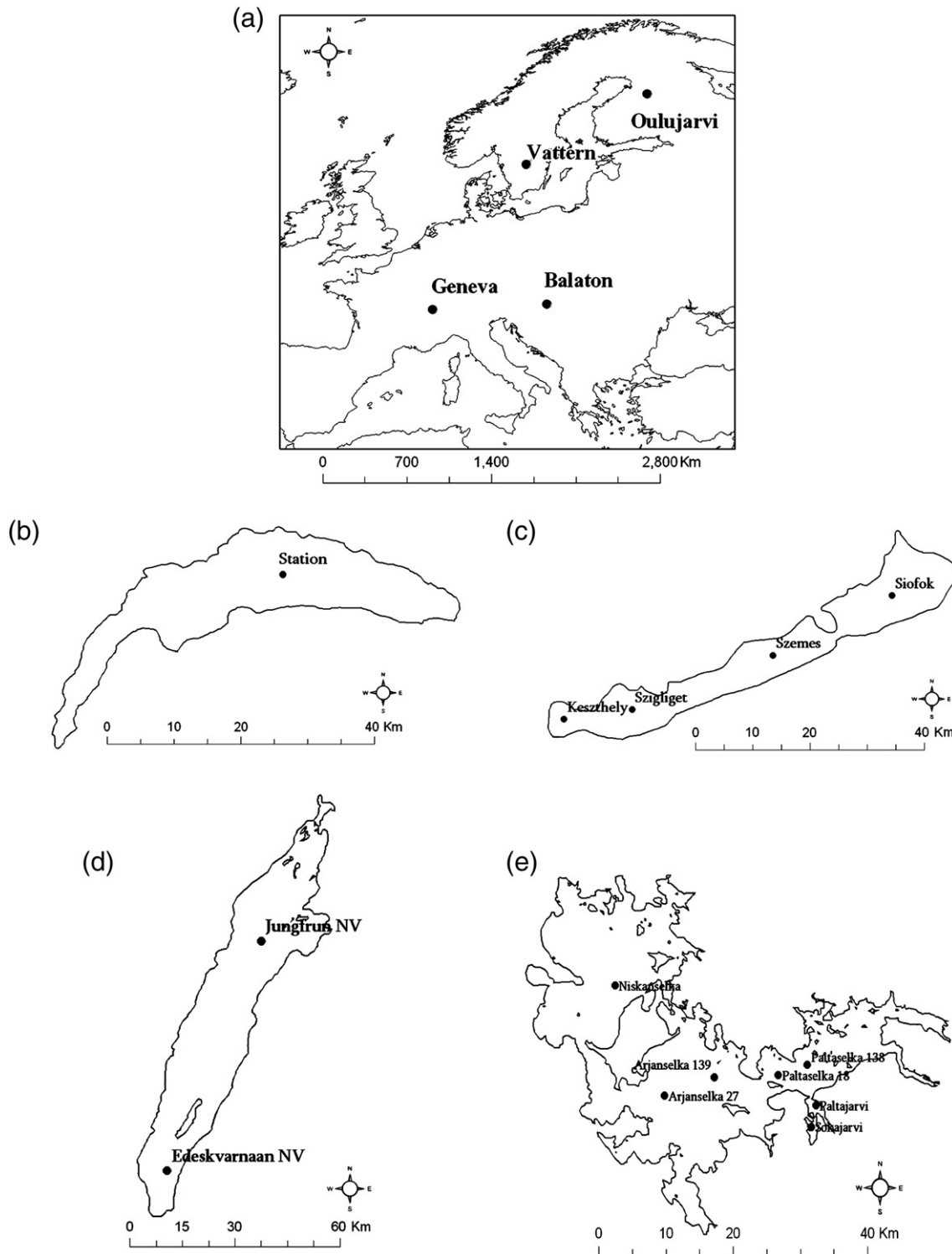


Fig. 1. Geographic map of Europe (a) showing the location of the four lakes and maps of Lakes Geneva (b), Balaton (c), Vättern (d) and Oulujärvi (e) showing the location of the *in situ* measurements.

2.7. The NOAA AVHRR LST estimation algorithms

For NOAA AVHRR, the split window approach combines an effective atmospheric correction of the thermal radiance emitted by a water body with the advantage of taking into consideration the variation of atmospheric path length with changing satellite zenith angle (Oesch et al., 2005). In this project both the linear multichannel SST estimation (MCSST) and non-linear SST estimation (NLSST) split window algorithms

were used to estimate LST. The applicability of both algorithms in lake water bodies was suggested for the first time by Oesch et al. (2005). These authors tested the accuracy of both AVHRR operational algorithms in three European alpine lakes; namely Lakes Constance, Geneva and Mond (in Austria) in 2002 and 2003 and found that the MCSST algorithm provided more accurate estimations of LST than the NLSST. Here, the accuracy of these algorithms was assessed in three lakes with different typology and at different ecoregions.

Table 4

Number of available cloud-free images, sampling stations and pairs of coinciding field and remote sensing data in the study periods at the four sites.

Lake	Period	Number images	Number of stations	Number of pairs
Geneva	1993–96 and 2001–04	58	1	58
Balaton	2001–04 ^a	34	4	110
Vättern	1993–96 and 2001–04	12	2	17
Oulujärvi	2001–04 ^a	16	7	22

^a There were no field data available for Lake Balaton and Lake Oulujärvi in 1993–96.

The general form of the MCSST and NLSST equations is given below:

$$\text{MCSST}[\text{°C}] = A_1(T_4) + A_2(T_4 - T_5) + A_3(T_4 - T_5)(\sec(\theta) - 1) - A_4 \quad (1)$$

$$\text{NLSST}[\text{°C}] = B_1(T_4) + B_2(T_4 - T_5)\text{Tsf}c + B_3(T_4 - T_5)(\sec(\theta) - 1) - B_4 \quad (2)$$

where T_4 and T_5 are the brightness temperatures of AVHRR bands 4 and 5 in degrees Kelvin; $\text{Sec}(\theta)$ is the secant of the satellite zenith angle θ ; MCSST and NLSST are results of the linear multi-channel and the non-linear SST algorithms, respectively, in degrees Celsius; $A_{1,2,3,4}$ and $B_{1,2,3,4}$ are constant coefficients; and $\text{Tsf}c$ is an *a priori* estimate of the water surface temperature in degrees Celsius. The constant coefficients in Eqs. (1) and (2) are estimated either from model simulations or correlations with field measurements and for each satellite are given in Tables 5–6. Since the input brightness temperatures (T_4 and T_5) were acquired from NEODAAS in degrees Celsius (°C), the last constants in Eqs. (1) and (2) (A_4 and B_4), which are used as converters from degrees Kelvin to Celsius, were omitted. The $\text{Tsf}c$ value can be a LST estimation derived from AVHRR data using one of the MCSST equations (Oesch et al., 2005). In this study, the MCSST values were used in the non-linear NLSST algorithm rather than *a priori* LST estimates obtained from analysis of past satellite LST data.

Uncertainty in LST estimations may be introduced due to distortions in the image pixels viewed at large viewing angles, because of greater attenuation caused by an increase in the atmospheric path length. At nadir, the IFOV is equal to approximately 1.1 km and increases with distance from the satellite nadir to 5 km (along track) and 6.8 km (across track) at the scanning extreme of 55.4° (Latifovic & Pouliot, 2007). Due to this distortion, adjacent off-nadir pixels overlap and cause off-nadir observations to be highly redundant (Cracknell, 1997). Oesch et al. (2005) suggested that pixels viewed with a satellite zenith angle greater than 53° should be excluded from any retrieval of LST. In this study, pixels viewed with a satellite zenith angle greater than 50° were excluded from analysis as the retrieval of LST can be compromised by such geometry effects (Oesch et al., 2005).

Table 5

Operational day-time linear multi-channel sea surface temperature (MCSST) estimation algorithm using a split window approach for AVHRR data (NOAA MOST, 2009).

Period of validation	NOAA	SST equation
30/03/1988–31/12/9999	9	$T_4 + 2.6084(T_4 - T_5) - 0.0269T_5 - 265.479$
11/06/1993–31/12/9999	11	$0.979224T_4 + 2.361743(T_4 - T_5) + 0.33084(T_4 - T_5)(\sec(\theta) - 1) - 267.029$
08/04/1994–31/12/9999	12	$0.963563T_4 + 2.579211(T_4 - T_5) + 0.242598(T_4 - T_5)(\sec(\theta) - 1) - 263.006$
20/03/1995–31/12/9999	14	$1.017342T_4 + 2.139588(T_4 - T_5) + 0.779706(T_4 - T_5)(\sec(\theta) - 1) - 278.43$
21/09/2000–31/12/9999	16	$0.999314T_4 + 2.30195(T_4 - T_5) + 0.628976(T_4 - T_5)(\sec(\theta) - 1) - 273.768$
27/07/2002–31/12/9999	17	$0.992818T_4 + 2.49916(T_4 - T_5) + 0.915103(T_4 - T_5)(\sec(\theta) - 1) - 271.206$

Table 6

Operational day-time non-linear sea surface temperature (NLSST) estimation algorithm using a split window approach for AVHRR data (NOAA MOST, 2009). Note that a NLSST equation has not been developed for NOAA-9 AVHRR data.

Period of validation	NOAA	SST equation
06/11/1993–31/12/9999	11	$0.92323T_4 + 0.082523(T_4 - T_5)\text{Tsf}c + 0.463038(T_4 - T_5)(\sec(\theta) - 1) - 250.109$
08/04/1994–31/12/9999	12	$0.876992T_4 + 0.083132(T_4 - T_5)\text{Tsf}c + 0.349877(T_4 - T_5)(\sec(\theta) - 1) - 236.667$
20/03/1995–31/12/9999	14	$0.939813T_4 + 0.076066(T_4 - T_5)\text{Tsf}c + 0.801458(T_4 - T_5)(\sec(\theta) - 1) - 255.165$
21/09/2000–31/12/9999	16	$0.914471T_4 + 0.0776118(T_4 - T_5)\text{Tsf}c + 0.668532(T_4 - T_5)(\sec(\theta) - 1) - 248.116$
27/07/2002–31/12/9999	17	$0.936047T_4 + 0.083867(T_4 - T_5)\text{Tsf}c + 0.920848(T_4 - T_5)(\sec(\theta) - 1) - 253.951$

2.8. Validation of the NOAA AVHRR algorithms

The two algorithms were applied to the NOAA AVHRR data and the performance of the algorithms was then tested. For that purpose, lists of coinciding field data and remotely sensed LST estimates were produced for each lake and year as described above. The remotely sensed data were averaged values of the parameters calculated from a 9-pixel squared grid centred around the pixel where the sampling station was located to avoid issues of geometric distortion and consequent imprecise determination of the location of sampling points in the images. The assumption was made that a point measurement from the sampling station was representative of the average value of the parameter studied for a 9 km^2 area containing the sample (Lavender et al., 2004), but clearly this would depend upon the intrinsic scale of variation of the parameter under consideration. Baban (1993) found that the use of a 3×3 pixel average, when comparing Landsat TM data to field measurements, was the optimum size of kernel, as opposed to smaller or larger sized kernels, because it reduced noise in the data or the selection of biased pixel values.

The relationship between estimated and observed LST values was assessed using Pearson's and/or Spearman's Rank correlation. Where the data were not normally distributed or the sample size (n) was small ($n < 6$) only the non-parametric Spearman's rho correlation coefficient (ρ) was applied (Wheeler et al., 2006). Both correlation coefficients were computed for all datasets with sample sizes between 6 and 30 for comparison. For datasets with n greater than 30 the choice of test depended upon normality.

Goodness of fit was established using the coefficient of determination (R^2), the root mean square error (RMSE) and the systematic error (bias) of prediction. The RMSE is a measure of accuracy (Atkinson & Foody, 2002) and it was calculated as shown below:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x[\text{pred}]_i - x[\text{true}]_i)^2} \quad (3)$$

where RMSE = root mean square error of prediction; n = number of observations (sample size); $x[\text{pred}]_i$ = predicted value of observation i ; and $x[\text{true}]_i$ = true value of observation i .

Bias is an expectation of over- or under-estimation and a measure of the systematic errors associated with the estimation (Atkinson & Foody, 2002). Bias was calculated according to the following equation, which is essentially the mean error of the estimation:

$$\text{bias} = \frac{1}{n} \sum_{i=1}^n (x[\text{pred}]_i - x[\text{true}]_i) \quad (4)$$

The significance of all statistical tests was calculated at the 99% (0.01) level of significance (2-tailed), unless otherwise stated.

Table 7
Correlation of field LST data with the NOAA AVHRR MCSST and NLSST estimates in lakes Balaton, Geneva and Vättern in 1993–96 and 2001–04. All results shown below are significant at the 0.01 level (2-tailed). No result indicates data were not normally distributed or that $n > 30$ so only parametric tests were performed.

Lake	Sample size (n)	Pearson's coefficient (r)		Spearman's rho (ρ)	
		MCSST	NLSST	MCSST	NLSST
Balaton	110	0.731	0.725	–	–
Geneva	58	0.952	0.952	–	–
Vättern	17	0.948	0.921	0.931	0.912
Combined data	185	–	–	0.891	0.890

3. Results

3.1. Performance of the NOAA AVHRR algorithms

The field LST data from lakes Balaton, Geneva and Vättern were strongly correlated with both NOAA AVHRR MCSST and NLSST estimates

on corresponding dates (Table 7, Fig. 2). Field LST data from Lake Geneva showed the strongest correlation with satellite estimates, followed closely by data from Lake Vättern and Lake Balaton. These results show that both MCSST and NLSST algorithms have a strong potential to estimate LST in lakes with different characteristics. In fact, field data from all three lakes (combined into a common dataset) were strongly correlated with corresponding NOAA AVHRR MCSST and NLSST estimates for all available years (Table 7, Fig. 3).

The bias and RMSE values for the three individual lakes and for the combined dataset (Table 8) showed promising results. For the combined dataset, the MCSST algorithm had a slightly larger bias (1.22 °C) than the NLSST algorithm (–0.89 °C). The accuracy (measured with the RMSE) of the MCSST algorithm was 2.29 °C and the accuracy of the NLSST algorithm was 2.22 °C.

The above results illustrate that both NOAA AVHRR MCSST and NLSST algorithms performed well in three individual lakes and when all three lakes were combined into a common dataset. As a result, they both showed strong potential for the estimation of LST in large European lakes with various ecological characteristics and

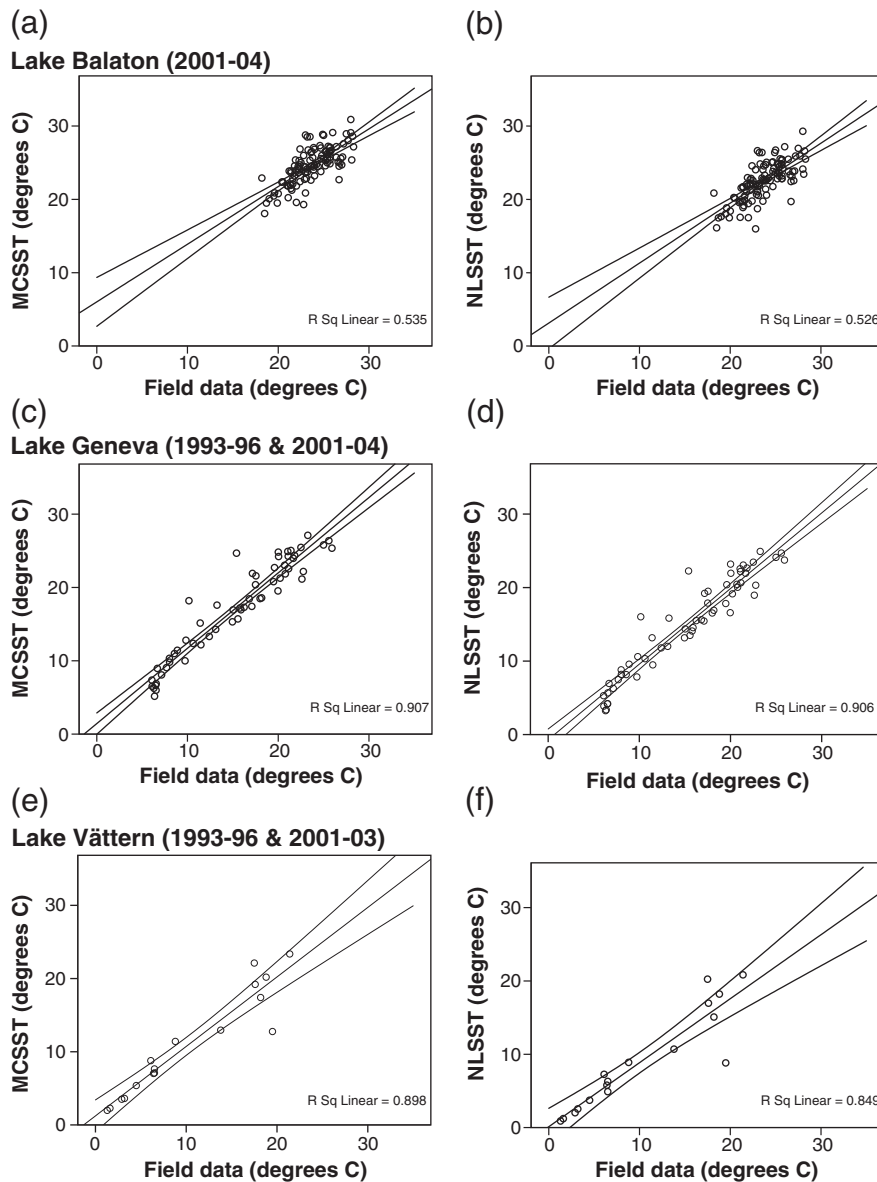


Fig. 2. Scatter-plot between the field LST data and the NOAA AVHRR MCSST and NLSST estimates in Lakes Balaton (a, b), Geneva (c, d) and Vättern (e, f) using data from 1993–96 and 2001–04. The lines were determined by linear regression. The 95% confidence intervals on the mean (outer lines) and the coefficient of determination (R^2) for each plot are also shown.

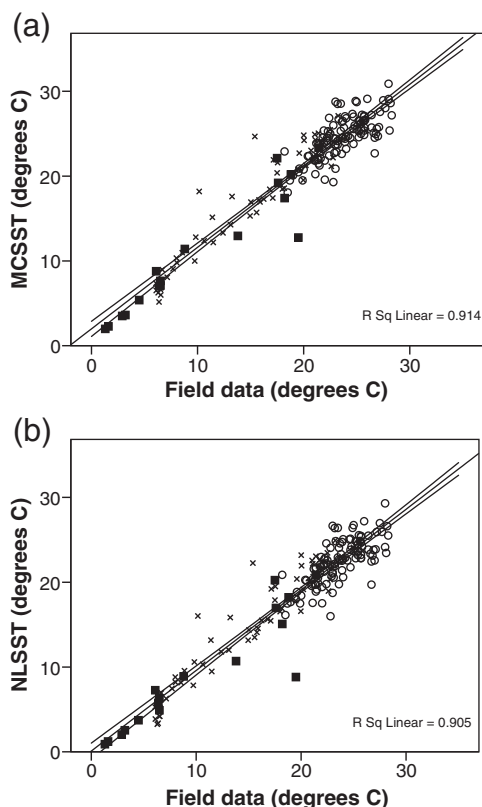


Fig. 3. Scatter-plot between the field LST data and the NOAA AVHRR MCSST (a) and NLSST (b) estimates in all three lakes combined: Balaton (white circles), Geneva (crosses) and Vättern (black squares). The lines were determined by linear regression. The 95% confidence intervals on the mean (outer lines) and the coefficient of determination (R^2) for each plot are also shown.

across different geographical areas. These results agree with the findings by Oesch et al. (2005, 2008).

In all cases, the NOAA AVHRR MCSST estimates showed similar or slightly stronger correlation with the field LST data than the NLSST estimates. In order to test the significance of differences between the two algorithms, related-samples T-tests were performed for each lake (Table 9). These tests showed that the MCSST estimates in all three lakes were significantly different from the corresponding NLSST estimates, with the MCSST algorithm producing higher values (by 2.11 °C in average) than the NLSST algorithm. Oesch et al. (2005) suggest that the difference between the two algorithms might be related to the fact that they were developed for different regions, with the NLSST algorithm being more suitable for regions of high water vapour. In other studies the NLSST was found to improve the bias compared to the MCSST, but increase the standard deviation of satellite-field data difference (e.g. Li et al., 2001). Following the aforementioned, the MCSST algorithm was chosen instead of the NLSST for further analysis.

Table 8

Calculated bias and RMSE values of the MCSST and NLSST algorithms when data from lakes Balaton, Geneva and Vättern were used separately and combined into a common dataset.

Lake	Sample size (n)	Bias		RMSE	
		MCSST	NLSST	MCSST	NLSST
Balaton	110	0.96	-1.18	2.02	2.20
Geneva	58	1.86	-0.27	2.72	2.01
Vättern	17	0.71	-1.19	2.36	2.95
Combined data	185	1.22	-0.89	2.29	2.22

Table 9

Results of related-samples T-test between the NOAA AVHRR MCSST and NLSST estimates in lakes Balaton, Geneva and Vättern in 1993–96 and 2001–04.

Lake	Descriptive statistics				df	t-statistic	p-value
	Mean (M)		Standard Deviation (SD)				
	MCSST	NLSST	MCSST	NLSST			
Balaton	24.66	22.53	2.51	2.64	109	52.914	0.000
Geneva	17.19	15.06	6.54	6.54	57	37.893	0.000
Vättern	10.98	9.08	7.17	6.78	16	10.692	0.000

3.2. Calibration of the NOAA AVHRR MCSST algorithm

The MCSST algorithm was then calibrated for lake waters using data from Lake Oulujärvi that were not employed during the assessment of its performance. Twenty-two NOAA AVHRR images from Lake Oulujärvi were used that coincided with field data measurements. The algorithm used for the calibration was the linear regression equation between field data and AVHRR MCSST estimates from lakes Balaton, Geneva and Vättern (Fig. 3(a)) in order to create a universal algorithm (i.e. not location-dependent):

$$\text{MCSST}_{\text{cal}} [^{\circ}\text{C}] = 0.951(\text{MCSST}) - 0.183 \quad (5)$$

The calibrated algorithm (Fig. 4) had a bias = 0.2 °C and a RMSE = 1.64 °C, which are less than those of the original MCSST.

3.3. Temperature trends in LST over the two study periods

Due to irregularities in sampling frequency (i.e. in this study ranging from daily to seasonal) interpolation is a common procedure in limnological studies when numerous past data are used for trend analysis (Livingstone, 2003). In this study, interpolation was used for illustration purposes only as the dataset for Lake Geneva was incomplete due to cloud cover and technical problems that delayed the acquisition of data. Interpolated remote sensing estimates from all available years in Lake Geneva were calculated at daily intervals using linear interpolation and plotted to provide seasonal and annual time series (Fig. 5). Fig. 5 shows that there seems to be no significant trend in LST in the two study periods, which is in accordance with what the field data have showed for the same time periods. However, more frequent data are required in order to investigate the latter further.

Figs. 6–7 demonstrate the usefulness of remote sensing that can provide information to fill in gaps in field sampling campaigns, when these

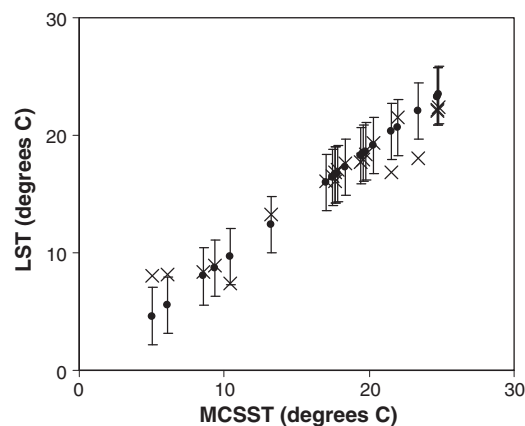


Fig. 4. Surface temperature (black dots) estimated in Lake Oulujärvi using the $\text{MCSST}_{\text{cal}}$ algorithm with the 95% confidence intervals of the mean also plotted (whiskers). The LST field measurements (crosses) are also presented for comparison.

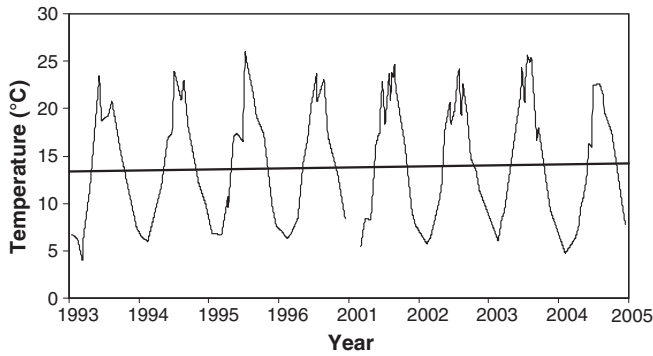


Fig. 5. Temporal patterns of LST in Lake Geneva in 1993–96 and 2001–04 using interpolated NOAA AVHRR MCSSTcal estimates. The trend line (bold) was determined by linear regression. Notice the break in time between the years 1996 and 2001.

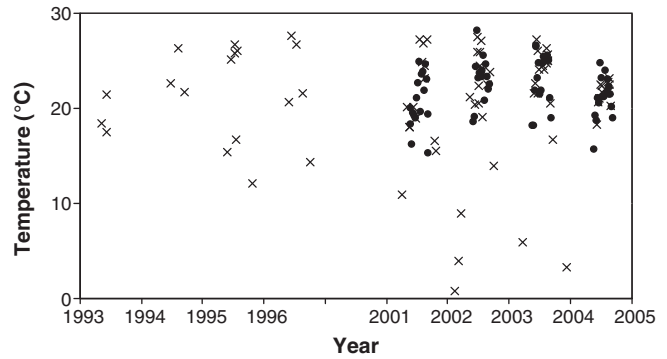


Fig. 7. Lake surface temperature in Lake Balaton (1993–2004): Field LST measurements (circles–solid line) and NOAA AVHRR MCSSTcal estimates (crosses–dotted line). Notice the break in time between the years 1996 and 2001.

are limited to one measurement every few months in a year (Fig. 6(a)) or just a specific season (Fig. 6(b)) or time period (Fig. 7).

3.4. Processing chain

Fig. 8 summarises the processing chain proposed in this study for the estimation of LST from NOAA AVHRR data in large European lakes.

4. Discussion and conclusions

The results of this study demonstrate that both NOAA AVHRR MCSST and NLSST algorithms were highly correlated with field LST measurements from lakes with various characteristics ($\rho=0.89$, $p<0.01$ for both algorithms). It was also found that the NOAA AVHRR thermal data were capable of estimating surface temperature in European lakes when the MCSST (RMSE = 2.29 °C) and NLSST (RMSE = 2.22 °C)

operational algorithms were used and that the accuracy of these algorithms could be further improved if they are calibrated with field data (e.g. bias = 0.2 °C and RMSE = 1.64 °C for MCSSTcal).

The proposed methodology has shown promising results towards the ultimate goal of being able to use remote sensing approaches to replace resource-intensive field-based lake monitoring programmes. The wider applicability of remote sensing is constrained by cloud cover issues and data processing demands that restricted the total number of images examined within the study periods. Wheeler et al. (2006) suggest 30–60 samples will provide the basis for a statistically sound interpretation. We have used a total of 185 samples to assess the accuracy of the algorithms and 22 samples for the algorithm calibration. These were collected over two different 4-year periods in all seasons, whenever that was possible. Even though the sample size was large enough to demonstrate the applicability of MCSST and NLSST in lake waters, a larger number of samples used for the calibration of the algorithm could potentially increase its accuracy. In addition, further analysis is needed to investigate why lower correlation was observed between field data and satellite estimates in Lake Balaton, in respect to the other two sites (Table 7), and explain the occurrence of outliers in Lakes Geneva and Vättern (Fig. 2).

Another limitation is the different sampling depths of the field data used in this study. The skin effect may have significantly influenced the accuracy of the calibrated algorithm and should be taken into consideration in future lake studies, as data from Lake Oulujärvi were collected at 1 m below the surface and were compared to skin temperatures detected by the sensor.

Despite the frequent revisit time of the NOAA AVHRR satellites and the reliability of night-time data for LST retrieval (Oesch et al., 2005), cloud cover might make it difficult to retrieve winter and annual mean temperatures in the frequency required for climate studies. A solution to this could be winter field campaigns and/or techniques such as interpolation (Livingstone, 2003). According to the proposed methodology, only lake bodies that are large enough can be mapped with NOAA AVHRR data in order to avoid the adjacency effect and geometric distortions that create mixed pixels. In Europe, only twenty four natural lakes have a surface area larger than 400 km², but up to 16 000 lakes are larger than 1 km² (EEA, 2010), which means there is a great potential for NOAA AVHRR data in lake studies.

In fact, there are several advantages when the NOAA AVHRR is used to derive estimates of water surface temperatures instead of other remote sensing instruments (e.g. GOES series, Nimbus-7 CZCS, Landsat TM/ETM+, ERS ATSR/ENVISAT AATSR, microwave scanners). Even though the NOAA AVHRR has a less frequent revisit capability than geostationary satellites, it has finer spatial resolution and much better calibration than these sensors (Cracknell, 1997). Also, the NOAA AVHRR thermal bands 4 and 5 have a high signal-to-noise ratio and a much longer archive than other systems (Cracknell, 1997). In fact, the NOAA AVHRR archive of data dates back to 1979,

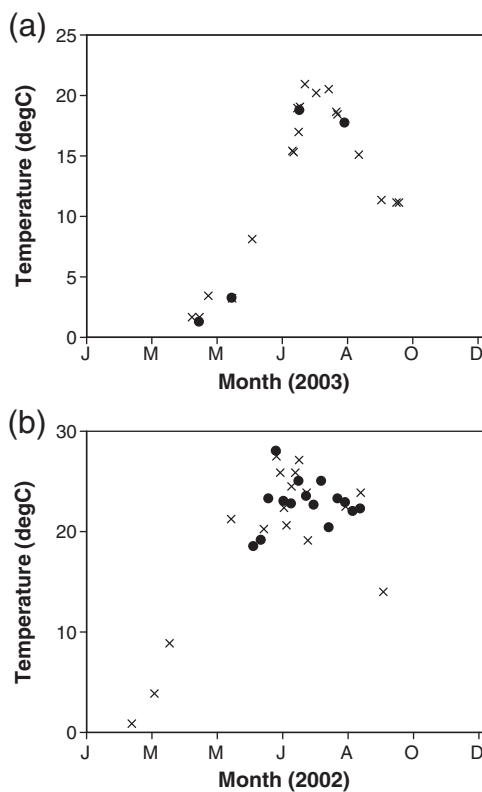


Fig. 6. Lake surface temperature in Lake Vättern (Station Jungfrun) in 2003 (a) and Lake Balaton (Station Siofok) in 2002 (b); field LST measurements (circles) and NOAA AVHRR MCSSTcal estimates (crosses).

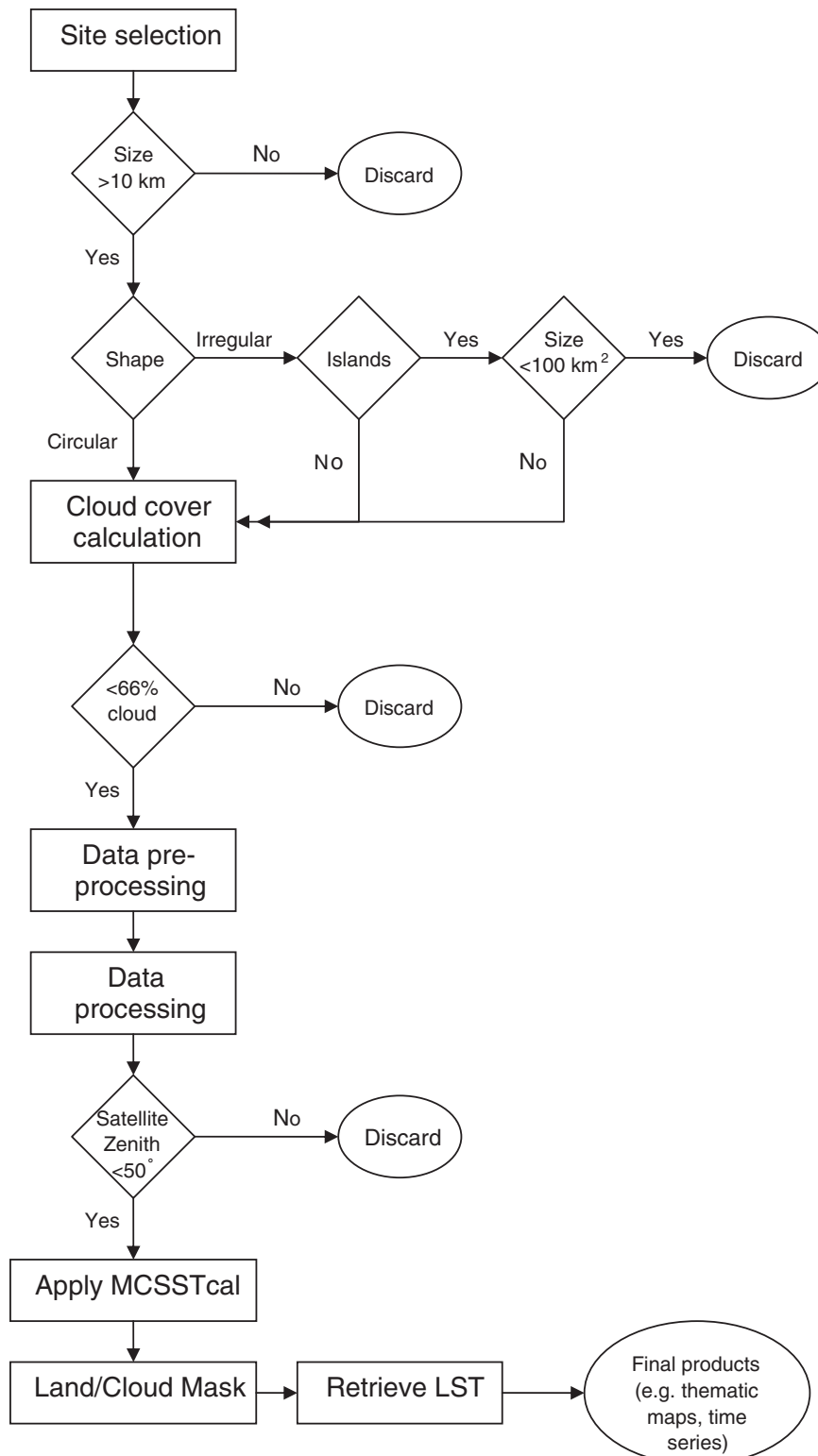


Fig. 8. Processing chain for the estimation of LST from NOAA AVHRR data in large ($\geq 10 \text{ km}^2$) lakes developed in this study.

providing morning day-time data over European lakes (and around the Globe) up to four times per day. When different sensors are combined (e.g. NOAA AVHRR and Terra/Aqua MODIS) for the estimation of the same parameter (e.g. LST), the temporal coverage increases up to, nominally, ten images per 24 h (Oesch et al., 2008). Assuming cloud conditions over the lakes are at minimum, this allows for a

much shorter sampling interval than most field sampling campaigns. In fact, Terra/Aqua MODIS data have been used over lake waters with very promising results (e.g. Crosman & Horel, 2009; Oesch et al., 2008). Landsat TM/ETM+ provide thermal data with a fine spatial resolution (60–120 m) that makes them useful for the study of small-scale phenomena in inland waters and also have the advantage of a long archive (since

1978 for thermal data), but their revisit capability is very infrequent (especially when cloud cover is considered) which gives them a disadvantage over the NOAA AVHRR.

The European Remote Sensing satellite (ERS-1, -2) Along-Track Scanning Radiometer (ATSR-1, -2) and Environmental Satellite (Envisat) Advanced ATSR (AATSR) are scanners that were designed to produce SST estimates of higher accuracy than the AVHRR, because they scan data from both nadir and 52° forwards of nadir, allowing corrections related to atmospheric scattering and absorption (Rees, 1990). The series have been operating since 1991, providing a long archive of data and at the similar spatial resolution (1 km) as the NOAA AVHRR (1.1 km). However, the ATSR and AATSR data are not as easily, rapidly and/or as cheaply available as NOAA AVHRR data (Cracknell, 1997). In addition, the NOAA AVHRR data can produce SST maps of near-real time, which makes them operationally important in oceanographic studies (Robinson, 1985) and in large lacustrine systems according to this study. Finally, estimates of water surface temperature can be derived from passive microwave sensors, but with a much coarser spatial resolution than that of the AVHRR, which makes them valuable only in continental- and global-scale environmental monitoring (Lillesand et al., 2008).

Climate variability is attributed partly to natural fluctuations and partly to human influence, the effect of which is not always easily separable (Hardy, 2003). However, both natural climatic variability and human-induced climate change have direct and indirect impacts on all surface waters, which need to be quantified and accounted for (Hickling, 1975). According to Page (2006) the actual effect and attribution of both natural and human-induced changes can be estimated only through careful comparative analysis of how multiple system indicators behave over space and time. A range of parameters are influenced by climate change and variability, but LST is considered the parameter most directly affected by climate, exhibiting strong response to climate forcing (e.g. Adrian et al., 2009; Kondratyev & Filatov, 1999; Livingstone & Dokulil, 2001; Livingstone & Padisák, 2007; Livingstone et al., 2005). Important features such as stratification and mixing patterns may vary due to climatic fluctuations (e.g. Elo et al., 1998; Livingstone, 1997; Livingstone & Lotter, 1998), according to the degree of increase of surface water warming. Warming can also change the species composition, distribution and growth, and oxygen solubility decreases at increased temperatures affecting the aquatic biota (Hardy, 2003; Munasinghe & Swart, 2005). As a result, continuous monitoring of lakes and their response to climate change can offer a valuable insight into the ecological behaviour of these vulnerable ecosystems.

However, the thermal structure of lakes is specific to each water body and thus, it is difficult to differentiate between the effects of regional climatic phenomena and local meteorology on the thermal characteristics of lakes unless the changes are well pronounced (Livingstone, 1997). Nevertheless, the direct response of lake water temperatures at all depths to air temperature fluctuations at regional and synoptic scales has been established (e.g. Livingstone & Dokulil, 2001; Livingstone & Lotter, 1998; Livingstone & Padisák, 2007). Even though the response of lake temperature to air temperature changes might vary seasonally and even monthly (McCombie, 1959), lake water temperature is an indicator of long-term climatic fluctuations, with a less pronounced response to short-term meteorological forcing (Livingstone, 1993). This study has showed that remote sensing is a powerful tool for the estimation of lake surface temperature at pan-continental scales and for a series of consecutive years in lakes with varying characteristics. The estimation of LST can be performed with remote sensing data across large spatial and temporal scales and produce comparable results.

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