Met Office

Lake Surface Water Temperature in the operational OSTIA system

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Abstract

Operational analyses of LSWT (Lake Surface Water Temperature) have many potential uses including improvement of NWP (Numerical Weather Prediction) models on regional scales. On 24 November 2011, LSWT was included in the Met Office operational SST (Sea Surface Temperature) and ice analysis product, OSTIA, for 248 lakes globally. This technical documentation provides an assessment of the accuracy of the OSTIA LSWT analysis using both a delayed-mode run for JJA 2009, and a pre-operational test run. The OSTIA analysis procedure for SSTs, including correlation length scales and background error covariances optimised for oceans, has been used for the lakes in this first version of the product. Infra-red satellite observations over lakes and in situ measurements were used for the LSWT analysis. The satellite observations are based on retrievals optimised for SST which may introduce inaccuracies into the LSWT data but are currently the only near-real-time information available. The accuracy of the LSWT analysis against independent data from the ESA ARCLake project at the University of Edinburgh gives a global RMS error of 1.31 K and a bias of 0.65 K. It is demonstrated that the OSTIA LSWT is an improvement over the use of climatology to capture the day-to-day variation in global lake surface temperatures.

1 Introduction

1.1 Motivation and overview

The Operational Sea Surface Temperature and Sea-Ice Analysis (OSTIA) system (Donlon et al., 2012) was developed at the UK Met Office, primarily for NWP purposes. The system produces a daily analysis of foundation temperature (the temperature below the diurnal warm layer, or the pre-dawn temperature (Minnett and Kaiser-Weiss, 2012)) on a 1/20^o grid. Lake Surface Water Temperature (LSWT) was included in OSTIA on 24 November 2011 as part of the daily foundation SST field, at the same resolution. Prior to this, the Caspian Sea had been the only lake included in OSTIA. A limited number of large lakes are currently included in the Met Office NWP land-sea mask. Prior to the inclusion of LSWT in OSTIA, a method involving either the nearest OSTIA SST measurements to the lake points or HadISST climatology was used to fill in the LSWT. Other users of the OSTIA product, for example ECMWF, used the OSTIA SST analysis but the LSWT from the NCEP RTG product (Gemmill et al., 2007). The development of OSTIA LSWT has therefore aimed to improve this situation. The Met Office is also involved with the Mobile Weather Alert project to produce weather warnings over Lake Victoria. This requires the high resolution (both temporal and spatial) LSWT for this region developed as part of the OSTIA system to run high resolution regional NWP.

Section 1.2 provides some background information and a description of the methods used to produce this first version of OSTIA LSWT follows in section 2. Section 3 presents a validation of the OSTIA LSWT analysis. A seasonal comparison of mean JJA (June/July/August) and DJF (December/January/February) OSTIA LSWT products is provided, using data from the ESA ARCLake project at the University of Edinburgh (Merchant and MacCallum, 2010) as an independent data set for validation. Global statistics and examination of case studies for three major lake systems are used for these investigations: Lake Victoria (centred on 33^oE, 2^oS), Lake Baikal (centred on 108^oE, 53^oN) and the North American Great Lakes (centred on 85^oW, 46^oN). An examination of the relationships between errors in the LSWT analysis and lake parameters such as lake elevation and surface area is also included. An analysis of the output of a pre-operational OSTIA run including LSWT is also presented, and finally summary and discussion and future work sections conclude the report in section 4.

1.2 Background

1.2.1 Potential uses of lake temperature information

An operational analysis of Lake Surface Water Temperature (LSWT) has many potential uses. Accurate estimates of LSWT should improve numerical weather prediction (NWP) models on regional scales (Oesch et al., 2003; Merchant and MacCallum, 2010; Dutra et al., 2010; Samuelsson et al., 2010; Balsamo et al., 2011). LSWT products can be used as lower boundary conditions for derivation of regional surface energy budgets in atmospheric models and are also required for lake energy balance models. Maps of LSWT are also valuable for understanding a wide variety of processes occurring in lakes, for example surface water transport patterns (Strub and Powell, 1986, 1987; Steissberg et al., 2005a; Oesch et al., 2008), river inflow patterns (Thiemann and Schiller, 2003; Oesch et al., 2008), water quality monitoring (Reinart and Reinhold, 2008; Coats, 2010), mixing regimes (Wooster et al., 2001), phytoplankton dynamics and primary production (Wooster et al., 2001; Thiemann and Schiller, 2003) and wind-induced upwelling events (Mortimer, 1952; Monismith, 1985, 1986; Imberger and Patterson, 1990; Steissberg et al., 2005b; Oesch et al., 2008). Surface temperature maps can provide information relevant to the vertical structure of the lake (Wooster et al., 2001).

Several studies have also used the surface temperature of lakes and inland water bodies as indicators of climate change, using both in situ observations (Coats et al., 2006; Quayle et al., 2002; Verburg et al., 2003) and infra-red satellite observations (Schneider et al., 2009; Schneider and Hook, 2010). Unlike the land surface it is possible to accurately monitor the surface temperature of lakes, as the emissivity of water is well known (Schneider and Hook, 2010). Results from these climate monitoring studies indicate that the global rates of warming in lakes are an order of magnitude greater than those found in the global oceans (Schneider et al., 2009). In addition, LSWT appears to be warming more rapidly than the mean surface air temperature around certain mid-latitude lakes, including the North American Great Lakes and in Northern Europe (Quayle et al., 2002; Austin and Colman, 2007; Schneider et al., 2009). Warming of lakes increases their thermal stability and resistance to mixing, which may have important impacts on the biology and biogeochemistry of the lake (Livingstone, 2003; Sahoo and Schladow, 2008; Coats, 2010; Blenckner et al., 2010). Increases in Arctic lake temperatures may also be an indicator of locally thawing permafrost (Smith et al., 2007; Hulley et al., 2011). Therefore accurate monitoring of LSWT has important applications.

1.2.2 Accuracy of LSWT retrievals

Retrieval coefficients for lakes suitable for the ATSR series of instruments (ATSR-1, ATSR-2 and AATSR) are available through the ARCLake project (Merchant and MacCallum, 2010) but do not yet form part of the operational processing chain. Although LSWT data are routinely available as part of GHRSST (Group for High Resolution Sea Surface Temperature) SST products for several other infra-red satellite data types used in OSTIA (NOAA and MetOp AVHRR, IASI), none of these currently include lake-specific processing. Therefore the LSWT data used in this report and for the daily operational OSTIA analyses are based on the current algorithms for SST retrieval. This will introduce errors into the LSWTs, owing to various issues. The use of cloud-clearing schemes (including cloud shadows) optimised for oceans will have a significant effect on the accuracy of retrievals over lakes (MacCallum and Merchant, 2010). There will also be errors associated with the elevation and continental location of the lakes, which affects the atmospheric thickness, water vapour column and aerosol corrections in the retrievals (Wooster et al., 2001; Thiemann and Schiller, 2003). Coastal contamination is also a potential issue, especially for long, narrow lakes, as are errors associated with the surface emissivity, which is salinity dependent. Errors in this latter quantity can lead to large errors in the derived surface temperature (Hook et al., 2003). Sampling is also an issue, contributing to artificial short-timescale variability in LSWT timeseries (Merchant and MacCallum, 2010). Sparse observations and subsequent sampling errors are likely to particularly affect retrievals for lakes in cloudy regions, or those for smaller lakes especially from satellite instruments with a narrow swath width such as the AATSR. Therefore the number of available observations may show considerable variation between lakes. In addition, sparse observations over lakes with large horizontal temperature gradients mean the observations may not be spatially representative of temperatures over the whole lake. However, although not ideal, the use of these SST retrievals over lakes is currently the only option for producing global operational analyses of LSWT and will bring the Met Office into line with other SST analysis products, for example NCEP RTG (Gemmill et al., 2007).

Table 1 summarises results from various studies into the use of SST retrieval algorithms over particular lakes. Nighttime results are shown where possible as they are likely to be significantly more accurate than those obtained during the daytime, owing to the absence of differential surface heating (Hook et al., 2003; Oesch et al., 2005). It can be seen from table 1 that the magnitude of both the bias and RMS errors in the retrievals vary depending on the lake or instrument/algorithm used. Results for Lake Mond are the poorest, but with a surface area of only 14 km^2 (Oesch et al., 2005) this lake is much smaller than the others shown in table 1. It is much more difficult to produce an accurate result for a lake of this size because of sparse data and coastal contamination. This lake is not included in the OSTIA mask (section 2). Results shown in table 1 for MetOp AVHRR (used in OSTIA) for the North American Great Lakes are particularly good, with a bias of 0.06 K and RMS error of 0.50 K against in situ temperatures from moored buoys (Marsouin, 2009). For the NOAA-17 AVHRR MCSST algorithm (closest to the operational NOAA-18 AVHRR MCSST currently used in OSTIA) the bias is -0.04 and 0.70 K and the RMS 0.88 and 1.12 K for Lakes Constance and Geneva respectively. This indicates the accuracy and bias of the data obtained varies widely depending on the chosen lake and it is therefore difficult to assess the general accuracy of the algorithms over lakes. Overall however, biases for instruments used in operational OSTIA are mainly of the order 0.5 K and RMS errors around 1.0 K (table 1).

Several other studies have evaluated LSWT algorithms designed for specific lakes (Hook et al., 2003; Thiemann and Schiller, 2003; Oesch et al., 2008). More recently these have been expanded to include larger numbers of lakes (Merchant and MacCallum, 2010; Hulley et al., 2011). Details of these accuracies are given in table 2. According to Thiemann and Schiller (2003), it should be suitable to apply regional algorithms derived for specific lakes to other lakes with similar climatic conditions, for example temperate or maritime/continental. A lower absolute accuracy compared to open ocean retrievals is found for lake-specific retrievals owing to the reduced spatial and temporal coverage over lakes (Oesch et al., 2005).

There are other studies relating to satellite-derived LSWT from other sensors, e.g. MODIS (Oesch et al., 2005, 2008; Reinart and Reinhold, 2008; Crosman and Horel, 2009) but as these are not currently used in OSTIA they have not been covered in this report. Results for older NOAA satellites (NOAA-11 and earlier) have also not been included. Currently, there are no GHRSST microwave satellite SST retrievals which include LSWT.

1.2.3 Accuracy requirements for LSWT retrievals

For climate studies, an absolute SST accuracy of less than 0.3 K is required (Walton et al., 1998; Li et al., 2001) and, for NWP, 0.5 K is necessary (Walton et al., 1998; Oesch et al., 2005; Edwards, 2012). Further, Walton et al. (1998) and Oesch et al. (2005) note these measurements should have high spatial resolutions of 0.5 to 10.0 km for NWP, with revisit times of between two and four measurements a day. It can be assumed the same criteria can be applied to LSWT retrievals.

1.2.4 Thermal structure and skin effect

A skin effect of a similar magnitude and variability to that seen in oceans (e.g. Katsaros, 1977; Fairall et al., 1996; Donlon and Robinson, 1998) can also be observed in lakes (Wooster et al., 2001; Hook et al., 2003; Oesch et al., 2005, 2008). This is similarly attributed to differential solar heating and variations in wind speed, leading to the top few centimetres of the lake (i.e. skin and subskin layers (Minnett and Kaiser-Weiss, 2012)) warming unevenly on clear, calm days compared to windy days when the top few centimetres become well mixed (Hook et al., 2003, and references

Table 1: Accuracy of operational SST algorithms for LSWT (std=standard deviation)

Instrument	Algorithm	Day/Night	Bias	RMS	Lake	Study
NOAA-12 AVHRR	NLSST	night	1.52 K	1.27 K (std)	N. Am. Great Lakes	Li et al. (2001)
NOAA-14 AVHRR	MCSST	day	1.35 K	1.35 K	Lake Constance	Thiemann and Schiller (2003)
	NLSST	night	0.41 K	0.80 K (std)	N. Am. Great Lakes	Li et al. (2001)
NOAA-16 AVHRR	MCSST	night	0.18 K	0.70 K	Lake Geneva	Oesch et al. (2005)
	”	night	-0.28 K	0.73 K	Lake Constance	Oesch et al. (2005)
	”	night	-2.08 K	1.47 K	Lake Mond	Oesch et al. (2005)
	NLSST	night	1.22 K	0.69 K	Lake Geneva	Oesch et al. (2005)
	”	night	0.61 K	0.64 K	Lake Constance	Oesch et al. (2005)
	”	night	-1.15 K	1.34 K	Lake Mond	Oesch et al. (2005)
NOAA-17 AVHRR	MCSST	night	0.70 K	0.88 K	Lake Geneva	Oesch et al. (2005)
	”	night	-0.04 K	1.12 K	Lake Constance	Oesch et al. (2005)
	”	night	-2.03 K	1.83 K	Lake Mond	Oesch et al. (2005)
	NLSST	night	1.53 K	0.81 K	Lake Geneva	Oesch et al. (2005)
	”	night	0.85 K	1.12 K	Lake Constance	Oesch et al. (2005)
	”	night	-1.10 K	1.91 K	Lake Mond	Oesch et al. (2005)
MetOp AVHRR		night	0.06 K	0.50 K (std)	N. Am. Great Lakes	Marsouin (2009)
ATSR-2	(each channel)	night	-0.49 - 0.35 K	0.51 - 0.68 K	various N America, Europe, Africa	MacCallum and Merchant (2010)
ATSR-2		night	0.69 K	0.38 K (std)	Lake Tahoe	Hook et al. (2003)
AATSR		night	-0.41 K	0.56 K	Lake Tahoe	Hulley et al. (2011)
		day	-0.41 K	0.75 K	Salton Sea	Hulley et al. (2011)
AATSR	(each channel)	night	-0.52 - 0.18 K	0.52 - 0.63 K	various N America, Europe	MacCallum and Merchant (2010)

Table 2: Accuracy of Lake-Specific LSWT algorithms. Nx=Nadir channel x, Dx=dual view channel x. ste=standard error

Instrument	Algorithm	Day/Night	Bias	RMS	Lake	Study
NOAA-11 AVHRR	split window	night	-0.02 K	0.68 K	Lake Malawi	Wooster et al. (2001)
	triple window	night	-0.17 K	0.41 K	Lake Malawi	Wooster et al. (2001)
NOAA-14 AVHRR	split window	day	-0.01 K	1.04 K	Lake Constance	Thiemann and Schiller (2003)
	triple window	night	0.06 K	0.51 K	Lake Malawi	Wooster et al. (2001)
NOAA-16 AVHRR	split window	day	0.16 K	0.71 K	Lake Constance	Thiemann and Schiller (2003)
ATSR-2	ARC-Lake (N2,N3,D2,D3)	night	-0.25 - -0.14 K	0.52 - 0.59 K	various N America, Europe, Africa	MacCallum and Merchant (2010)
	N2,N3 (bulk)	night	0.18 K	0.18 K (ste)	Lake Tahoe	Hook et al. (2003)
	N2,N3 (skin)	night	-0.37 K	0.28 K (ste)	Lake Tahoe	Hook et al. (2003)
AATSR	split window	night	-0.02 K	0.30 K	Lake Tahoe	Hulley et al. (2011)
	split window	day	0.18 K	0.46 K	Salton Sea	Hulley et al. (2011)
	ARC-Lake (N2,N3,D2,D3)	night	-0.48 - -0.28 K	0.51 - 0.60 K	various N America, Europe	MacCallum and Merchant (2010)
	ARC-Lake (D3)	night	-0.17 K	0.53 K	N. Am. Great Lakes	MacCallum and Merchant (2010)

therein). Therefore it is sensible to use the same criterion to remove diurnal warming contaminated LSWT data in OSTIA as is currently used for SST; i.e. only nighttime data or daytime data where the windspeed is greater than 6 m s^{-1} is used (Donlon, 1999). Thus a constant cool skin effect can be assumed.

The magnitude of the skin-bulk correction applied to the AATSR SST observations in OSTIA (0.17 K, Donlon et al., 2002) may not be appropriate for LSWT. Hook et al. (2003) demonstrate that the average nighttime skin effect for Lake Tahoe is 0.46 K. However, this is dependent on the diurnal wind speed pattern and particular mixing conditions for the lake, meaning this result is not necessarily applicable to other lakes. For example, at Lake Geneva, Oesch et al. (2008) found a mean nighttime skin effect of 0.03 K, with a range of -0.18 to 0.20 K. At Lake Malawi, Brown (1994) found a mean skin effect of -0.32 K, with a range of -0.47 K to -0.17 K over the diurnal cycle. The wind regime is likely to be different over lakes than for the open ocean, related to the available fetch as well as summer circulation features of land and lake breezes. These will vary in direction over the diurnal cycle, depending on the characteristics of the site (Oesch et al., 2008).

Lakes have a complex temperature structure in both vertical and horizontal dimensions. The vertical temperature structure of a deep lake is similar to that of the ocean, with a surface layer (the epilimnion), separated from the deep layer (hypolimnion) by a region of steep temperature gradient equivalent to a thermocline (metalimnion) (Brown, 1994). As well as differential diurnal heating, horizontal temperature gradients can also be caused by water temperatures for shallower parts of lakes being more closely coupled with the land temperature than are the deeper parts (Bussiéres and Granger, 2007). Variations in lake depth can lead to shallower areas warming more rapidly in the spring, and thermal barring during spring and summer can also develop, which is a circulation pattern tending to preserve cooler temperatures in the centre of large lakes (Merchant and MacCallum, 2010).

Tropical lakes are known to have modest annual thermal cycles whereas mid-latitude lakes display characteristically distinct thermal regimes, with one or more annual isothermal mixing events resulting from the maximum density of freshwater being at 4^{o}C (Austin and Colman, 2007). Within 10^o latitude of the equator the seasonal variability of LSWT is less than 2.5 K; the largest amplitude variability lies between 30^{o}N and 60^{o}N, rapidly decreasing poleward of 60^{o}N (Merchant and MacCallum, 2010). However, independent of latitude, for lakes with small water volumes, a more prominent annual cycle is seen as the heat diffusivity is higher compared to larger lakes (Oesch et al., 2003).

1.2.5 Ice Cover

Wintertime freezing of a lake is dependent on the regional air temperature and depth of the lake (Austin and Colman, 2007). Some lakes remain ice-covered for all or part of the year (Brown, 1994) and in situ measurements, for example in the North American Great Lakes, stop as shipping ceases and the moored buoys are retrieved for safe storage over the winter months. Ice cover also prevents satellite measurements of LSWT, meaning wintertime observations can be scarce. It has been observed in the North American Great Lakes that surface temperatures will not normally exceed 4 ^oC if both ice and open water are present (Irbe, 1992). A surface temperature above the 4 ^oC threshold can therefore be used to indicate that the water body is ice-free (Bussiéres et al., 2002; Reinart and Reinhold, 2008).

Ice cover has a significant impact on the surface heat budget. As well as reducing the interaction between the surface of the lake and the overlying air, it increases the albedo of the surface, which reduces the ability of the lake or water body to absorb shortwave radiation (Austin and Colman, 2007). The ice-out date in lakes (the springtime date on which the lake becomes ice-free) has been investigated as a climate change indicator (Austin and Colman, 2007, and references therein). In general, on northern hemisphere lakes and rivers the percentage of ice cover has been decreasing over the previous few decades (Magnuson et al., 2000). For example, if the current rate of decline continues, in a typical winter Lake Superior will be ice-free in about 30 years (Austin and Colman, 2007). For large northern lakes, the start of the summertime stratified season is a strong function of the previous winter ice coverage, which is itself sensitive to small variations in atmospheric forcing (Austin and Colman, 2007).

2 LSWT analysis method

A full description of the OSTIA system is provided by Donlon et al. (2012) but a brief introduction is included here for clarity. After quality control, near-real-time in situ data, extracted from the GTS (Global Telecommunication System) and various L2p (level 2 pre-processed) satellite SST data, available through GHRSST (Group for High Resolution SST), are assimilated daily on to a background field on a 1/20^o ($\sim$6 km) grid, using an optimal interpolation type scheme. The background field is produced from the analysis for the preceding day, with a slight relaxation to climatology. New data straying too far from the previous day's analysis are rejected before assimilation. AATSR and in situ observations are used as reference data for bias-correction of the other satellite data. Observation error information provided in the GHRSST files is used in the analysis. In order to produce the foundation temperature described in section 1.1, the only satellite SST data used are nighttime data and daytime data when wind speeds are greater than 6 m s^{-1} (Donlon, 1999) (see section 1.2.4).

In the new implementation of OSTIA including lakes, the land/lake mask used is that defined by the University of Edinburgh ARCLake Project (www.geos.ed.ac.uk/arclake/). The full mask includes all lakes with a surface area greater than 500 km^2, plus an additional 10 lakes, giving a total of 263 lakes. The ARCLake nighttime reconstructed AATSR climatology has been used to initialise the OSTIA LSWT, for comparisons to climatology in the following sections, and for the relaxation to climatology step during the OSTIA assimilation procedure. The climatology is on the same 1/20^o grid as OSTIA, so no spatial interpolation was required in order to use it. A linear temporal interpolation was performed on the ARCLake data to produce daily files from the original twice-monthly dataset.

This ARCLake climatology dataset contains the 248 lakes with enough data to produce a climatology, so 248 lakes of the full 263 are included in OSTIA (see Appendix for list). Figure 1(a) shows an example of the global OSTIA SST mask including lakes and figure 1(b) shows the same mask for Europe. The global mask used for calculation of statistics in the following sections is the MyOcean land/lake/river mask which covers everything not defined as land or ocean, i.e. lakes only for OSTIA. As the mask is fixed, it is not possible for OSTIA LSWT to take into account ephemeral lakes or regions of flooding.

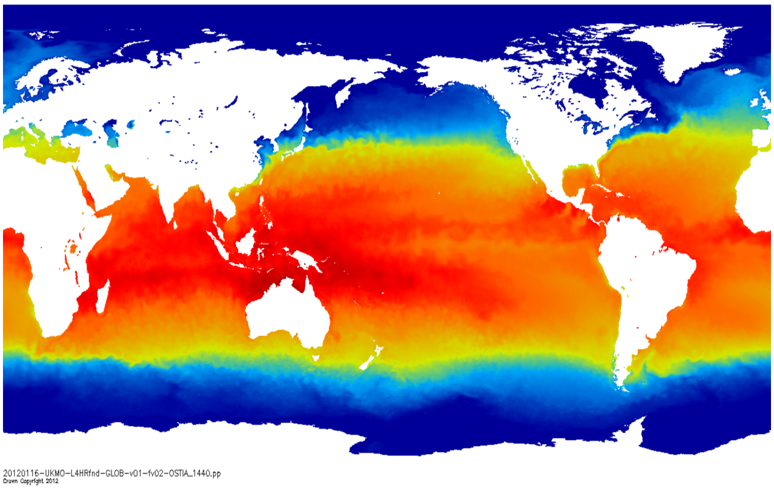
It should be noted there are differences between masks used by different centres, for example the NCEP mask and the ARCLake mask. The position of larger lakes tends to be more consistent between masks than for the smaller lakes. An international comparison of masks is underway through the GHRSST IWWG (Inland Waters Working Group) in an effort to standardise the masks adopted by different data providers and users. Since a decision had to be taken on which mask to use in order to begin work on OSTIA LSWT, the ARCLake mask was adopted. This was practical because the ARCLake climatology has been used in the OSTIA processing and it is necessary to have a complete climatology for each lake.

As described in section 1.2.2, the satellite surface temperature retrievals used for LSWT in OSTIA are optimised for SST and not LSWT. In addition, the OSTIA analysis method has not been optimised for lakes and hence lakes are treated in the same way as the oceans for this first version. This means the error covariances, length scales etc are not specific to lakes, but use of this method provides a starting point for future development work.

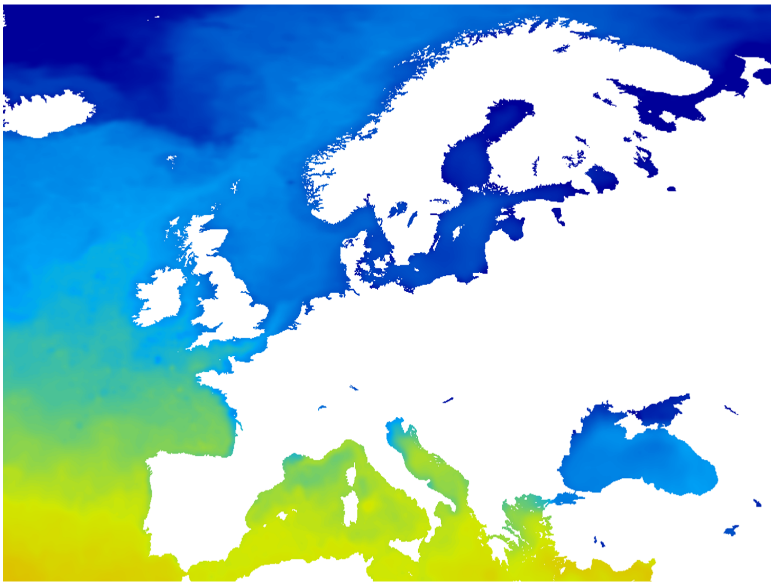
Analyses of two case studies are provided in the following sections: a delayed-mode JJA (June/July/August) and DJF (December/January/February) run for 2009, conducted for a seasonal comparison to independent ARCLake observations, plus a near-real-time run for October 2011, originally used for pre-operational testing. The delayed-mode runs were given generous 6-month spin-up periods, giving the analysis enough time to depart from the climatology it was initialised with, allowing for the fact that observations over lakes can be sporadic owing to satellite orbits and cloud cover. This long spin-up should minimise the number of 'good' observations rejected through the background check. It was not possible to include a spin-up period for the near-real-time run owing to time constraints.

Although there are many different satellite data types used in OSTIA, comparisons and analyses are shown here for only the data types which provide lake 'SSTs', namely the NOAA-18 AVHRR, MetOp AVHRR and AATSR instruments. In-situ data are also available for lakes through the GTS (Global Telecommunication System) in the same way as in situ SST measurements. There are currently no global microwave satellite SST datasets used in OSTIA so no microwave LSWT measurements have been investigated. In improvements to OSTIA made for an operational change on 24 November 2011, additional lake temperature data from IASI and NOAA-19 AVHRR have also become available, but these data sources were not available for the case study periods.

No lake-ice mask is currently available for OSTIA, but this will be included in future developments



(a) Global



(b) Europe

Figure 1: Example OSTIA SST field for 16 January 2012 showing land/sea/lake mask for (a) global and (b) close-up of Europe.

for NWP requirements. Investigation of the operational LSWT output indicates the satellite data assimilated over ice-covered lakes is sensible and thus the quality control is working to prevent any poor data over ice from entering into the analysis. When the lake is completely frozen and there are no data available, the OSTIA LSWT will relax towards the ARCLake climatology. When a lake ice mask is included this relaxation will be replaced with a relaxation towards freezing (0^oC), in a similar way as is currently performed for the SST (towards -1.8^oC).

3 Validation of OSTIA LSWT

3.1 Delayed-mode runs

3.1.1 Seasonal comparisons

OSTIA LSWT data were produced for DJF (December/January/February) and JJA (June/July/August) periods to compare the products for different seasons with each other. In order to also compare this dataset to ARCLake observations, the year 2009 was chosen to make use of the most recent ARCLake data available at the time of writing as ARCLake data for the period of the near-real-time run were not available. As the majority of the lakes in the OSTIA mask are located in the northern hemisphere (figure 1(a)) DJF and JJA correspond predominantly to winter and summer respectively. It should be noted that, unlike in the northern hemisphere, there are no lakes included in the OSTIA mask that freeze in the wintertime in the southern hemisphere.

Table 3 shows the observation minus background statistics for OSTIA LSWT for the DJF and JJA periods. For each data type, the observations for a particular day are compared against a background field constructed from the analysis for the previous day with a relaxation to climatology. Depending on the assumed accuracy of the observation type, this comparison gives a measure of the accuracy of the analysis. Although the errors in the observations are not independent from the errors in the analysis, this method has been shown to provide useful results on comparison with independent data (Roberts-Jones et al., 2011). The daily results are then averaged over the three-month period to give the results shown in table 3.

The mean number of daily observations for DJF is very small in comparison to JJA (table 3). For the in situ data, the majority of the global observations are located in the Great Lakes, which freeze in the winter and thus provide little opportunity for LSWT measurement. However, many more LSWT satellite data are available over this period than have been assimilated. This is due in part to the observations failing the OSTIA background check, despite the long spin-up period described in section 2. It is also partly related to the flagging of some of the observations as poor by the data providers, which prevents these data being included in the analysis. The total number of observations for lakes is so small that this presents more of a problem for the LSWTs than for the SSTs. The suitability of altering the flagging thresholds for lakes and raising the background check rejection threshold over lakes will be investigated. The number of LSWT observations entering the current operational system for December 2011/January 2012 are comparable to JJA 2009, i.e. there is not the same problem of lack of wintertime data for the operational system. A quick check for December 2009 reveals the same issue as for December 2008. This indicates fewer data are currently failing the background check than would have done for previous years. This implies the conditions this year are closer to climatology or there may have been changes made to the quality flagging by the data providers.

As the number of observations for DJF is very small and thus the statistics are not robust, further analysis will only be described for the JJA period. Overall, the JJA statistics shown in table 3 are encouraging. The global RMS error of the OSTIA LSWT to in situ data is 1.02 K and the bias is -0.13 K. These global statistics are similar to those shown in table 3 for the Great Lakes, which is unsurprising as the majority of the in situ data are located in this lake system.

Compared to the Great Lakes and Lake Victoria, Lake Baikal has the largest biases and RMS errors for most of the satellite data types. This could be related to coastal contamination owing to the long, thin shape of the lake. The exception is the bias with MetOp AVHRR, which is marginally worse in the Great Lakes (0.42 K for Lake Baikal, 0.46 K for Great Lakes). The magnitude of this bias is an interesting result, given the bias of MetOp AVHRR shown in table 1 of 0.06 K on comparison to in situ moored buoys (Marsouin, 2009). Table 3 indicates the RMS error of the observation minus background for NOAA-18 AVHRR is smaller than for the MetOp AVHRR for each of the cases shown. The magnitude of the bias for NOAA-18 AVHRR is also smaller globally and for the Great Lakes than for MetOp AVHRR, but is slightly larger for Lakes Baikal and Victoria. Overall, Lake Victoria has smaller biases and RMS errors compared to the other lakes. Its low-lying position on the equator and large, round size mean a more accurate LSWT analysis is possible. Reasons for this are discussed in more detail in the following sections, particularly section 3.2.

3.1.2 Comparison to independent data

The ARCLake LSWT retrievals employ lake-specific coefficients, a cloud clearing scheme designed for lakes and a salinity-dependent emissivity. This not only means the observations are independent from the AATSR data assimilated into OSTIA, which uses the operational SST algorithm, but that they can be considered the best global satellite observations of LSWT available. Therefore a validation of the OSTIA LSWT against this dataset was undertaken. It should however be noted the ARCLake observations are measurements of skin temperature whereas the OSTIA analysis is a foundation temperature. Nighttime ARCLake observations have been used in the comparison to avoid the effects of diurnal warming but a cool skin effect of around 0.2 K should be assumed present (MacCallum and Merchant, 2010). Only the JJA 2009 period described in section 3.1.1 has been compared with the ARCLake observations because, as noted above, a lack of observations in the DJF OSTIA LSWT analysis means quality assessment of this data would be unrepresentative of the errors expected in the operational system.

Globally, the accuracy of the OSTIA LSWT against the ARCLake observations is 1.31 K (table 4).

Table 3: Observation minus background statistics for OSTIA LSWT comparing period 01 December 2008 to 28 February 2009 to period 01 June 2009 to 31 August 2009, for all lakes (global) and 3 case studies.

	December 08/January 09/February			June/July/August 09		
Observation type	Mean Error	RMS Error	Mean Daily No. Obs	Mean Error	RMS Error	Mean Daily No. Obs
Global						
In situ	0.11	0.85	9	-0.13	1.02	600
AATSR	-0.00	0.39	67	0.08	0.83	1826
MetOp AVHRR	0.04	0.60	22	0.20	1.12	4740
NOAA-18 AVHRR	-0.02	0.38	56	-0.08	0.49	1153
Great Lakes						
In situ	4.80	8.47	1	-0.14	1.01	498
AATSR	-	-	-	0.13	0.97	447
MetOp AVHRR	-4.65	4.65	1	0.46	1.29	1699
NOAA-18 AVHRR	-2.74	2.74	1	-0.06	0.55	230
Lake Baikal						
In situ	-	-	-	-	-	-
AATSR	-	-	-	0.49	1.20	35
MetOp AVHRR	-	-	-	0.42	1.65	159
NOAA-18 AVHRR	-	-	-	0.59	1.14	7
Lake Victoria						
In situ	-	-	-	-	-	-
AATSR	0.02	0.34	37	0.07	0.32	193
MetOp AVHRR	0.08	0.44	19	0.06	0.44	621
NOAA-18 AVHRR	-0.12	0.37	28	-0.14	0.30	206

Table 4: OSTIA LSWT minus ARCLake observations and ARCLake climatology minus ARCLake observations for June/July/August 2009. Lakes listed in order of descending surface area.

	OSTIA-ARCobs		ARCclim-ARCobs		
Observation type	Mean Error	RMS Error	Mean Error	RMS Error	Mean Daily No. ARCobs
Global	0.65	1.31	0.00	1.78	4453
Great Lakes	1.41	1.78	0.45	2.13	822
Lake Victoria	0.40	0.44	0.08	0.29	137
Lake Baikal	1.83	2.76	1.21	2.11	140
Salton Sea	-0.13	1.45	-0.15	1.44	7
Lake Geneva	-0.06	0.63	1.00	1.67	2
Lake Constance	-0.06	1.02	0.95	1.87	1
Lake Tahoe	-0.46	0.83	0.28	0.82	2

However, at 0.65 K, the magnitude of the bias indicates that the bias correction using AATSR and the limited in situ data could be improved. However, as noted above, this bias does include the error introduced by comparing a skin measurement (ARCLake) with a foundation measurement (OSTIA), which is approximately 0.2 K, meaning the bias is likely closer to 0.45 K. The global statistics given in table 4 indicate that generally the RMS error for OSTIA minus ARCLake observations is better (lower) than for ARCLake climatology minus ARCLake observations, demonstrating that overall the OSTIA LSWT is more accurate than the climatology. Since the ARCLake climatology is derived from the ARCLake observations, the bias of the climatology against these observations would be expected to be smaller than that for OSTIA and indeed is zero when taking all lakes into account (table 4).

Case studies of particular lakes are also shown in table 4. Both the Great Lakes and Lake Baikal have large biases and RMS errors compared to the other lakes and, in the case of Lake Baikal, the analysis performs worse than the climatology in terms of the RMS error. However, results for other lakes are relatively good, particularly Lakes Geneva and Constance. The magnitude of the OSTIA minus ARCLake observation bias and RMS errors are generally larger than the observation minus background errors shown previously (compare tables 4 and 3).

Comparisons of table 4 with table 1 yield mixed results. For Lakes Geneva and Constance, compared to results using the NOAA-17 AVHRR MCSST algorithm (the closest to the assimilated NOAA-18 data), the OSTIA LSWT RMS errors are reduced and the bias is the same or better. For Lake Tahoe, the bias is improved but the RMS is worse for the OSTIA data compared to the operational AATSR SST retrievals, and similarly for the Salton Sea. For the Great Lakes, the OSTIA results are poorer than those found for both the MetOp AVHRR and the AATSR operational retrievals. This indicates the OSTIA LSWT results for the Great Lakes are worse than expected. This could potentially be due to poor quality in situ data used in the analysis for bias correction. The in situ data used in this assimilation have not undergone the operational monthly check against OSTIA data for potential inclusion on a blacklist. In addition, the majority of these data come from ships which are known to provide data of reduced quality than that obtained from moored (or drifting) buoys (Roberts-Jones et al., 2011). This could also suggest that the accuracy of the retrievals summarised in table 1 may not be consistently as good as the published results suggest. Comparison of table 4 with table 2 indicates the OSTIA LSWT analysis is not as accurate and has greater biases than LSWTs obtained from lake-specific non-operational LSWT retrieval algorithms.

As described in section 1.2.3, the target accuracy of the LSWT analysis for NWP purposes is at least 0.50 K. At 1.31 K against independent ARCLake observations, the global RMS error of the OSTIA LSWT analysis does not meet this requirement. However, the use of the OSTIA LSWT data in the Met Office NWP system is an improvement over the previous method (Bovis, 2011), described in the introduction (section 1.1) and it has been demonstrated in this report that the analysis is an improvement over climatology. As would be expected, owing to the use of retrieval algorithms and analysis techniques optimised for SST rather than LSWT (section 2), the accuracy of the OSTIA LSWT analysis is poorer than for the SST (global RMS errors of 1.31 K (for JJA) and 0.55 K respectively).

3.2 Investigation of relationships to lake parameters

Various metadata for each lake in the mask have been collated by the ARCLake project. In this section, the relationships between the RMS error and bias of the OSTIA LSWT analysis calculated using the ARCLake observations, and parameters including the elevation, area, and latitude of the lakes have been investigated.

Figure 2 shows the mean bias for each lake over JJA 2009 with lake area, with an indication of lake elevation. There is not a clear relationship between the magnitude of the bias and the lake area, although it can be said that the smaller lakes are more likely to have a larger bias, and the largest lakes are more likely to have a bias closer to zero. Most of the lakes shown here have a minimum area of 500 km^2 so it is possible the lakes would need to be smaller for an effect of area on bias to become apparent. As demonstrated for Lake Mond in table 1, very small lakes can have large biases.

Figure 2 also indicates that lakes at high elevations are more likely to have a negative bias, although lakes at low elevations can also have a negative bias. The difference of the JJA mean of the bias for all lakes lying above 2500 m elevation (-0.37 K) is statistically significantly different from that of lakes below 2500 m (0.12 K) at the 0.05 level. This statistic was calculated using Welch's t-test for unequal sample sizes and variances, and the Welch-Satterthwaite equation for calculating degrees of freedom. This method assumes the two samples are independent (non-paired), although this may not be strictly true for this case as the errors are correlated. As indicated by the global OSTIA LSWT minus ARCLake observations statistics (table 4), overall the OSTIA LSWT has a positive bias. As noted by Schneider and Hook (2010), large lakes at modest elevations might be expected to provide the best results for LSWT using the SST products. According to figure 2, these lakes have a positive bias. This means that the LSWT for higher altitude, smaller lakes may have compensating errors, thus reducing the bias.

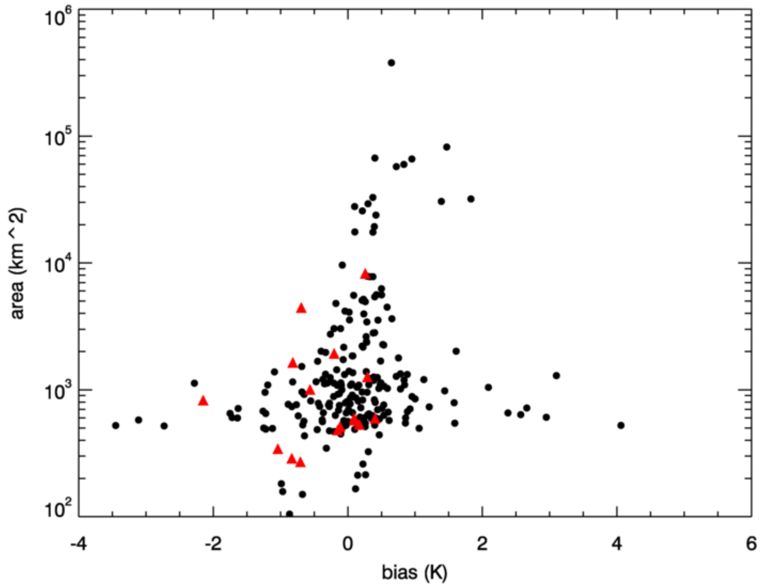


Figure 2: Mean OSTIA LSWT minus ARCLake observations for each lake, over JJA 2009, with lake area. A red triangle indicates the elevation of the lake is greater than 2500 m. Note log-scale on y axis.

There is little obvious relationship between RMS error with lake area and elevation (figure 3). In order to affect the accuracy of surface temperature retrievals, according to Oesch et al. (2005) the elevation needs to be extreme. In their study of Alpine LSWT, they did not find that the smaller water vapour content at around 400 m elevation exerted a significant influence on the accuracy of the retrievals. According to Schneider et al. (2009), larger uncertainties in LSWT may be expected for lakes at more extreme elevations on the Tibetan Plateau and in the Andes although figure 3 indicates this does not appear to be the case for the OSTIA data. However, other compensating errors may be masking any effect.

Figure 4 shows the bias of all OSTIA lakes for JJA versus the area divided by the perimeter, where these data are available. This metric provides a measure of the shape of the lake, where a high number indicates the lake is an even, smooth shape and a low number indicates the boundary is an uneven, irregular shape. More accurate satellite measurements should be possible for lakes with an even perimeter and shorter coastline as this minimises potential contamination of the retrieval from land. It can be seen that lakes with a shorter perimeter compared to the area (i.e.

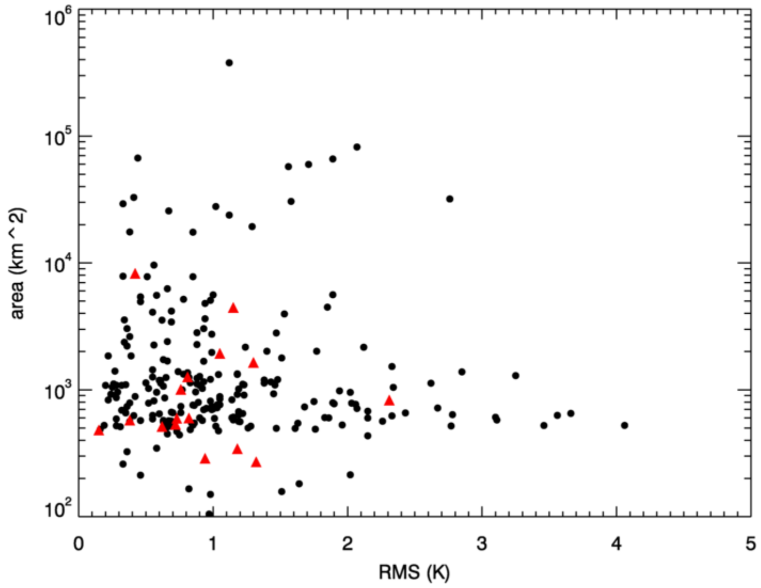


Figure 3: RMS error of OSTIA LSWT minus ARCLake observations for each lake, over JJA 2009, with area. A red triangle indicates the elevation of the lake is greater than 2500 m. Note log-scale on y axis.

a high number for this metric) have a positive bias (figure 4), implying the bias must be related to other factors.

Figure 5(a) is the equivalent plot using length divided by breadth as the metric. A high number indicates the lake has a long, narrow shape and a low number a rounder shape. This metric does not show the same relationship as figure 4, i.e. long, narrow lakes have similar results to rounder/squarer lakes. This implies the shape of the lakes used in the mask have a large enough length to breadth ratio that this metric makes no difference to the accuracy of the analyses. However, bias with breadth alone (the shortest lake axis) indicates that lakes with the largest breadth, which would be expected to produce the most accurate results with less land contamination, have a more positive bias than those with a smaller breadth (figure 5(b)). Again, this implies other factors are contributing to the positive bias for these lakes.

As might be expected, a greater number of observations generally contributes towards a smaller RMS error for any particular lake, whereas a low number of observations may lead to a large RMS error (figure 6(a)). Figure 6(b) shows the RMS error with the observation density, i.e. the number of observations divided by the lake area. However, this does not illustrate the same relationship as figure 6(a), implying a large number of observations are important for accurate LSWTs regardless of lake size. The four lakes with a number of daily observations per unit area (km^2) greater than 0.01 are the smallest four lakes with enough data to produce this metric (lakes Almanor, Clear, Mono and Walker).

Figure 7(a) shows the bias with latitude for each lake. At first glance it appears as though analyses of LSWT for the southern hemisphere have a smaller bias than for the northern hemisphere,

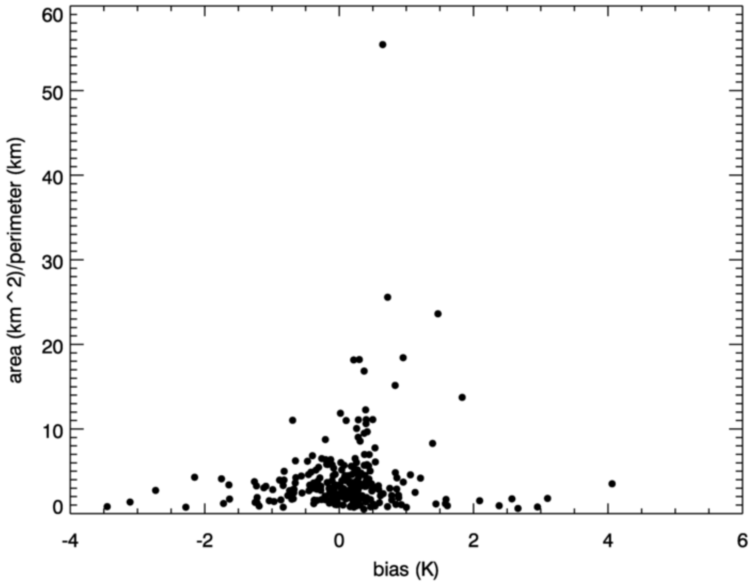
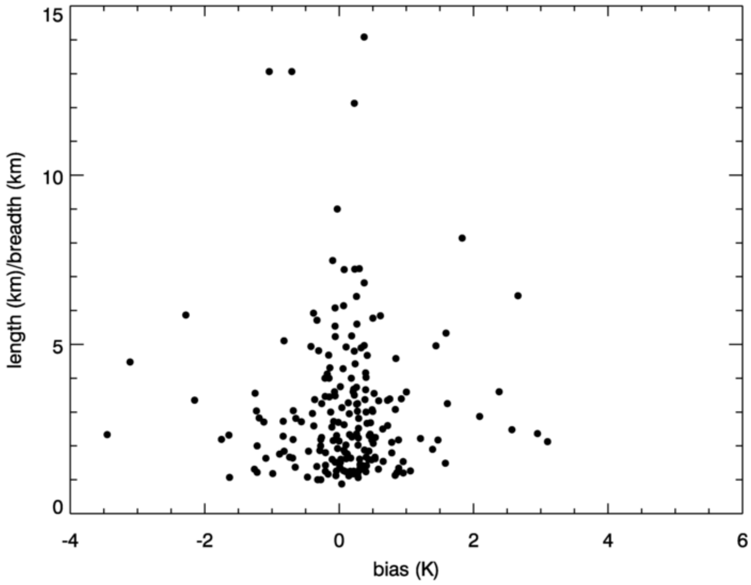


Figure 4: Mean error of OSTIA LSWT minus ARCLake observations for each lake, over JJA 2009, with area divided by perimeter, a measure of the regularity of the shape of the lake.

but as figure 1 also demonstrates, the majority of lakes are in the northern hemisphere, meaning the sample of lakes in the southern hemisphere is too small to show such a spread of biases. The difference between the mean bias of the lakes in the two hemispheres is thus not statistically significantly different from zero.

Figure 7(b) shows the bias with the absolute latitude, i.e. disregarding whether the lakes are located in the northern or southern hemisphere. Also shown are the elevation and area of the lakes. It is clear from this plot that higher altitude lakes are likely to have a negative bias and larger lakes a positive bias, as discussed above. Lakes at latitudes below 30^o have a smaller annual surface temperature cycle compared to lakes at higher latitudes (section 1.2.4), which suggests it could be easier to capture variability in a LSWT analysis. Indeed, figure 8 shows there is a difference between the RMS error of lakes with latitudes above 30^o (1.41 K) and those below 30^o (0.74 K), and this difference has been found to be statistically significantly different from zero. The mean biases of these two groups are not however statistically significantly different from zero indicating that latitude is not a contributing factor to biases in the LSWT analysis.

Figure 9(a) shows that the bias correction using the in situ data is working well, as the observation minus background bias for in situ data remains around zero for all elevations. The exception to this is the outlier, which is located in Lake Ladoga. Clearly this particular in situ observation is suspect as it must be disagreeing with the rest of the data in the analysis for this lake. In comparison to figure 9(a), the equivalent plot for the AATSR (figure 9(b)) shows more of a spread in the bias at different elevations, despite this also being a reference dataset. This may be related to the temporal sampling of the AATSR data, as there could potentially be several days or more between these measurements, allowing the LSWT analysis to drift away from the reference.



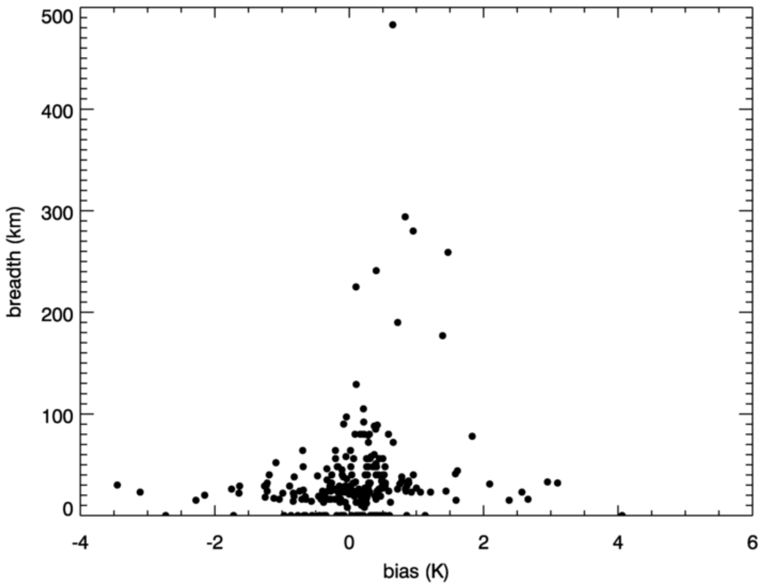


Figure 5: Mean error of OSTIA LSWT minus ARCLake observations for each lake, over JJA 2009, with (a) width divided by breadth and (b) breadth.

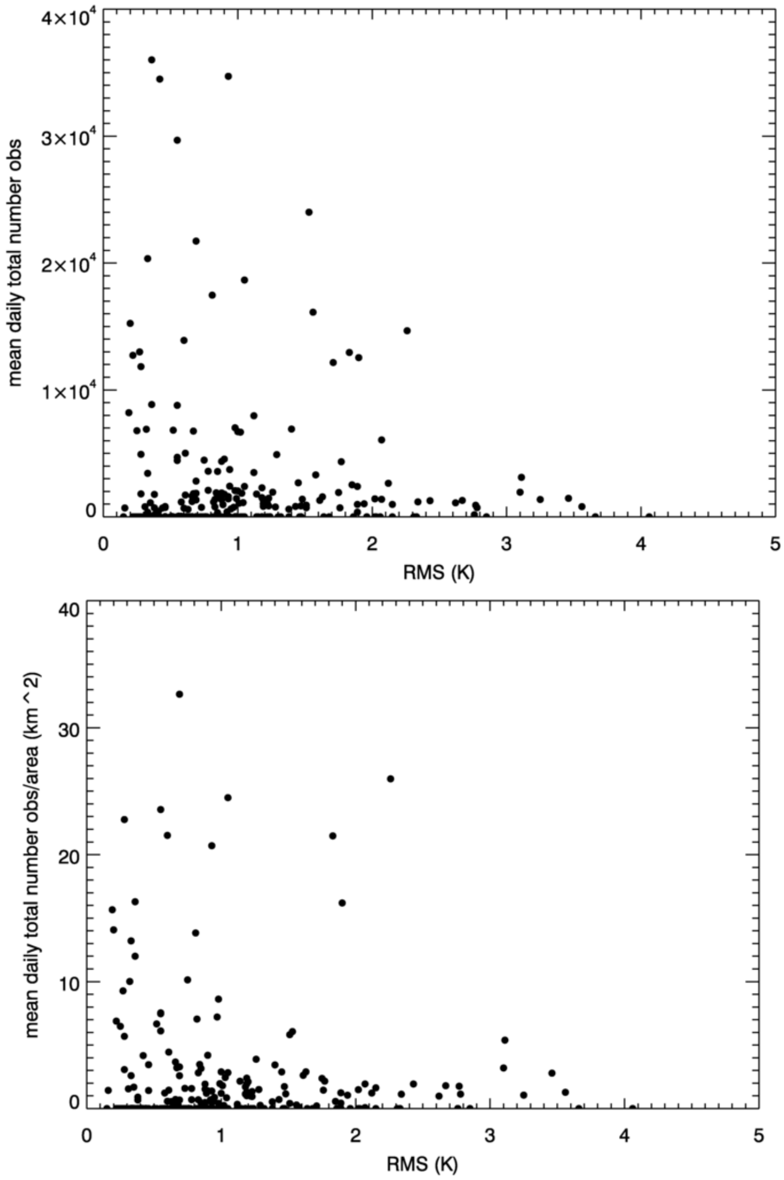


Figure 6: RMS error of OSTIA LSWT minus ARCLake observations for each lake, over JJA 2009, with (a) mean number of daily observations (all data types) used in OSTIA analysis for each lake, and (b) observation density (as figure (a) but divide number of observations by lake area in km^2).

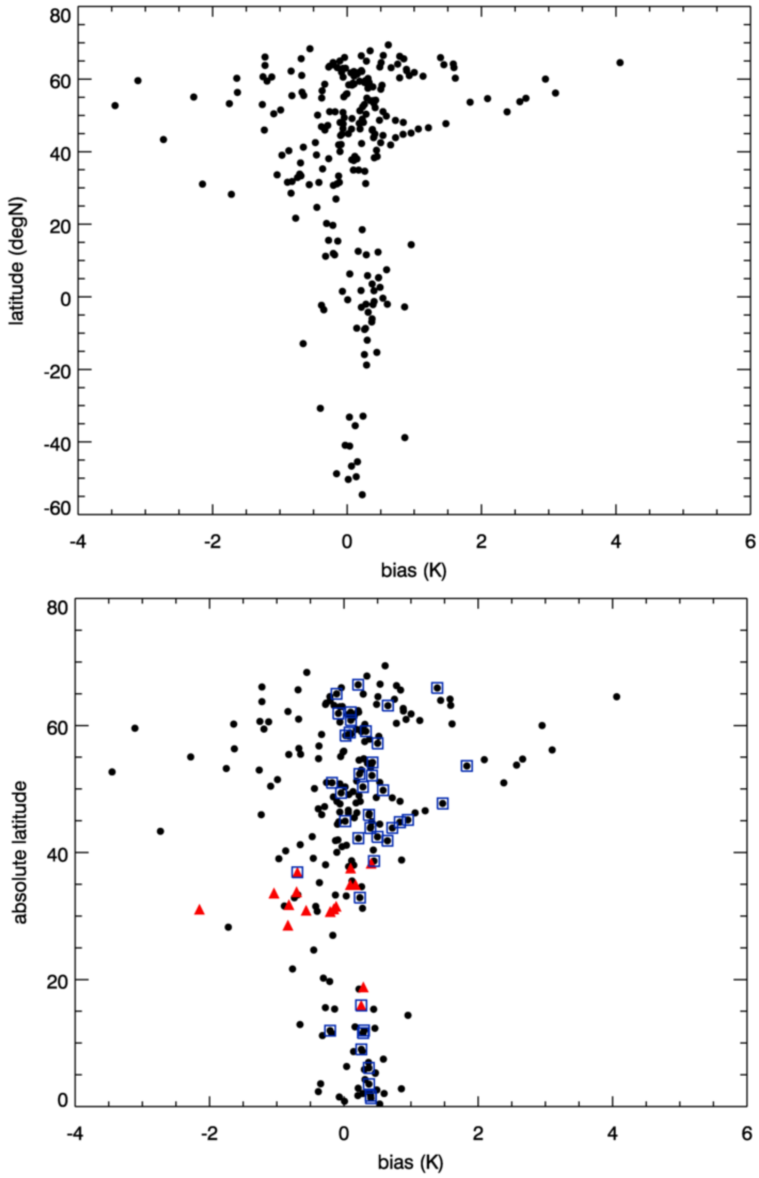


Figure 7: Mean error of OSTIA LSWT analysis minus ARCLake observations for each lake, over JJA 2009, with (a) latitude and (b) absolute latitude (i.e. disregarding which hemisphere). Each point represents the mean error for a lake. For (b), a red triangle indicates the lake has an elevation over 2500 m, and a black dot equal to or under 2500 m. A blue square indicates the lake also has a surface area of greater than 3000 km^2.

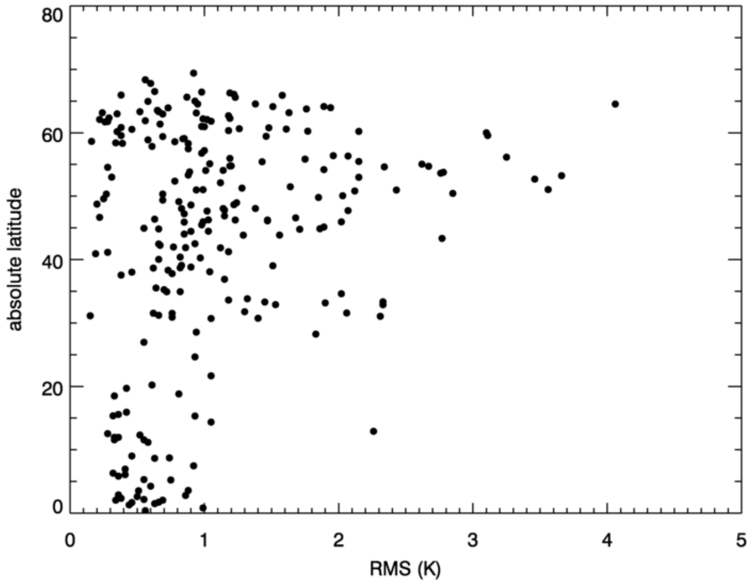


Figure 8: RMS error of OSTIA LSWT analysis minus ARCLake observations for each lake, over JJA 2009 with absolute latitude (i.e. disregarding which hemisphere).

Similar plots for bias and RMS error were examined for any relationships with lake depth and volume but none were seen.

3.3 Operational monitoring and assessment

A version of the pre-operational OSTIA suite including lakes was run for just over one month (2 September 2011 to 5 October 2011) prior to operational implementation. Results from the analysis of this output are given in the following sections.

3.3.1 Number of Observations

The data used for the LSWT analysis test runs have undergone the usual OSTIA quality control procedures (Donlon et al., 2012). However, the in situ data have not been included in the usual monthly check against OSTIA data for potential inclusion on a blacklist, but in the operational system this procedure will be carried out in a similar way as for in situ data over the ocean. The thresholds used for inclusion on the blacklist will also be investigated to check they are suitable for lakes.

The number of available infra-red satellite observations is affected by cloud cover meaning there is large day-to-day variability in the volume of data, as demonstrated in figures 10, 11 and 12. For MetOp AVHRR (figure 11), at 6 km resolution (after OSTIA subsampling), the spatial coverage over the lakes is the best of the satellite LSWT data sources (compare figures 10, 11 and 12). In contrast, the narrow swath width of the AATSR instrument means it takes 4 days to achieve complete global coverage (Robinson, 2004) and thus the number of observations can be sparse and very variable from day to day (figure 12).

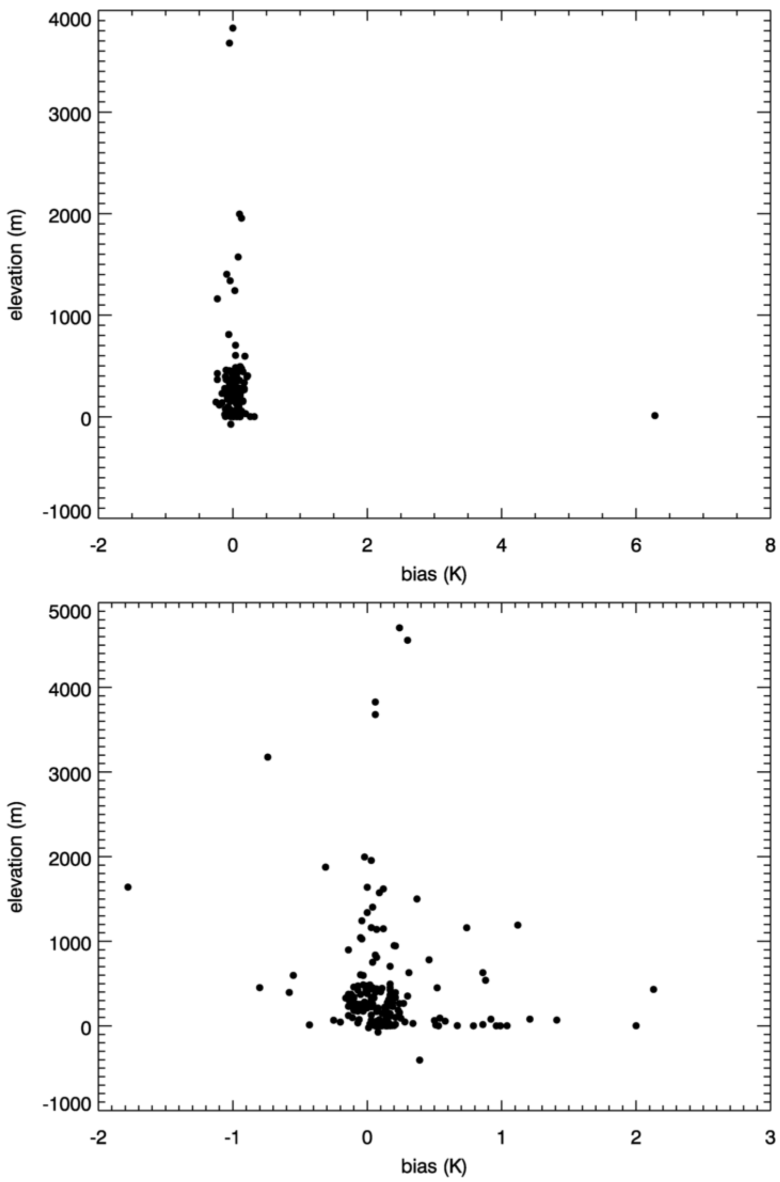


Figure 9: Mean error of (a) in situ observations minus OSTIA LSWT background and (b) AATSR obsrevations minus OSTIA LSWT background for each lake, over JJA 2009 with elevation.

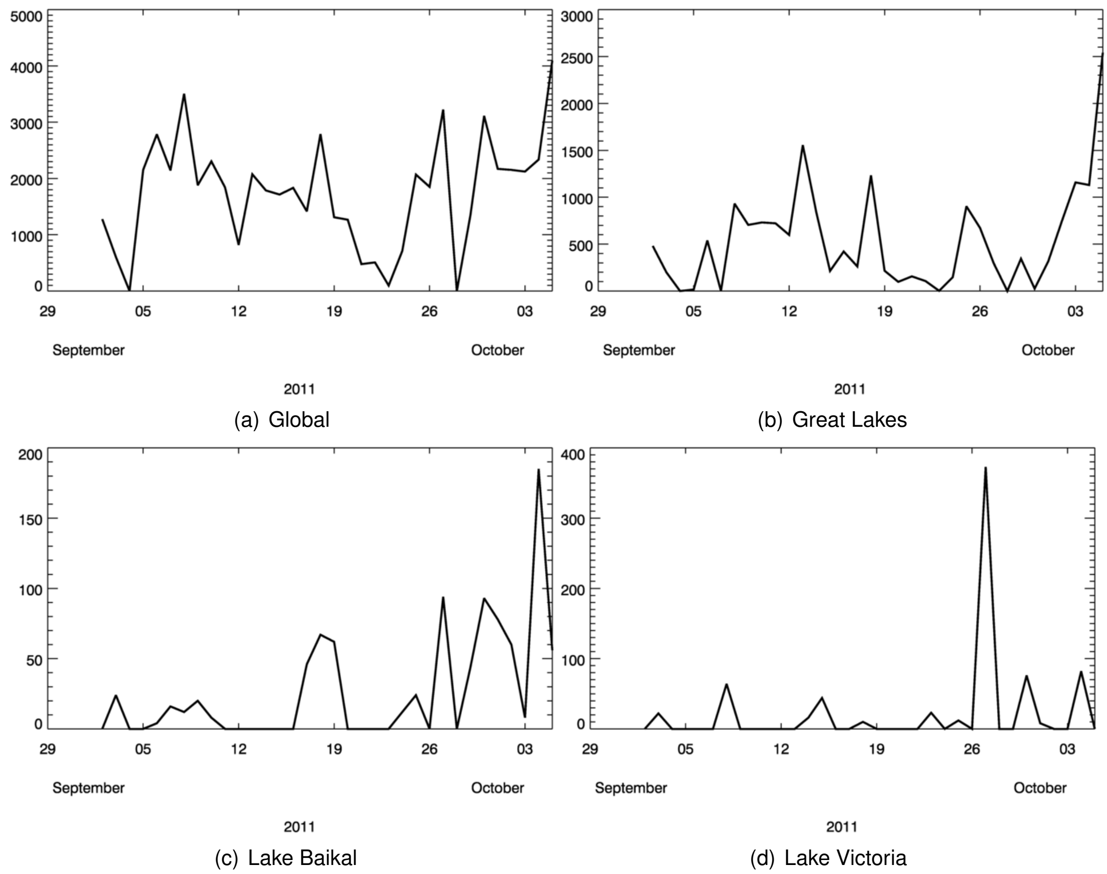
Comparison of the global number of in situ observations (figure 13(a)) with that for the Great Lakes (figure 13(b)) indicates the majority are located on the Great Lakes. The bias correction method in OSTIA LSWTs, as for the SSTs, is a correction to the in situ data and the AATSR. This indicates that for most of the lakes the only reference data for the bias correction is the AATSR dataset, which is uncorrected for lakes (section 1.2.2). It would therefore be a major benefit to the OSTIA LSWT analysis if the ARCLake processing were included in the operational AATSR processing chain.

There are currently no in situ observations collected over Lake Victoria but this should be improved soon as part of the Mobile Weather Alert pilot project mentioned in the introduction.

3.3.2 RMS and Mean Error statistics

Figure 14 shows timeseries of observation minus background and observation minus ARCLake nighttime AATSR climatology for the four data types: in situ, AATSR, MetOp AVHRR and NOAA-18 AVHRR. These results should be treated with caution because the observations are not strictly independent from the background, as the observation errors will be correlated. As the satellite data may contain biases, particularly as the retrievals are optimised for SST rather than LSWT (section 1.2.2), the in situ observations are likely to be the most reliable. If these are considered 'truth', figure 14(a) indicates that globally, OSTIA LSWT is clearly an improvement over climatology in terms of both accuracy and RMS error. Results over the entire period are summarised in table 5. This improvement over climatology is also the case for the Great Lakes (table 5) but unfortunately there are currently no in situ observations available for the other lakes featured in this table. Figure 14 also indicates that the OSTIA LSWT data require a spin-up period of several weeks to depart from the climatology used to initialise the analysis, and possibly longer for those lakes with limited data (e.g. Lake Victoria). This will have a detrimental effect on the mean statistics given in table 5.

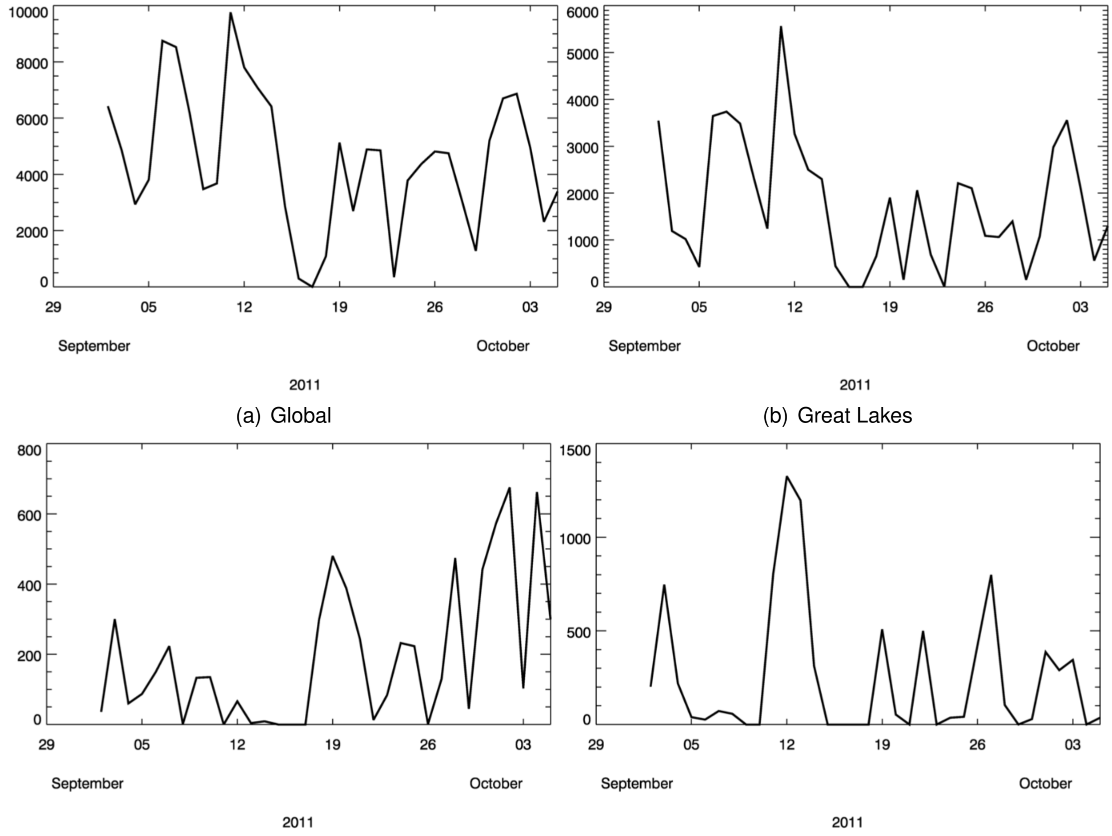
The satellite data also indicate that both the bias and RMS error are reduced for the observation minus background compared to the observation minus climatology, both globally (figure 14, table 5) and for the case studies of the Great Lakes and Lake Baikal (table 5). This improvement in the RMS is not the case for Lake Victoria (although the bias is improved) for a number of possible reasons. As there is no in situ data available (figure 13), a bias correction of the MetOp and NOAA AVHRR data is performed using only AATSR and this data may itself contain errors as it is not optimised for lakes. Additionally there are few days over this period when AATSR data are available (figure 12). In the absence of new data the field used for the bias corrections will decay exponentially (Donlon et al., 2012). Fewer observations for all data types mean that this lake will require a longer spin-up time than other, better sampled lakes, to diverge from the climatology it has been initialised with. Additionally, its position across the equator means that it does not experience large variations in temperature and is thus likely to remain closer to climatology than lakes at more temperate latitudes, for example the Great Lakes and Lake Baikal. This also means the surface temperature is easier to represent, so the RMS errors for Lake Victoria are notably smaller than for the other lakes.



(a) Global (b) Great Lakes

(c) Lake Baikal (d) Lake Victoria

Figure 10: Number of observations: NOAA-18 AVHRR (note differing scales on y-axis)



(a) Global (b) Great Lakes (c) Lake Baikal (d) Lake Victoria

Figure 11: Number of observations: MetOp AVHRR (note differing scales on y-axis)

3.3.3 Lake case studies

Figure 15 shows the spatial distribution of mean observation minus background errors over the test period 2 September to 5 October 2011 for the Great Lakes and also illustrates the spatial pattern of observations for this lake system. The coverage of the in situ data in the Great Lakes is very good, owing to the presence of ship-based observations, although the accuracy of the data is spatially variable (figure 15(a)). Data from the two AVHRR satellites, MetOp and NOAA-18, indicate that in the northern lake, Lake Superior, these observations are generally warm compared to the background (figures 15(b) and 15(c)). Similarly, both sets of AVHRR observations in the southern lakes (Lake Ontario and Lake Erie) are generally cool, with Lake Michigan-Huron perhaps in the middle, compared to the background. Biases are generally higher around the lake edges, particularly for MetOp AVHRR (figure 15(c)) which seems to have a larger mask than the NOAA AVHRR (figure 15(b)) and so provides more data around the lake edge. This could also be related to the use of the quality flags for the data in the OSTIA processing, which deserves further investigation. There are notably no observations available in the northern part of the lakes for the AATSR (figure 15(d)) which also needs to be investigated. This means no bias corrections of the other satellite instruments will take place in the northern parts of the lakes if there are no in situ data available,

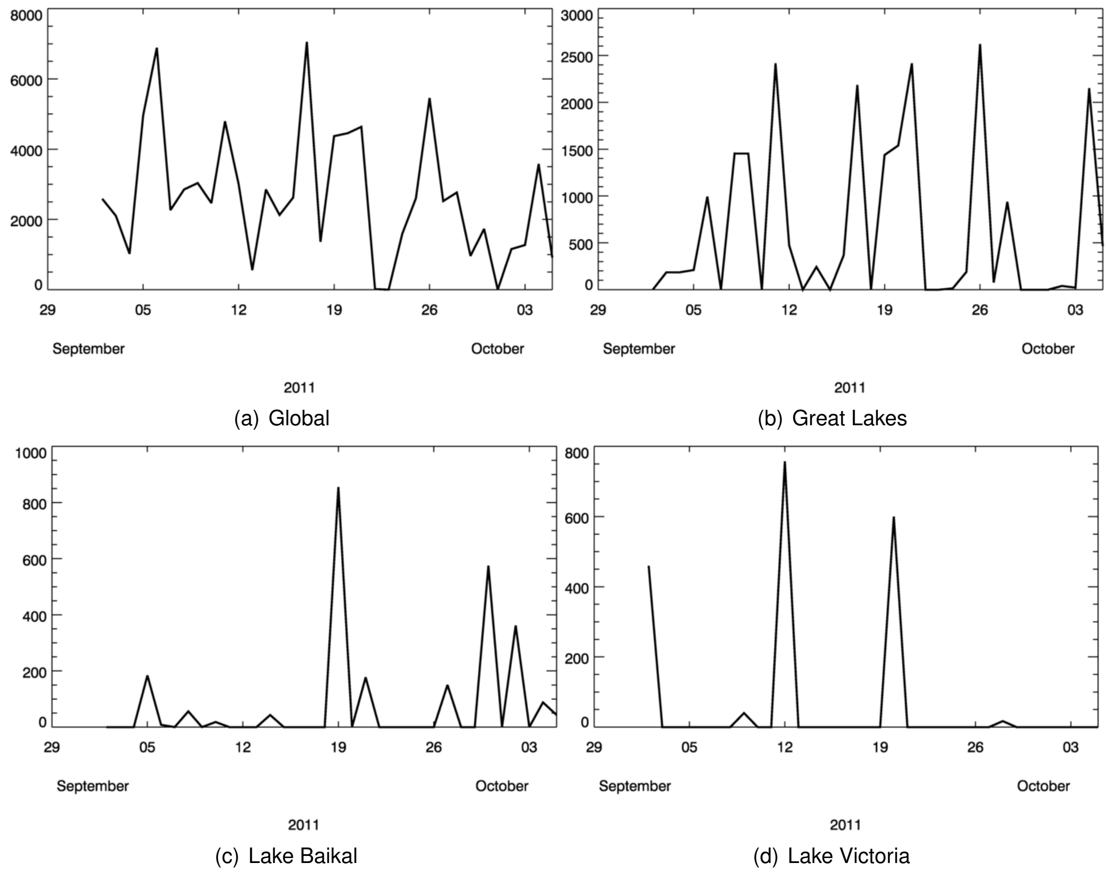
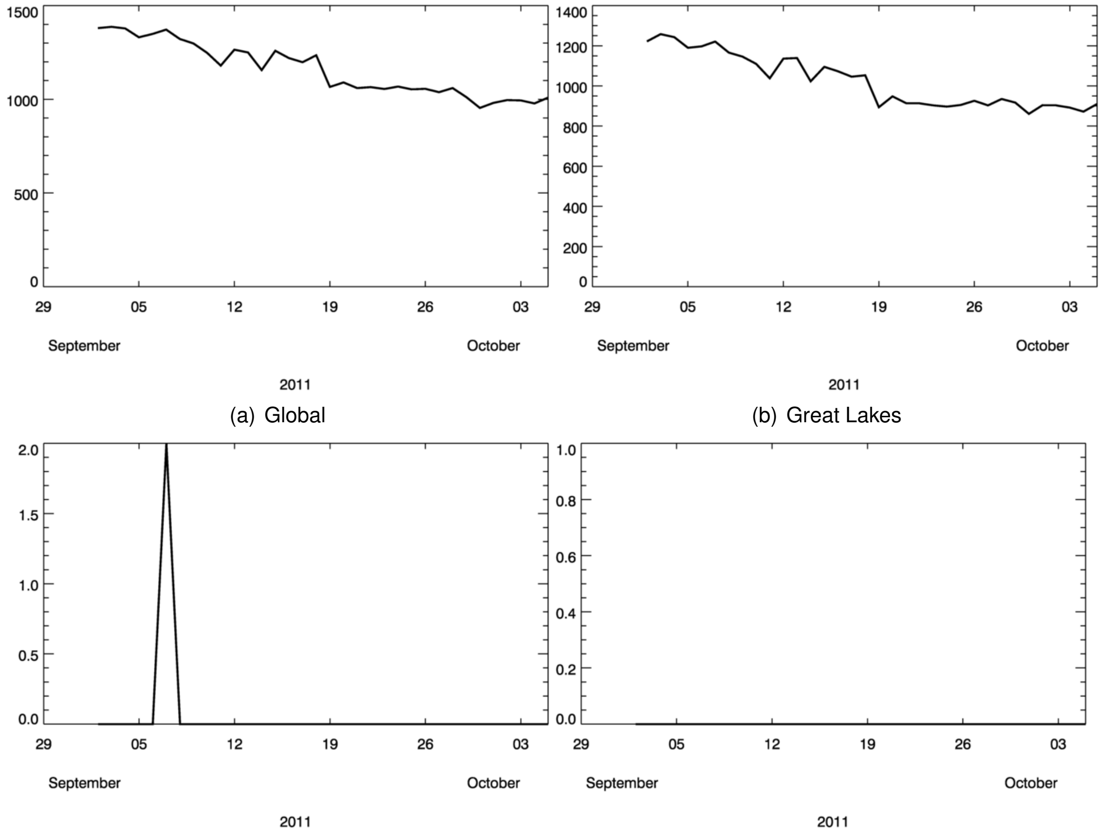


Figure 12: Number of observations: AATSR (note differing scales on y-axis)

other than from information in the bias field spread from the southern parts of the lakes. This will be the case for the majority of the lakes in the mask.

Figure 16(a) shows in situ observations at a single location for Lake Baikal, which are very warm compared to the background. In the same location the NOAA AVHRR data are very cold compared to the background (figure 16(b)) - it is possible the contribution from this in situ observation has warmed up the analysis which agrees better with the MetOp AVHRR and AATSR than the NOAA AVHRR. Similar to figures 15(c) and 15(d) for the Great Lakes, the MetOp AVHRR shows biases around the edge of Lake Baikal (figure 16(c)), and little data for AATSR in the northern part of the lake (figure 16(d)).

Figure 17 shows the same plots for Lake Victoria. The best coverage is again achieved by the MetOp AVHRR, as in figures 15 and 16. Similar to figures 15 and 16, there is again an issue with the spatial coverage of the AATSR data for Lake Victoria (figure 17(d)) which requires investigation.



(a) Global (b) Great Lakes

(c) Lake Baikal (d) Lake Victoria

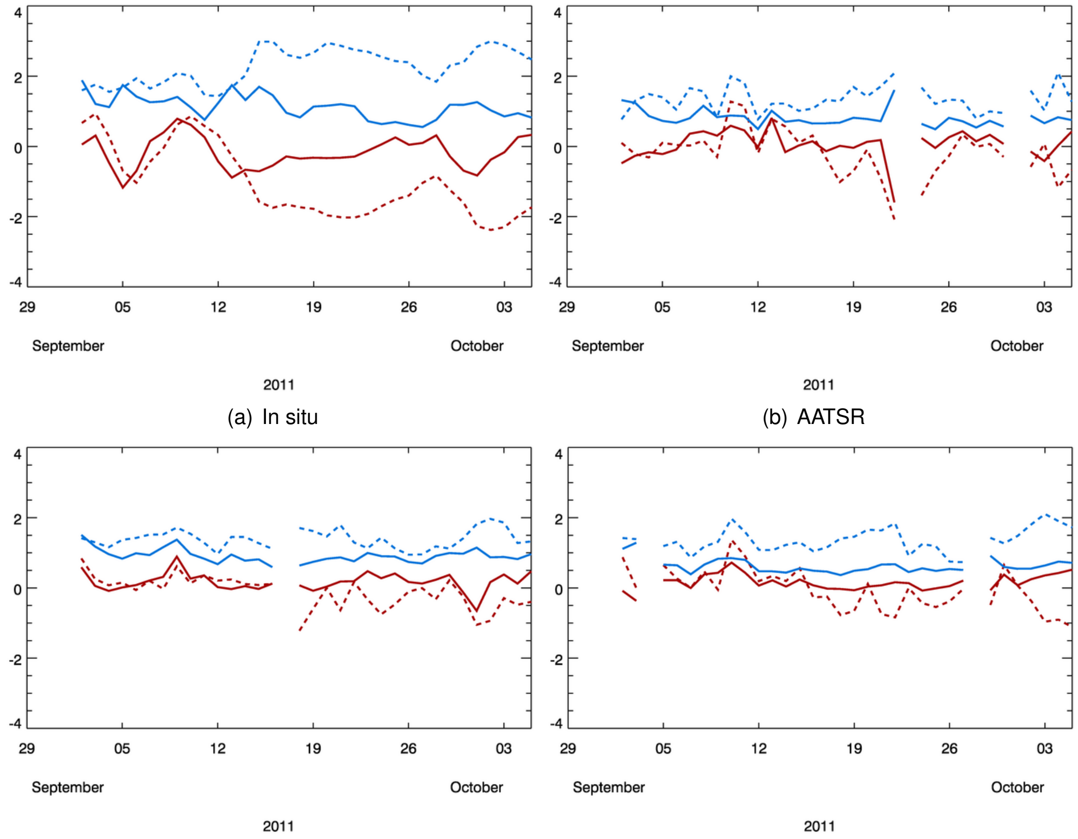
Figure 13: Number of observations: In situ (note differing scales on y-axis)

4 Conclusions

4.1 Summary and discussion

Operational analyses of LSWT (Lake Surface Water Temperature) have many potential uses including improvement of NWP models on regional scales, and thus LSWT was included in the Met Office operational OSTIA product on 24 November 2011 for 248 lakes globally. The OSTIA LSWT analysis is produced in the same way as the SST analysis using in situ data from the GTS (Global Telecommunication System) where available and GHRSST (Group for High Resolution SST) L2P (Level-2 pre-processing) satellite data. Not all satellite data types used in OSTIA contain LSWT information so it was only possible to use MetOp and NOAA AVHRR, and AATSR data, at the time of writing. There is significant day-to-day variation in the number of infra-red satellite surface temperature observations available over lakes because of cloud cover. As the retrievals for these instruments are optimised for SST they will introduce inaccuracies when used for a LSWT analysis but there are currently no other data sources available to produce a near-real-time analysis. The OSTIA analysis procedure uses correlation length scales and background error covariances designed for oceans for this first version of the LSWT product.

The global accuracy of the OSTIA LSWT product for JJA (June/July/August) 2009 against inde-



(a) In situ
(b) AATSR
(c) MetOp AVHRR
(d) NOAA-18 AVHRR

Figure 14: Global RMS (blue) and mean (red) errors for observation minus background (solid line) and observation minus ARCLake climatology (dashed line).

pendent satellite observations from the ESA ARCLake project at the University of Edinburgh is an RMS error of 1.31 K and a bias of 0.65 K (OSTIA minus ARCLake, and including a skin-bulk error of around 0.2 K). Against in situ observations the global statistics are 1.02 K and -0.13 K for the same period, although most of these observations (83%) are located in the North American Great Lakes. The global accuracy of the OSTIA LSWT analysis is poorer than that of the operational SST analysis (RMS error 0.55 K) as would be expected and does not meet the ideal accuracy requirement for NWP of 0.5 K. However, it has been demonstrated that the OSTIA LSWT is an improvement over the use of climatology to capture the day-to-day variation in global lake temperatures.

There are clearly a number of factors which can potentially affect the accuracy of an LSWT analysis for an individual lake. It might be expected that LSWT analyses for larger lakes at lower altitudes, i.e. those which approximate the seas for which the retrievals and analysis methods are optimised, would produce the best results. This would also apply to those lakes with a larger breadth, and higher area to perimeter ratio (more even coastline). It has been shown that analyses for these lakes tend to have a positive bias, so it is possible that compensating errors in analyses exist for smaller lakes at higher altitudes, or narrower lakes with more uneven coastlines, reducing the bias found for these lakes. It has also been demonstrated that the analyses for lakes within

Table 5: Global and regional statistics: Observation minus background and observation minus climatology for lakes globally, and three case studies. Mean and RMS errors shown for time period of pre-operational test run (2 September 2011 to 5 October 2011). A dash (-) indicates too few data to produce statistics.

Observation type	Observation minus Background Mean Error	Observation minus Background RMS Error	Observation minus Climatology Mean Error	Observation minus Climatology RMS Error
Global				
In situ	-0.18	1.20	-0.95	2.30
AATSR	0.08	0.79	-0.12	1.39
MetOp AVHRR	0.15	0.95	-0.08	1.44
NOAA AVHRR	0.21	0.64	-0.05	1.41
Great Lakes				
In situ	-0.21	1.23	-1.09	2.38
AATSR	0.28	0.90	-0.71	1.66
MetOp AVHRR	0.23	1.05	-0.52	1.64
NOAA AVHRR	0.30	0.64	-0.91	1.67
Lake Baikal				
In situ	-	-	-	-
AATSR	-0.15	0.84	-1.61	2.04
MetOp AVHRR	-0.09	0.83	-1.10	1.59
NOAA AVHRR	0.21	0.78	-0.69	1.32
Lake Victoria				
In situ	-	-	-	-
AATSR	0.09	0.49	0.32	0.49
MetOp AVHRR	-0.10	0.49	0.14	0.49
NOAA AVHRR	-0.10	0.32	0.01	0.31

30^o of the equator are more accurate and that a greater number of observations leads to a more accurate analysis, independent of lake size. Using all these criteria, the three “best” lakes in the OSTIA LSWT analysis are Lake Nyasa/Malawi (bias 0.30 K, RMS 0.33 K), Lake Tangany (bias 0.37 K, RMS 0.41 K) and Lake Victoria (bias 0.40 K, RMS 0.44 K). Note these lakes meet the target accuracy requirement for NWP of 0.50 K RMS discussed above. Each of these lakes also has an average of several hundred observations per day for JJA. Sampling issues are however clearly an important source of error for many lakes in the LSWT analysis as cloud cover and the frequency of satellite overpasses mean the number of observations can be sparse. Although no lake ice mask is currently included in the analysis, the wintertime operational LSWT analysis produces sensible results (not shown).

4.2 Future work

There are a number of possible improvements which could be made to the OSTIA LSWT, as follows:

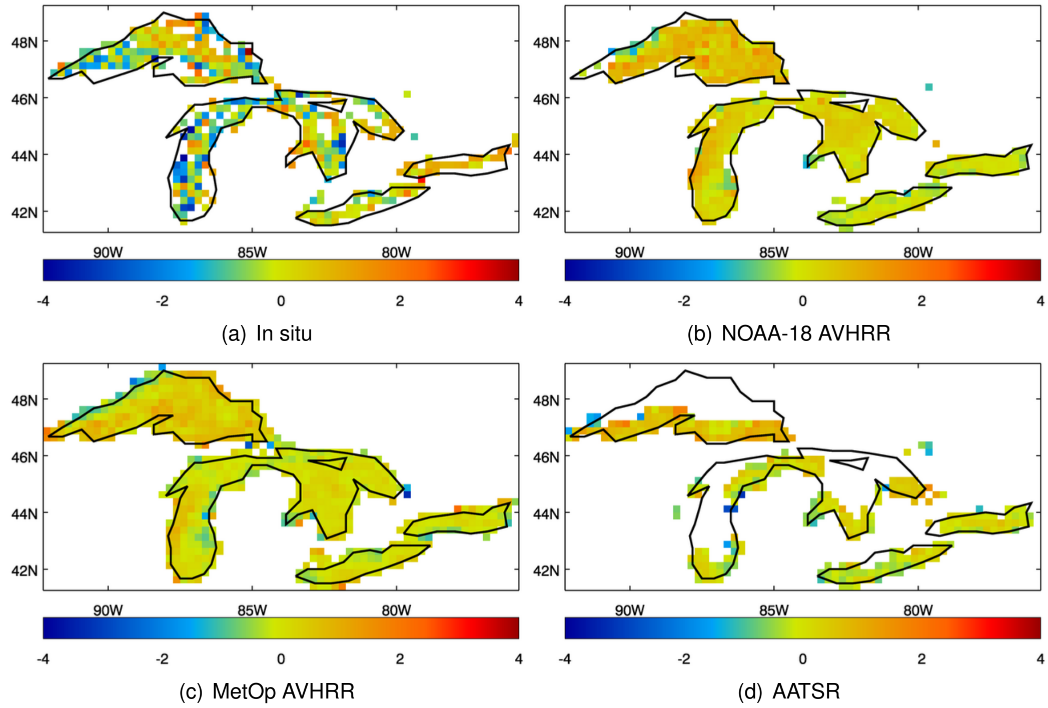


Figure 15: North American Great Lakes: Mean observation minus background (K) 2 September 2011 to 5 October 2011.

- The ARCLake land/lake mask has been used for the OSTIA LSWT. There are plans within the international LSWT community to produce a standard mask as the position of the lakes can vary significantly between different data providers depending on the data source used. A consensus mask would allow easier transfer of data between the various providers and users. However, as more users at the Met Office begin to adopt the ARCLake mask through OSTIA it may become difficult to alter it.

- The bias correction for the OSTIA LSWT analysis is performed using AATSR and in situ data as a reference, as for the SSTs. Little in situ data is available outside of the Great Lakes and therefore most of the bias correction takes place against the AATSR data. The issue of the lack of AATSR data in the northern parts of lakes is therefore an important one and needs investigation (see below). In addition, as this AATSR data is uncorrected for use over lakes, it would be of major benefit to the accuracy of the OSTIA analysis if the ARCLake processing were included as part of the operational AATSR processing chain. Failing this, a cloud-clearing scheme optimised for lakes could be introduced as part of the OSTIA processing to improve results. In addition, the magnitude of the global skin-bulk correction applied to the AATSR data may not be suitable for lakes, owing to the different wind regimes over lakes compared to oceans.

- The absence of AATSR data in the northern part of lakes needs to be investigated, and checked for in the delayed-mode run. Possible causes of these issues are the use of data

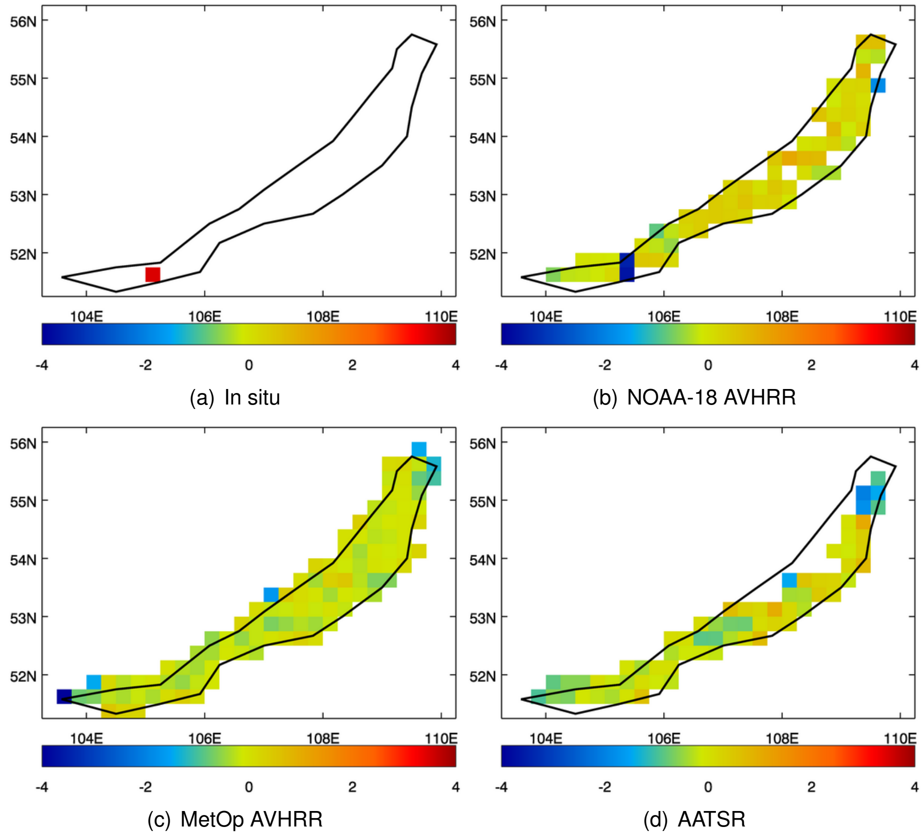
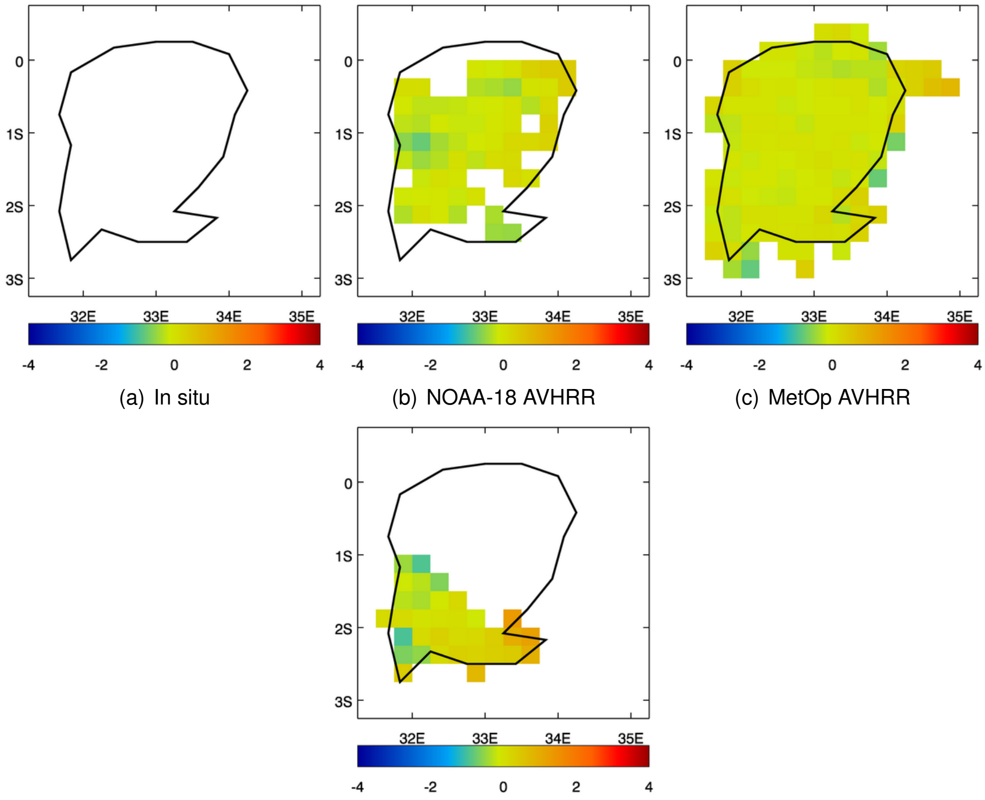


Figure 16: Lake Baikal: Mean observation minus background (K) 2 September 2011 to 5 October 2011.

quality flags appropriate for SSTs but not LSWTs. However, altering the minimum quality flag used may introduce poor data over ice-covered lakes into the analysis.

- An increase in the amount of in situ data available outside of the North American Great Lakes for use as a reference for bias correction would be beneficial. As part of the Mobile Weather Alert project in situ data may soon become available from Lake Victoria which will be used firstly for validation purposes and then for near-real-time assimilation as a reference dataset. This is expected to improve LSWT in Lake Victoria. There are very few suitable independent in situ observations of LSWT available to use for verification of OSTIA LSWT. We have plans to collaborate with Simon Hook of NASA JPL who has undertaken extensive monitoring of Lake Tahoe and the Salton Sea in the US. It would be useful to use this in situ data as independent verification of a run assimilating ARCLake observations, and a control run using the operational AATSR retrievals.

- Many of the northern lakes freeze over in the wintertime and therefore the inclusion of an ice mask is necessary, particularly for NWP uses. Similar methods currently used for the high latitude SSTs in OSTIA could be employed, where the LSWT would be relaxed towards 0^{o}C (rather than the -1.8^{o}C used for oceans) in the presence of a certain concentration of ice (set



(a) In situ (b) NOAA-18 AVHRR (c) MetOp AVHRR (d) AATSR

Figure 17: Lake Victoria: Mean observation minus background (K) 2 September 2011 to 5 October 2011.

at 50% in the oceans). The OSI-SAF (providers of OSTIA sea ice data) have plans to shortly add the Caspian Sea to their sea ice field but further lakes will not be included until 2013. In the meantime, investigations into using the NCEP lake ice concentration product will be conducted. Once a lake ice mask is introduced, improvements to the way the Surface Fields Processing System (SURF, which handles the passing of SSTs to the NWP system) deals with sea ice in OSTIA can be undertaken.

- The spreading of negative increments can push the LSWT (and SST) below freezing even if the original observations are accurate. For example, on 19 January 2012 the minimum temperature in Lake Baikal in the OSTIA LSWT was below 0^{o}C at -0.97^{o}C, which should be improved. In addition, the minimum temperature for observations in OSTIA is set to -2^{o}C but this is not suitable for freshwater lakes.

- In situ data undergoes a monthly check against OSTIA for potential inclusion on a blacklist. As the OSTIA LSWT data is less accurate than the OSTIA SST data, it may be necessary to alter the threshold for blacklisting in situ data over lakes.

- Biases are generally higher around the edges of lakes, particularly for the MetOp AVHRR data. This may be solved by altering the quality flags or may be an issue with the data itself. It may be appropriate to introduce a 'buffer zone' around the shore, as recommended by Oesch et al. (2008) for NOAA AVHRR who suggest 1 pixel.

- The suitability of using a background error covariance matrix and correlation length scales appropriate for oceans for a LSWT analysis should be investigated. Long length scales may mean lakes erroneously influence each other. The absence of wintertime data in test runs indicates that the background error check should be investigated and relaxed if necessary. The error estimates of the data over lakes may also require adjustment.
- Comparisons of OSTIA LSWT to other operational LSWT analyses (e.g. NCEP RTG, Great Lakes Coastwatch daily analysis) could be set up in a similar way to GMPE (GHRSST multi-product ensemble (Martin et al., 2012)).
- The effect of new instruments on the LSWT analysis could be investigated, e.g. IASI, NOAA-19 AVHRR.

Acknowledgements

The work of Stuart MacCallum and Chris Merchant on the ARCLake data climatology and observations used in this analysis is gratefully acknowledged. Thanks also to Stuart MacCallum for supplying the ARCLake metadata.

Appendix

List of 248 lakes in OSTIA mask in alphabetical order, with centre latitude (^{o}N) and longitude (^{o}E).

Lake name	**Latitude**	**Longitude**
ABAYA	6.30	37.83
ABE	11.17	41.79
ABERDEEN	64.55	-98.59
ABY	5.23	-3.23
ALAKOL	46.11	81.75
ALBERT	1.67	30.91
ALEXANDRINA	-35.52	139.09
ALMANOR	40.26	-121.19
AMADJUAK	64.99	-71.13
ANG-LA JEN	31.53	83.09
ARAL	45.13	60.08
ARGENTINO	-50.33	-73.03

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Lake Name	Latitude	Longitude
ARTILLERY	63.17	-107.82
ASHUANIPI	52.69	-66.14
ATHABASCA	59.10	-109.96
ATLIN	59.57	-133.75
AYAKKUM	37.55	89.35
AYLMER	64.15	-108.46
BAGHRASH	41.98	87.07
BAIKAL	53.63	108.14
BAKER	64.13	-95.28
BALATON	46.88	17.83
BALKHASH	45.91	73.95
BANGONG	33.61	79.71
BARUN-TOREY	50.07	115.81
BAY	14.36	121.26
BECHAROF	57.85	-156.40
BELOYE	60.18	37.64
BEYSEHIR	37.78	31.52
BIENVILLE	55.05	-72.98
BIG TROUT	53.77	-90.02
BIWA	35.25	136.08
BLACK	59.05	-105.73
BRAS D'OR	45.95	-60.83
BUENOS AIRES	-46.66	-72.50
BUFFALO	60.22	-115.49
BUYR	47.81	117.69
CARATASCA	15.35	-83.85
CASPIAN	41.85	50.36
CAXUANA	-2.04	-51.50
CEDAR	53.33	-100.14
CHAMPLAIN	44.45	-73.27
CHAO	31.57	117.57
CHAPALA	20.21	-103.05
CHILKA	19.69	85.38
CHILWA	-15.32	35.71
CHIQUITA	-30.74	-62.61

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Lake Name	Latitude	Longitude
CHISHI	-8.71	29.72
CHURCHILL	55.96	-108.29
CLAIRE	58.59	-112.08
CLEAR	39.02	-122.77
CLINTON COLDEN	63.94	-107.45
COARI	-4.25	-63.37
COLHUE HUAPI	-45.47	-68.76
CONSTANCE	47.65	9.28
CONTWOYTO	65.59	-110.66
CORO	11.56	-69.86
CREE	57.47	-106.64
CROSS	54.71	-97.58
DAUPHIN	51.27	-99.77
DEAD	31.52	35.49
DESCHAMBAULT	54.78	-103.45
DORE	54.76	-107.28
DUBAWNT	63.13	-101.44
EAU CLAIRE	56.15	-74.40
EBI	44.86	82.92
EBRIE	5.30	-4.26
EDWARD	-0.39	29.61
EGRIDIR	38.07	30.85
ENNADAI	60.96	-101.31
ENRIQUILLO	18.49	-71.58
ERIE	42.25	-81.16
ESKIMO	69.10	-132.76
EVANS	50.97	-77.02
EVORON	51.48	136.51
EYASI	-3.58	35.04
FAGNANO	-54.55	-68.03
FERGUSON	69.41	-105.27
GARRY	65.95	-99.40
GENEVA	46.37	6.25
GODS	54.62	-94.21
GRANVILLE	56.40	-100.21

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Lake Name	Latitude	Longitude
GRAS	64.54	-110.38
GREAT BEAR	65.91	-121.30
GREAT SLAVE	62.09	-114.37
GUILLAUME-DELISLE	56.33	-76.28
HAR	48.05	93.21
HAR US	48.06	92.30
HAR-HU	38.31	97.59
HAUKIVESI	62.10	28.52
HOTTAH	64.95	-118.44
HOVSGOL	51.02	100.48
HULUN	48.97	117.38
HUNGTZE	33.34	118.53
HURON	44.78	-82.21
HYARGAS	49.13	93.30
ILIAMNA	59.56	-154.90
INARI	69.04	27.83
INDIAN RIVER	28.24	-80.64
ISLAND	53.85	-94.70
ISSYKKUL	42.46	77.25
ISTADA	32.48	67.92
IZABAL	15.57	-89.11
KAGHASUK	60.79	-164.22
KAMINAK	62.20	-94.90
KAMINURIAK	62.96	-95.79
KAMILUKUAK	62.28	-101.73
KAOYU	32.87	119.31
KARA-BOGAZ-GOL	41.23	53.54
KASBA	60.34	-102.27
KHANKA	44.94	132.42
KHANTAYSKOE	68.36	91.18
KIVU	-2.04	29.23
KOKO	36.89	100.18
KRASNOE	64.53	174.44
KULUNDINSKOE	52.98	79.58
KWANIA	1.72	32.65

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Lake Name	Latitude	Longitude
KYARING	31.13	88.32
KYOGA	1.50	33.01
LABAZ	72.27	99.57
LADOGA	60.84	31.39
LESSER SLAVE	55.43	-115.49
LIMFJORDEN	56.78	9.17
LLANQUIHUE	-41.14	-72.79
LUANG	7.46	100.38
MACKAY	63.96	-111.30
MADRE	24.64	-97.66
MALAREN	59.44	16.19
MALHEUR	43.34	-118.83
MANAGUA	12.32	-86.35
MANGUEIRA	-33.16	-52.84
MANITOBA	50.99	-98.80
MANYCH-GUDILO	46.26	42.98
MARTRE	63.33	-117.91
MICHIGAN	43.86	-87.09
MILLE LACS	46.24	-93.65
MIRIM	-32.89	-53.25
MISTASSINI	50.82	-73.81
MONO	38.01	-118.96
MURRAY	-6.95	141.53
MWERU	-9.01	28.74
NAHUEL HUAPI	-40.92	-71.52
NAKNEK	58.64	-155.67
NAM	30.71	90.66
NATRON	-2.34	36.02
NERPICH'YE	56.39	162.77
NETILLING	66.42	-70.28
NGORING	34.93	97.71
NICARAGUA	11.57	-85.36
NIPIGON	49.80	-88.55
NIPISSING	46.24	-79.92
NONACHO	61.82	-108.92

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Lake Name	Latitude	Longitude
NORTH MOOSE	54.05	-100.16
NUELTIN	60.25	-99.40
NYASA	-11.96	34.59
OKEECIIOBEE	26.95	-80.86
OLING	34.92	97.27
OMULAKH	72.29	145.59
ONEGA	61.90	35.35
ONTARIO	43.85	-77.77
ORIVESI	62.35	29.59
PAIJANNE	61.71	25.49
PANGONG	33.82	78.61
PAYNE	59.40	-73.82
PEIPUS	58.41	27.59
PERLAS	12.54	-83.67
PETER POND	55.84	-108.55
PIELINEN	63.16	29.71
PLAYGREEN	54.07	-97.75
POMO	28.55	90.40
POOPO	-18.81	-67.06
PRINCESS MARY	63.93	-97.66
PURUVESI	61.77	29.02
PYA	66.07	30.98
PYHAJARVI	61.00	22.28
PYRAMID	40.03	-119.55
RAINY	48.61	-92.97
RAZELM	44.83	28.97
RED	48.04	-95.08
REINDEER	57.19	-102.27
ROGOAGUADO	-12.91	-65.73
RONGE	55.11	-104.83
RUDOLF	3.53	36.08
SAINT CLAIR	42.50	-82.73
SAINT JEAN	48.66	-72.02
SAINT JOSEPH	51.04	-90.81
SAKAMI	53.22	-76.75

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Lake Name	Latitude	Longitude
SALTON	33.30	-115.83
SAN MARTIN	-48.75	-72.84
SANDY	53.00	-93.03
SARYKAMYSHSKOYE	41.88	57.61
SASYKKOL	46.58	80.91
SEG	63.32	33.76
SELAWIK	66.51	-160.73
SELETYTENIZ	53.23	73.18
SELWYN	60.00	-104.68
SEVAN	40.39	45.29
SHAMO	5.83	37.55
SHERMAN	67.79	-97.73
SIMCOE	44.47	-79.42
SMALLWOOD	54.19	-64.31
SNOWBIRD	60.64	-102.94
SOUTH HENIK	61.37	-97.29
SOUTH MOOSE	53.83	-100.04
SUPERIOR	47.72	-88.23
SYVASH	45.96	34.74
TAHOE	39.09	-120.04
TAI	31.21	120.24
TAKIYUAK	66.28	-113.17
TAMIAHUA	21.66	-97.57
TANA	11.95	37.31
TANGANYIKA	-6.07	29.46
TANGRA	31.05	86.59
TAPAJOS	-2.88	-55.14
TATHLINA	60.54	-117.64
TAUPO	-38.81	175.90
TEBESJUAK	63.76	-98.98
TENGIZ	50.44	68.90
TERINAM	30.90	85.61
TESHEKPUK	70.59	-153.60
TITICACA	-15.92	-69.30
TOBA	2.61	98.90

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Lake Name	**Latitude**	**Longitude**
TOP	65.62	32.09
TOWUTI	-2.79	121.52
TROUT	60.58	-121.13
TULEMALU	62.99	-99.48
TUMBA	-0.82	17.98
UBINSKOE	55.47	80.05
ULUNGUR	47.22	87.30
UPEMBA	-8.65	26.40
UVS	50.33	92.81
VAN	38.66	42.98
VANERN	58.88	13.22
VATTERN	58.33	14.57
VESIJARVI	61.09	25.39
VICTORIA	-1.30	33.23
VIEDMA	-49.59	-72.56
VYG	63.54	34.84
WALKER	38.70	-118.71
WEISHAN	34.61	117.24
WINNEBAGO	44.02	-88.42
WINNIPEG	52.12	-97.25
WINNIPEGOSIS	52.37	-100.05
WOLLASTON	58.30	-103.33
WOODS	49.38	-94.91
XINGU	-2.16	-52.20
YATHKYED	62.69	-98.07
ZILING	31.77	88.95

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