Daily Minimum and Maximum Surface Temperatures from SEVIRI

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Introduction

Observations of daily minimum and maximum air temperatures, $T_{\text{min}}$ and $T_{\text{max}}$, have traditionally been obtained through in situ observations at meteorological stations. While the station network is extensive, many land masses are poorly observed. Moreover, observations at stations are ‘point’ observations and may not be representative of air temperatures at neighbouring locations. Satellites provide the means to observe surface skin temperatures at spatial scales of tens of metres to kilometres. But although skin and near-surface air temperatures may be strongly coupled, the two quantities can differ by several degrees over land, where the magnitude of the difference is variable in both space and time. This study describes how satellite data have been used to estimate daily $T_{\text{min}}$ and $T_{\text{max}}$ at the pixel scale over European land masses. The data derived here are not designed to replace traditional gridded station air temperature data sets, but to augment them. Satellite surface temperature data usually have larger uncertainties than in situ data sets, but they can offer spatial detail and coverage that the latter may not provide.

Land surface air temperature (LSAT) at screen level (1.5 or 2 m) cannot be observed directly by satellites. However, a number of methods to infer LSAT from satellite data are documented in the literature. Nearly all of these efforts are based on empirical regression models, whereby LSAT is predicted from the land surface skin temperature (LST) observed by satellites. Although LST and LSAT are usually closely related, they may differ by several degrees, where the magnitude and sign of the difference varies in both time and space (Figures 1 and 2). This difference depends on several factors, including time of day, meteorology, surface type, geographical location and elevation. Regression methods achieve accuracies of the order of 1-5 K and uncertainties are usually lower where additional predictors are included in the regression to account for these factors.

Existing studies have generally focused on deriving empirical relationships at the local to regional scale, over discrete time periods, and include LST and vegetation as predictors for LSAT. For example, Nieto et al. (2011) adopt the Temperature Vegetation Index (TVX) method to estimate day time LSAT over Spain during 2005 using data from the Meteosat Second Generation (MSG), achieving accuracies of around 3-5 K. The TVX method assumes LSAT approaches LST with increasing NDVI, such that the two are
equivalent at full canopy cover. An issue with this method is establishing the value of NDVI for full canopy cover: Nieto et al. (2011) offer improvements on previous studies that use the TVX method by defining different NDVI values for different vegetation types. In another study, Kawashima et al. (2000) use spatially-averaged LSTs and Normalised Difference Vegetation Index (NDVI) derived from Landsat to predict LSAT over Japan for four winter nights between 1984 and 1986 with a reported accuracy of better than 1 K.

![Diurnal cycle observed by SEVIRI and in situ WMO station 60735 (35 40N, 10 06E – Tunisia) on 2 July 2008.](image)

Figure 1: Diurnal cycle observed by SEVIRI and in situ WMO station 60735 (35 40N, 10 06E – Tunisia) on 2 July 2008.

Other studies present regressions that use predictors in addition to LST and vegetation. For example, Vancutsem et al. (2010) use LSTs from the MODerate resolution Imaging Spectroradiometer (MODIS) together with the NDVI and solar zenith angle (SZA) to estimate Tmin and Tmax for 28 stations in Africa for various overpasses occurring between 2002 and 2008. They report a mean absolute error (MAE) of 1.73 K and a standard deviation of 2.4 K in their study. Cristobal et al. (2008) use latitude, distance from coast, altitude and solar radiation in addition to LST and NDVI over the Iberian Peninsula to estimate daily, monthly and annual mean, minimum and maximum LSAT (Tmean, Tmin and Tmax) between 2000-2005 using Landsat, MODIS and NOAA satellite data. They achieve an impressive averaged root mean square error (RMSE) of 1.75 K for daily LSATs and 1.00 K for monthly and annual temperatures.
Figure 2: Histograms showing the difference between LST from the Spinning Enhanced Visible and Infrared Imager (SEVIRI) onboard MSG and temporally and spatially collocated HadISD (Dunn et al., 2012) station temperatures over Europe between 0 and 20 degrees longitude for each month during 2010.
Several studies report success in estimating LSAT without using vegetation parameters. Zhang et al. (2011) use MODIS LST data to calculate daily Tmean, Tmax and Tmin over China during 2003. They find that improved results are obtained by including solar declination in their regression, and report uncertainties of less than 3 K for 60-85% of their estimated LSATs. Kilibrarda et al. (2014) use spatio-temporal regression kriging with in situ data using 8-day LST composites from MODIS together with topography to predict global LSAT during 2011. Kilibrarda et al. (2014) report errors in their method of around 2 K for station-dense regions, 2-4 degrees for station sparse regions, with errors of up to 6 degrees for Antarctica. Kriging methods have also been trialled in other studies with some success. Florio et al. (2004) compare the traditional regression-based approaches with three kriging methods over N. America using data from the Advanced Very High Resolution Radiometer (AVHRR) for six days during 2000. They conclude that the kriging methods are superior to regression, achieving average errors of 0.9 K and 1.4 K, respectively.

An interesting non regression-based method has also been proposed by Sun et al. (2005), who derive LSAT using thermodynamics. They define an equation for LSAT that requires inputs of LST, NDVI, net radiation, aerodynamic resistance and crop water stress index (CWSI). Sun et al. (2005) trial their method for two MODIS overpasses in 2002 over a 2x9 degree region on the North China Plain to estimate instantaneous LSAT and report an accuracy of better than 3 K for 80% of the estimated LSATs.

Most studies reported in the literature use data from infrared sensors, but microwave data can also be used since this wavelength is also sensitive to the surface. Unlike infrared sensors, microwave sensors have the advantage of providing observations during cloudy conditions. However, the spatial resolution is much lower (several tens of km vs a few km or better), which may be a disadvantage for many applications. Early in the satellite era, Davis and Tarpley (1983) used a multiple linear regression model to estimate LSAT from base atmospheric temperature, skin temperature and microwave channel-2 top of atmosphere (TOA) temperatures derived from the TIROS Operational Vertical Sounder (TOVS) system. They obtained errors of around 1.6-2.6 K under cloud-free and partially cloudy conditions and 2.9-4.0 K under cloud conditions (microwave data only). Later, Basist et al. (1998) used data from the seven channels of the Special Sensor Microwave/Imager (SSM/I) to estimate LSAT with a reported standard error of approximately 2.0 K. The authors also trial a blended station-satellite gridded
temperature product and demonstrate this offers improved performance over one derived from station data alone.

The approach used in this study is a regression-based model following the studies discussed above, in particular that of Cristobal et al. (2008). LST data from the Spinning Enhanced Visible and InfraRed Imager (SEVIRI) are used to estimate daily minimum and maximum LSTs (LST\(_{\text{min}}\) and LST\(_{\text{max}}\)). These LST data are then regressed with vegetation fraction, latitude, urban fraction, elevation and distance from coast against station Tmin and Tmax data collocated in both space and time. Separate regression models are produced for Tmin and Tmax; the derived regression coefficients are applied to every available SEVIRI LST\(_{\text{min}}/\text{max}\) observation providing estimates of Tmin and Tmax where station data are absent. Evaluation of the predicted satellite Tmin and 2009 with in situ station data not used in the model training. The method has been applied to the 2012-2013 public archive of SEVIRI LST data available from the Land Surface Analysis Satellite Applications Facility (LSA SAF) over Europe.

**Data Sets**

**Satellite Land Surface Temperatures and Fraction of Vegetation Cover**

The data used here are from the Spinning Enhanced Visible and InfraRed Imager (SEVIRI) onboard the geostationary Meteosat Second Generation (MSG) platforms, which have been the operational 'weather' satellites for Europe since 2004. The MSG-1 was launched in August 2002, and was re-designated Meteosat-8 in January 2004 when it became operational. MSG-2 and MSG-3 then followed in December 2005 and July 2012, respectively. SEVIRI has twelve spectral channels covering visible and infrared wavelengths and provides full-disc images every 15 minutes with a spatial resolution at the sub-satellite point (0 degrees longitude/latitude) of 3 km (1 km for the high-resolution visible channel).

An operational LST product is provided by the LSA SAF in near-real time at the full space/time resolution of the SEVIRI. The product is available from 2009 and can be obtained by users through the LSA SAF website (http://landsaf.meteo.pt/), or automatically in near-real-time through the EUMETCAST dissemination service. LSTs are calculated using a generalised split window algorithm, following Wan and Dozier (1996), with estimated errors and quality information also provided in the product for each pixel. Pixel cloud information is sourced from the Satellite Application Facility to support NoWCasting and very-short-range forecasting (SAFNWC). The estimated errors for the product are thought to be 1-2 K under cloud free conditions (Freitas et
al., 2010; Trigo et al., 2008). However, undetected cloud can cause errors in the LST retrievals that may exceed this.

The LSA SAF also produces a daily Fraction of Vegetation Cover (FVC) product. As for LST, data are available at the full spatial resolution of the SEVIRI instrument from 2009 onwards from the LSA SAF website and EUMETCAST service. FVC is estimated from the weighted combination of the probability that an observation is bare soil or fully vegetated, where the probability is computed using a Bayesian model (see LSA-SAF Product User Manual for Vegetation Parameters, v2.1, 200, available from the LSA-SAF website). The data are expressed as values between 0 and 100%, with estimated errors and quality information given per pixel; the overall accuracy of the FVC product is expected to be within 10% for 70-75% of land pixels.

Ancillary Data
The latitude, longitude and elevation for each SEVIRI pixel is available from the LSA-SAF static data products archive (http://landsaf.meteo.pt/). In this study, sub-pixel land use information was also considered using data from the European Space Agency’s 300-m GlobCover data set (http://due.esrin.esa.int/globcover/). These data were used to estimate the urban and water fraction (UF and FoW) for each SEVIRI pixel by calculating the fraction of 300-m GlobCover pixels nominally contained within each SEVIRI pixel for each of these surface classes. The GlobCover data were also used to calculate the distance from coast (DfC) for each SEVIRI land pixel.

Station Data
In situ minimum and maximum near-surface air temperatures, Tmin and Tmax, were sourced from the European Climate Assessment and Dataset (ECA&D; Klein Tank et al., 2002). This data set includes observations from 7852 meteorological stations throughout Europe, where more than half the station records are available for public download from the ECA&D website (http://eca.knmi.nl/). The data used here were from the archive of ‘blend and update’ station data. The blended station data were used in this analysis to ensure coverage during the analysis period used in this study (2012-2013) as some stations have a lag time of several months or more before they are updated by their contributing countries. In these cases, ECA&D ‘blend and update’ station records are in filled with data from the Global Telecommunication System (GTS) or other stations within 12.5 km distance and 25m elevation. This method means that some observations are duplicated in two or more station records. The source for each station observation is provided by ECA&D as metadata and this
has been used in this analysis to remove any duplicate entries. Data from the public ECA&D archive were used to build the regression relationships in this study (example shown in Figure 3). Additional data from the non-public ECA&D archive were provided for this study by the Royal Netherlands Meteorological Institute (KNMI) for Germany and the UK. These additional data were used as independent validation data for the satellite-derived Tmin and Tmax produced in this study.

Figure 3: ECA&D stations (publicly available) with Tmin/Tmax data for 2012/2013.

**Estimation of LSAT from Satellite Data**

Figure 4 shows a flow chart of the process used to estimate Tmin and Tmax from the SEVIRI data. Each stage of the process is explained in detail below.

**Calculation of LSTmin and LSTmax**

The 15-minute SEVIRI LST data from the LSA-SAF are processed to obtain the minimum and maximum LSTs for each pixel for each day (LSTmin and LSTmax). Observations are only considered between the local times of 23:00 and 08:00 for LSTmin, and 11:00 and 16:00 for LSTmax. These temporal windows are employed to ensure only realistic data are considered for each observation type, for example to avoid daily LSTmax data being sourced from night time hours, since a high proportion of SEVIRI observations may be cloud-contaminated with no valid LST retrievals. Use of these temporal windows also achieves some consistency with conventional meteorological station observations of Tmin and Tmax. LST values are only recorded where the number of valid observations (cloudy and non-cloudy) exceeds 33 for the
LSTmin window and 18 for the LSTmax window, which equates to approximately 90% valid observational coverage in each window. This is a necessary step as satellite data are prone to missing observations, for example due to data feed interruptions or corruption. For the LSA-SAF archive, 4.9% of slots (i.e. entire 15-minute full-disc images) are missing or corrupt for the years 2012-2013. No limit on the number of valid cloud-free observations in each window is employed in deriving LSTmin and LSTmax. However, the fraction of cloud-free observations in each window is recorded at this stage of the processing as additional user information.

Figure 4: Process of deriving minimum and maximum land temperatures. Input data sets are in green and output data sets are in yellow.

Regression Formulation
The linear regression model is constructed by regressing the observed station Tmin/Tmax data against temporally and spatially collocated LSTmin/LSTmax, fraction of green vegetation (FVC), latitude (Lat), elevation (Z), urban fraction (UF) and distance from coast (DfC):
These variables were selected as they are all strongly and significantly correlated with LSAT (p << 0.05; also see Figures 5b and 6b). Other variables, such as wind speed, solar zenith angle (SZA) and albedo were also considered but were not selected as they did not improve the regression model enough to warrant their inclusion. For SZA and albedo this is partly because these parameters are strongly co-linear with LST/latitude and FVC, respectively. For wind speed, the issue is also one of practicality as reanalysis or operational analyses provide the only viable source of wind speed data for locations without stations.

Satellite-station matchups are excluded from the regression where the DfC is less than 1 km, the fraction of water within the SEVIRI pixel is more than 50%, or the elevation is more than 1500 m. These are excluded as the satellite LST retrievals are likely to be unreliable under these conditions and because satellite-station agreement is likely to be influenced by factors that cannot be accounted for easily (e.g. the moderating effect of water bodies on local air temperature, coastal winds and sharp changes in elevation and challenging landscape at very high elevations).

The analysis is performed for each day with a moving 11-day window such that each day has a different set of regression coefficients and offset. The moving window approach was selected for two reasons. Firstly, the relationship between LSAT and several of the predictor variables varies with time, both on seasonal and local timescales (Figures 5b and 6b). Secondly, the approach ensures that a large enough pool of data is available to perform a meaningful regression analysis, since the presence of cloud can significantly reduce the number of LST and FVC data available. The FVC data are less affected by cloud as the LSA-SAF product uses observations from previous days for cloudy pixels. Data from up to the preceding two days are used to infill gaps in the LSA-SAF FVC archive (22 daily files are missing between 2009 and 2013). A regression relationship is only formulated for situations with at least 200 valid matchups.

\[ T_{\text{min}} = \alpha_{\text{min}} + \beta_{\text{min}} \cdot LST + \chi_{\text{min}} \cdot FVC + \delta_{\text{min}} \cdot Z + \phi_{\text{min}} \cdot UF + \varphi_{\text{min}} \cdot Lat + \gamma_{\text{min}} \cdot \text{DfC} \]

\[ T_{\text{max}} = \alpha_{\text{max}} + \beta_{\text{max}} \cdot LST + \chi_{\text{max}} \cdot FVC + \delta_{\text{max}} \cdot Z + \phi_{\text{max}} \cdot UF + \varphi_{\text{max}} \cdot Lat + \gamma_{\text{max}} \cdot \text{DfC} \]
Figure 5: Analysis of station air temperatures vs empirical model predictor variables for Tmin for 2012/2013. Regression coefficients formed from moving 11-day window centred on day in question. Panels show (a) number of cloud-free satellite-station matchups on day of observation (i.e. central day in window), (b) correlation coefficient between station air temperature and collocated predictor variables (black line indicates multiple linear regression coefficient), (c) normalised multiple linear regression coefficients, (d) T-values for coefficients, (e) regression coefficients, (f) regression offset, and (g) residuals (i.e. satellite minus station air temperatures) on day of observation (i.e. central day in window), the solid black line indicates the median.
Figures 5 and 6 show an illustration of the regression analysis for 2012-2013 for Tmin and Tmax, respectively. The figures include the time series of regression coefficients using normalised (panel c; normalisation of variables achieved by subtracting the mean and dividing by the standard deviation) and non-normalised data. The coefficients for the normalised regression data allow the relative contribution of each predictor in the model to be assessed. The dominant predictor variable is found to be the satellite LST, which accounts for around 70-80% of the variance in air temperature. Latitude is the second strongest predictor. The other predictors have lower weighting but are nonetheless important in the regression model as they can have significant effect on the predicted air temperatures in certain regimes. Figures 7 and 8 show the range of $\Delta$Tmin and $\Delta$Tmax values resulting from the elevation, UF and DfC regression
components. These figures show that the $\Delta T$ values for elevation and DfC may amount to a few degrees. The UF correction is smaller, ranging between about $\pm 2$ °C in heavily urbanised areas (e.g. capital cities). The $\Delta T$ values for FVC range between approximately -5 and +6 °C for Tmin and -2 and 8 °C for Tmax. For latitude, the $\Delta T$ values are large in magnitude (40 °C), but this is largely counteracted by the regression offset, which is typically between 10 and 30 °C; if latitude is removed from the predictor variables used in the regression the offset reduces to a few degrees.

Figure 7: Magnitude of $\Delta T_{min}$ in 2012/2013 with respect to (a) minimum correction for elevation, (b) maximum correction for elevation, (c) minimum correction for distance from coast and (d) maximum correction for distance from coast, (e) minimum urban fraction correction and (f) maximum urban fraction correction. Values are calculated by applying the minimum and maximum values of the regression coefficients for these variables to each pixel in the static data set.
Figure 8: As for figure 7 but for $\Delta$Tmax.

Evaluation of Predicted LSATs

Analysis of regression residuals
The bottom panel in Figures 5 and 6 show the residuals of the multiple-linear regression for the central analysis day (i.e. day 6 in the 11-day moving window). Statistics for the residuals are only shown where at least 50 valid matchups occur to ensure the results are statistically robust. The results are slightly better for Tmax than for Tmin, with the latter generally exhibiting more noise in the median satellite-minus-station difference. For nearly all days, 50% of the predicted LSATs are within 2 °C. In general, the Tmax 10th/90th percentiles are close to ±2.5 degrees, indicated by the dotted line on the plots, with the 5th/95th percentiles occurring around the ±4 °C mark. For Tmin, these limits are about 0.5 °C or so larger in magnitude. A slight reduction in
variance is evident during the summer months, which is likely to be a result of increased data availability during this time due to less cloud. A larger data pool will permit a more robust regression and reliable statistics. Other than this, no seasonality is apparent in the results, which is to be expected given the moving 11-day analysis window used in the regression.

Figure 9: Validation of satellite Tmin over Germany & UK for 2012-2013 showing (a) the number of satellite-station matchups, (b) the correlation between station Tmin and LSTmin, and station Tmin and satellite Tmin, (c) satellite LSTmin minus station Tmin and (d) satellite Tmin minus station Tmin distributions for each day.

**Independent station validation**
Figures 9 and 10 show a summary of the comparison between collocated non-public ECA&D German & UK station data, and satellite LSTs and LSATs. The correlation between LSTmin/LSTmax and the station data is notably lower than for the satellite
Tmin/Tmax vs station data analysis (Figures 9b and 10b). The Tmin comparison shows the satellite LSTmin data are typically cold-biased by about 5 °C with respect to the station data (Figure 9c), where as the mean bias for the estimated satellite Tmin data is quite close to zero (Figure 9d). The satellite Tmin minus station Tmin differences also have much lower variance compared with the LSTmin comparison. Overall, the satellite-station Tmin agreement is slightly worse than that obtained from the analysis of the regression residuals discussed above.

Figure 10: As for Figure 9 but for Tmax.

Similar results are obtained for Tmax: the correlation between satellite Tmax and station Tmax is higher than for satellite LSTmax vs station Tmax, and the agreement between the modelled LSATs is better than between the LSTmax and station Tmax data. The LSTmax minus station Tmax differences show strong seasonal variability
where the difference is negative in winter months and more positive during the summer (Figure 10c). This seasonal variability is considerably reduced (nearly absent) in the satellite vs station Tmax data, which is encouraging and suggests that the dynamic approach adopted for the regression model is valid. In fact, the performance of the Tmax regression is actually quite good, with high proportion of matchups falling within the ±2.5 °C limits marked on the plot (dotted line), particularly during the spring to autumn months.

Discussion

In reality, the satellite LSAT data are likely to be more accurate than the evaluation performed in this and other studies suggest. In situ temperatures can only be measured at specific spatial points and can therefore only be representative of the air immediately around the station at the time of the observation. In many cases, the observation can be extrapolated beyond the measurement location with confidence, depending on the siting of the station. Indeed, meteorological station locations are chosen with this in mind but choices are limited by practicality and therefore in reality, the measured temperatures may not be representative of even close-neighbouring locations. Satellite sensors such as the SEVIRI, on the other hand, view the radiation emitted by every point within their field of view and therefore the observed surface temperatures they provide are truly area-averaged. For SEVIRI, this area is several km (3 km at the satellite point of 0 deg latitude/longitude and around 4-10 km over Europe) and therefore a SEVIRI pixel temperature observation may be inherently different from an in situ observation located within the same SEVIRI pixel. Spatio-observational discrepancies between the satellite and in situ station may also occur because of parallax effects resulting from the interaction between the SEVIRI line of sight (view angle) and topography. In the extreme case, for example, SEVIRI might view only one side of a mountain when the station is located on the other side. In this study, the regression formulation is only performed using a large pool of station data, which should minimise the uncertainties on the regression parameters that occur as a result of these problems as these satellite-station spatial mis-match errors are expected to be random. For the evaluation component of the study, using a large pool of data will help to reduce any effects on the mean bias but not the variance, which is likely to be inflated as a result of the issues discussed here.

Figures 11 and 12 shows an example of the satellite temperature maps for 21 August 2013, showing both LSTmin and LSTmax, and predicted Tmin and Tmax for this day.
The temperature difference between the LST and LSAT images is marked, particularly for LSTmax/Tmax, where a change of several degrees can be observed for some places – for example, Spain, where the LSTmax is more than 5 °C warmer. Also of note are the (white) gaps in the satellite data, for example in north-eastern Europe. This is where SEVIRI observations of either LSTmin/LSTmax or FVC are not available owing to cloud obscuring the satellite view of the surface. Cloud contamination is a major disadvantage of using infrared and visible satellite data for surface temperature applications. Not only does it lead to gaps in the data coverage, but undetected cloud may lead to large errors in the surface temperature retrievals. The effects of this problem are minimised in this study through the use of multi-hour temporal windows for estimating LSTmin and LSTmax. This increases the probability of obtaining a cloud-free observation for each temperature. In the case of LSTmax, the chance of using an observation contaminated with undetected cloud is also reduced as the maximum LST in the window is the observation most likely to be cloud-free as cloud almost always results in a cold-bias in the retrieved LST. For Tmin, therefore, the effect is the opposite with the minimum LST being that most likely to be contaminated with undetected cloud. This may, at least in part, explain why the evaluation results for satellite Tmin data are not as good as for Tmax.

Figures 13 and 14 illustrate the cloud problem. The figures show that fewer day time observations are available due to presence of cloud compared with night (Figure 13 and 14b). This may be a real effect, or a result of the SEVIRI cloud detection methods, which include visible channel checks that cannot be carried out at night leading to increased incidences of missed cloud at night (cloud detection using infrared is carried out both at night and during the day). As expected, incidences of cloud-free observations are higher in southern Europe, dropping off to around 30% coverage above a latitude of 50 degrees (Figure 14a). The availability of cloud-free observations is highest during the summer (typically 40-70% depending on time of day) and lowest during northern hemisphere winter months (20-30%).
Figure 11: Example of satellite temperature data on 21 August 2013 showing (a) LSTmin, (b) Tmin and (c) Tmax for the Iberian Peninsula.

Figure 12: As for Figure 11 but for Tmax (note the different temperature scale).

Figure 13: Percentage of days in 2010 with cloud-free SEVIRI observations at synoptic times (labelled on plots).
Conclusions

This study describes a method for estimating daily Tmin and Tmax from satellite data, based on empirical regression of satellite-observed and auxiliary parameters against collocated station observations. The method, which has been trialled over Europe for five years of data, allows the prediction of Tmin and Tmax for locations without station data at the spatial resolution of the satellite data (3 km at the sub-satellite point). Analysis of the model residuals and evaluation with independent station data from the UK and Germany not used in the regression process suggests that for most days at least 50% of the estimated LSATs are within 3 °C of collocated station observations, with around 80% within 4 °C and 90% within 5 °C. Results for Tmax are better than for Tmin. The mean bias of the satellite-estimated LSATs oscillates around zero and shows no seasonal variation, although the variance is noted to be slightly lower during summer months. The results presented in this study are consistent with those of previous studies of this nature, although it should be noted that this study is more extensive in both space and time than most previous studies. The evaluation results presented in this and other studies may be worst-case scenario as the variance will be inflated through the inherent,
random discrepancies that arise from comparing satellite area-averaged with in situ point temperature observations. However, errors in the satellite data due to undetected cloud may cause significant biases in the estimated LSATs, particularly for Tmin.

References


