Validation of Satellite-Retrieved Land Surface Temperature (LST) Products at Gobabeb, Namibia

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Abstract

Global land surface temperature (LST) data derived from satellite-based infrared radiance measurements are highly valuable for various applications in climate research. LST is a fundamental state variable for land surface processes and has long been available from satellite observations in the thermal infrared (TIR). LST is also increasingly important for studies assessing land surface conditions, e.g., studies of urban climate, evapotranspiration, and vegetation stress. LST is usually retrieved from satellite-based radiance measurements in the infrared (IR) or microwave (MW) range and it is well suited to provide global coverage. Due to the spatial scale mismatch between ground and satellite-based measurements and the heterogeneity of natural land surfaces, the validation of satellite LST data sets is a challenging task. However, *in situ* validation is essential for obtaining quantitative information on the accuracy of LST satellite products. Permanent, continuous *in situ* measurements of up- and downwelling TIR radiance allow the analysis of long timeseries of satellite LST observations, which can reveal seasonal cycles and potential deviations; these can originate from surface anisotropy, topography, heterogeneous land cover, or spatial variations in soil moisture. Many of the validation results obtained over the Namib gravel plains demonstrate the maturity of the LST products investigated over the past 15 years. They also highlight the need to carefully consider their temporal and spatial properties when using them for scientific purposes. Total uncertainty of *in situ* LST obtained from the TIR radiance measurements at the Gobabeb wind tower is estimated as 0.8 ± 0.12°C, which is highly accurate for a bare soil site with diurnal LST amplitudes of up to 40°C. Analyses of spatial representativeness performed on the meter to kilometer scale near Gobabeb Namib Research Institute yielded an absolute bias of 0.5°C compared to *in situ* LST, a value mainly achieved thanks to the Namib's hyper-arid desert climate and the spatial homogeneity and temporal stability of the gravel plains. The Namib gravel plains were found to be suitable for validating LST with pixel sizes of up to 100 km^2 and the continued availability of the *in situ* measurements from Gobabeb is of high importance for accurately validating and monitoring current and future satellite LST products.

1 Introduction

Land surface temperature (LST), also called skin temperature, is the temperature of the Earth's surface (Dash et al. 2002, Hulley et al. 2019). LST is one of the main quantities governing the energy exchange between surface and atmosphere and it is a highly useful quantity for applications within climate research. This includes an improved understanding of the climatic effects of land use and land cover change (Mallick et al. 2012), drought monitoring (Rhee et al. 2010), detection of changes in land cover and energy balance (Mildrexler et al. 2011), monitoring of heatwaves (Dousset et al. 2010), estimation of evapotranspiration (Li et al. 2015), or investigations of urban heat islands (Weng 2009, Bechtel et al. 2019). Furthermore, it is used as input for land surface models (Reichle et al. 2010) and numerical weather prediction (Dash et al. 2002). The Global Climate Observing System (GCOS) specifies LST as an essential climate variable (ECV), i.e., important variables to understanding and prediction of Earth's climate (Guillevic et al. 2018).

LST is usually retrieved from remote sensing data in the thermal infrared (TIR) or microwave (MW) range and global coverage can be achieved by using satellite-based measurements. For a meaningful scientific use of satellite LST, information about the quality of the data sets has to be available. Therefore, the availability of long-term and quality-controlled observations of ECVs is very important. Such information can be obtained in several ways, most commonly from validation against *in situ* data, radiance-based validation, satellite-satellite intercomparisons, and time series analysis (Guillevic et al. 2018, Hulley et al. 2019).

Operational LST products are currently retrieved from a variety of space-borne TIR sensors, e.g., the Spinning Enhanced Visible and Infrared Imager (SEVIRI) onboard the Meteosat Second Generation (MSG) satellites, the Advanced Very High Resolution Radiometer (AVHRR) onboard the MetOp satellites (Trigo et al. 2021), the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard EOS-Terra and EOS-Aqua, the Sea and Land Surface Temperature Radiometer (SLSTR) onboard Sentinel-3A/B, and the various versions of the Thematic Mapper (TM) onboard the Landsat series.

For current TIR sensors, e.g. SEVIRI, MODIS and SLSTR, LST is most often estimated through the application of a Generalized Split-Window (GSW) formulation and similar. The uncertainty of LST retrievals depends on a wide range of factors such as land surface type (related to emissivity uncertainty), water vapor content in the atmosphere, or viewing geometry (Freitas et al. 2010, Ermida et al. 2017, Ghent et al. 2019). In order to ensure that LST retrievals are stable in time and consistently meet their expected accuracy, operationally derived LST have to be continuously monitored and assessed. Relative accuracy can be assessed by cross-validation between LST products obtained with different retrieval algorithms and/or for different sensors (Guillevic et al. 2018). Such exercises allow analyses of the consistency between different products but provide limited information on their actual accuracy. Therefore, *in situ* measurements ("ground truth") are ultimately needed for validating satellite LST and surface emissivity (LST&E) products (Guillevic et al. 2018, Göttsche et al. 2016). In principle, LST products can readily be validated with ground-truth radiometric measurements. Unfortunately, this so-called "temperature-based validation" is considerably complicated by the spatial scale mismatch between satellite and ground based sensors (Guillevic et al. 2018): areas observed by ground radiometers usually cover about $10\,m^2$, whereas satellite measurements in the thermal infrared typically cover between $1\,km^2$ and $100\,km^2$. Therefore, for *in situ* LST to be representative for the area observed by the satellite, they have to be obtained over areas that are sufficiently homogenous at the scale of the *in situ* measurements as well as on the satellite pixel scale. The size of the area that needs to be viewed by the validation instrument at the ground depends on within-pixel variability and how well this can be represented with *in situ* measurements. Therefore, for temperature-based validation, the accurate characterization of LST spatial variability is critical.

The Gobabeb LST validation station (23.551°S, 15.051°E, 450 m a.s.l.) lies about 2 km northeast of Gobabeb Namib Research Institute (https://www.gobabeb.org). Because of the hyper-arid desert climate, the site is temporally stable, which is essential for long-term validation studies (Göttsche et al. 2013, Göttsche et al. 2016, Masiello et al. 2018). While the *in situ* measurements are primarily performed to validate satellite LST derived by the Land Surface Analysis Satellite Application Facility (LSA SAF) from MSG/SEVIRI, they are equally suited to validate LST from other sensors (Trigo et al. 2021, Martin et al. 2019, Hulley et al. 2022). In the following sections, the two most popular LST retrieval algorithms are briefly introduced, *in situ* LST validation concepts are explained and results for Gobabeb are summarized. Finally, a table with the—quite numerous—abbreviations used in this article is provided.

2 Satellite LST Retrieval

LST from a satellite is estimated from top-of-atmosphere (TOA) radiance measurements, e.g. in MSG/SEVIRI's split-window channels 9 and 10 (Freitas et al. 2010). Most LST retrieval methods are based on measurements in two pseudo-contiguous TIR channels, *i.e.*, split-window algorithms, and exploit the differential absorption in the two bands for atmospheric correction (Dash et al. 2002, Hulley et al. 2019). The uncertainty associated with satellite LST retrievals lies typically between 1°C and 2°C.

2.1 Generalized Split Window (GSW) Algorithm

For current TIR sensors, e.g. SEVIRI, MODIS and SLSTR, LST is most often estimated through the application of a Generalized Split-Window (GSW) formulation (Wan 1997) or similar (Yang et al. 2020). LSA SAF adapted the GSW to the response functions of the SEVIRI channels (Freitas et al. 2010):

$$LST = (\mathrm{A}_1 + \mathrm{A}_2 \frac{1-\varepsilon}{\varepsilon} + \mathrm{A}_3 \frac{\Delta\varepsilon}{\varepsilon^2}) \frac{T_{10.8} + T_{12.0}}{2} + (\mathrm{B}_1 + \mathrm{B}_2 \frac{1-\varepsilon}{\varepsilon} + B_3 \frac{\Delta\varepsilon}{\varepsilon^2}) \frac{T_{10.8} - T_{12.0}}{2} + C + \Delta LST \qquad (1)$$

where ε is the average of the two channel-effective surface emissivities; Δε their difference ($\varepsilon_{10.8}$–$\varepsilon_{12.0}$); channel radiances are expressed as brightness temperatures $T_{10.8}$ and $T_{12.0}$; A_j, B_j, (j = 1,2,3) and C are the GSW parameters; and ΔLST is the uncertainty of the LST retrieval. The GSW parameters were calibrated for different ranges of satellite zenith angle and total column water vapor. In operational LST retrievals with such algorithms, total column water vapor is generally obtained from forecasts; in case of the LSA SAF, these are the three-hourly forecasts of the European Center for Medium-range Weather Forecasts (ECMWF). Since GSW algorithms are only applicable to clear sky conditions, cloudy pixels have to be removed through multispectral thresholding tests performed for the available sensor channels in the visible, near-infrared, and thermal atmospheric window (Bulgin et al. 2018). Recently a variety of similar LST retrieval algorithms for Sentinel-3A/B SLSTR was compared by (Yang et al. 2020): the most conclusive and accurate results over land were obtained for Gobabeb.

2.2 Temperature—Emissivity Separation (TES) Algorithm

Emissivity ε is a unitless measure ($0 \leq \varepsilon \leq 1$) indicating how effectively a surface radiates in comparison to an idealized 'black-body' (Dash et al. 2002, Hulley et al. 2019). Therefore, for LST retrieval from space-based and ground-based radiance measurements, accurate land surface emissivity (LSE) estimations are essential (Guillevic et al. 2018). Over semi-arid regions, where bare soils dominate and the atmosphere is generally dry, LST error is mainly controlled by uncertainty in LSE. Especially sites with larger fractions of bare ground are prone to be misrepresented in satellite-retrieved LSEs based on land cover classification and remotely sensed vegetation fraction: *in situ* measurements revealed that LSE estimations over arid regions can be wrong by more than 3%, causing LST uncertainties of up to 3°C (Schädlich et al. 2001, Göttsche & Hulley 2012). However, with algorithmic improvements, e.g., Temperature-Emissivity Separation (TES) (Gillespie et al. 1998, Hulley & Hook 2011) LST and LSE can be retrieved simultaneously from TIR data with an accuracy of 1.5%.

3 Determination of *in situ* LST

Continuous *in situ* observations from Gobabeb are available since the beginning of 2008. The main instrument for determining LST is the precision radiometer "KT15.85 IIP" produced by Heitronics GmbH, Wiesbaden, Germany. The radiometer measures the radiance between the wavelengths 9.6 µm and 11.5 µm, has a temperature resolution of 0.03°C, and an accuracy of ±0.3°C over the relevant temperature range (Göttsche et al. 2013). The drift of the KT15.85 IIP is less than 0.01% per month: this is achieved by linking the radiance measurements via beam-chopping (a differential method) to internal reference temperature measurements. The ground-observing radiometer at the Gobabeb wind tower is mounted at 25 m height, which results in fields of view (FOV) of about 12 m^2 (Figure 1). While atmospheric attenuation between the surface and the radiometer is negligible, the measurements contain surface emitted radiance (i.e., the target signal) as well as reflected downwelling 'sky radiance'. Depending on LSE and downwelling longwave radiance (e.g., a cold clear sky *vs.* a warm humid atmosphere), the reflected component can cause differences of several degrees Celsius (Schädlich et al. 2001). Therefore, an additional KT15.85 IIP measures downwelling longwave radiance at 53° zenith angle, which is representative of downwelling hemispherical sky radiance (Göttsche et al. 2013, Guillevic et al. 2018). For areas >10m^2 it was found that the gravel plains can be represented by a single 'surface end-member' consisting of a homogeneous mixture of bare soil (75% sand/gravel) and dry grass (25%).

3.1 LST Derivation from *in Situ* Measurements

Planck's law relates the radiance emitted by a black body (emissivity $\varepsilon = 1$) to its temperature (Dash et al. 2002, Hulley et al. 2019). However, most objects relevant to remote sensing applications are non-black bodies. Spectral emissivity $\varepsilon(\lambda)$ is defined as the ratio between the spectral radiance R_k emitted by surface component k at wavelength λ, and the spectral radiance emitted by a black body at the same wavelength and temperature. Spectral radiance emitted by a non-black body can be obtained by multiplying Planck's function $B(T_k, \lambda)$ with $\varepsilon(\lambda)$:

$$R_k(T_k, \lambda) = \varepsilon(\lambda) \cdot B(T_k, \lambda) \qquad (2)$$

where R_k is in $W \cdot m^{-3} \cdot sr^{-1}$, T_k is the measured component temperature in Kelvins, and λ is the wavelength in meters. For a sensor located near the surface and measuring within an

(a) (b)

Figure 1: Land Surface Temperature (LST) at validation station Gobabeb. (a) wind tower (b) installation of different radiometers during the 2017 ESA FRM4STS field inter-comparison experiment

atmospheric TIR window, the influence of the atmosphere can be neglected. With known emissivity, the simplified radiative transfer equation (Dash et al. 2002, Göttsche et al. 2013) can be used to account for reflected downwelling TIR radiance from the atmosphere and for the non-black body behavior of the surface. Switching for simplicity to channel-effective values, a single surface component and dropping the variable dependencies, emitted blackbody-equivalent radiance *B* can be expressed as

$$B = \frac{R_L - (1 - \varepsilon) \cdot R_S}{\varepsilon} \tag{3}$$

where R_L is the upwelling land surface radiance and R_S the downwelling sky radiance; in practice, the latter is measured by a dedicated KT15.85 IIP radiometer aligned at the zenith angle of 53°. Once *B* is known, inverting Planck's law gives the surface temperature. The spectral response functions of the KT15.85 IIP radiometers are approximately symmetric and the Planck function as well as the spectral emissivity of natural surfaces varies slowly over the radiometer's spectral range, e.g. see (Hulley & Hook 2011). Therefore, LST is retrieved by evaluating Planck's function at the radiometer's center wavelength of 10.55 µm (Göttsche et al. 2013).

3.2 *In situ* LSE Determination

During December 2011, measurements with the "one-lid emissivity box" method (Figure 2a) were performed at Gobabeb to determine channel-specific emissivities for the KT15.85 IIP radiometer over relevant surface types. Combining box measurements from 2011 and 2012, the emissivity for the KT15.85 IIP radiometer at Gobabeb wind tower is estimated as 0.940 ± 0.015. With a dry grass fraction of 25%, LSE over the gravel plains is estimated as 0.944 ± 0.015 for SEVIRI channel 9. This value is in good agreement with results obtained for ASTER and MODIS (Göttsche & Hulley 2012). In June 2017 the French Aerospace Laboratory ONERA performed *in situ* measurements with a Fourier Transform IR (FTIR) spectrometer (Figure 2b) and confirmed these values (Göttsche et al. 2018). From the emissivity spectra obtained by ONERA, channel-specific emissivities of arbitrary TIR sensors can be determined. Based on these findings, total uncertainty of *in situ* LST at Gobabeb wind tower has been estimated as 0.80 ± 0.12°C (Göttsche et al. 2016).

(a) (b)

Figure 2: Land Surface Emissivity (LSE) determination at Gobabeb. (a) single-lid emissivity box (2011-12-22) and (b) BOMEM MR304SC FTIR spectrometer during field inter-comparison experiment (2017-06-28)

3.3 Spatial Homogeneity of LST

For reliable LST validation, the effect of the small-scale material variations (e.g., dry grass, rock outcrops) and topography needs to be fully characterized. Using a mobile radiometer system, various field experiments were performed during which the radiometer was driven along tracks of up to 40 km length (Figure 3). The results show a high level of homogeneity and a stable relationship between station LST and LST obtained along the tracks (Figure 4) with an absolute bias of about 0.5 °C (Göttsche et al. 2013, Göttsche et al. 2018).

Figure 3: Characterizing LST homogeneity of the gravel plains between Gobabeb and Mirabib. The five TIR radiometers participating in the ESA FRM4STS field inter-comparison experiment (Göttsche et al. 2018) provided spatially resolved in situ *LST along the driven track.*

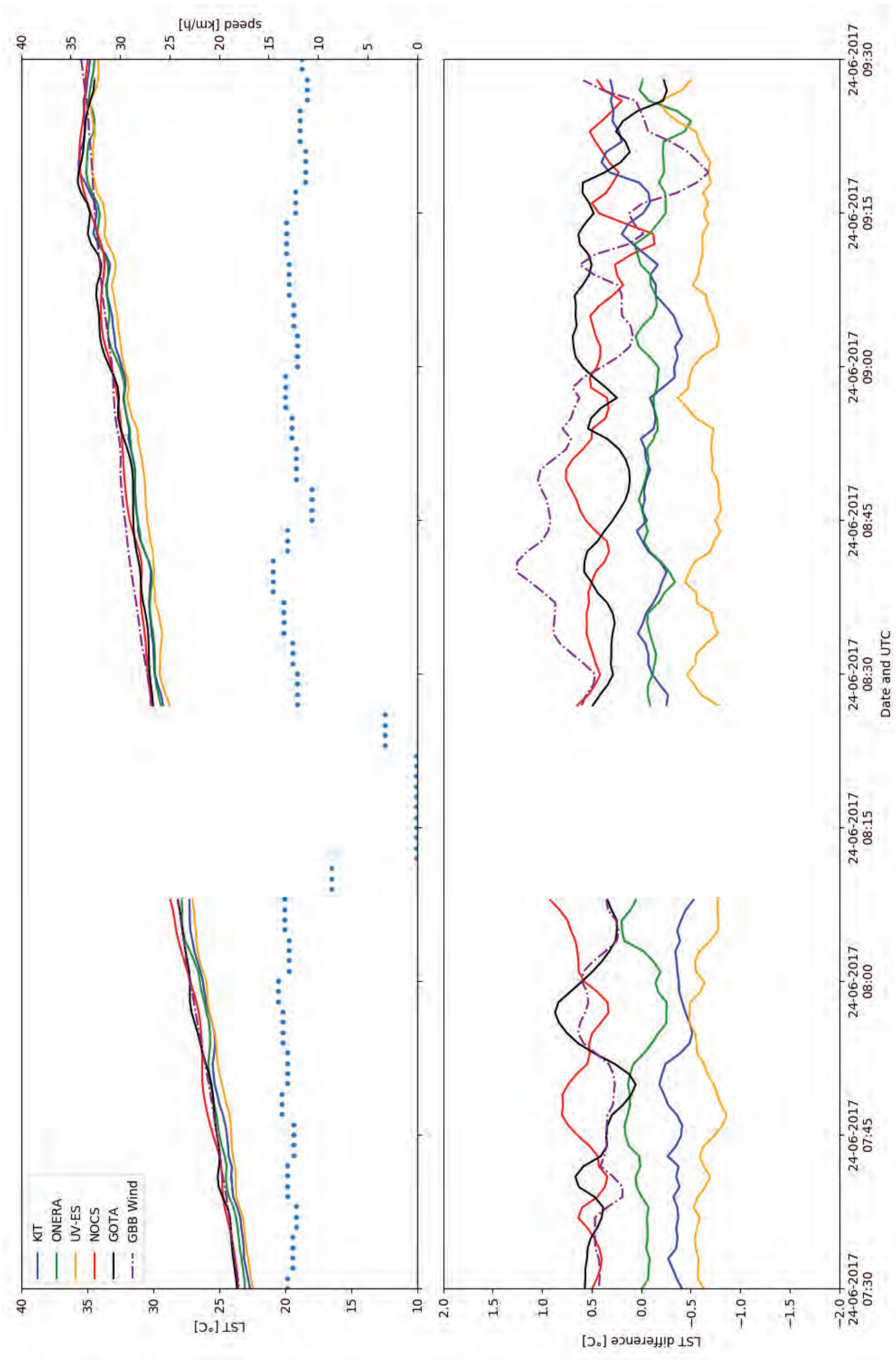

Figure 4 Top: In situ *LSTs obtained from the radiometers operated by different teams as they were driven across the gravel plains (see Figure 3);* in situ *LST from Gobabeb wind tower (i.e. the permanent validation station) is also shown. Right axis indicates driving speed. Bottom: LST differences of the radiometers with respect to their average. Data courtesy: ESA FRM4STS project (Göttsche et al. 2018).*

4 Results

While the *in situ* validation of satellite LST data sets is a challenging task, it is needed to obtain quantitative information on their accuracy (Guillevic et al. 2018). The time series of *in situ* LST from Gobabeb starts in 2008 and has since then been used to validate a variety of LST products from numerous satellite sensors. *In situ* LSE at Gobabeb was obtained with the 'emissivity box method' as well as FTIR spectroscopy. (Göttsche & Hulley 2012) used this knowledge to validate six LSE products retrieved from MODIS, ASTER, and SEVIRI over the gravel plains and sand dunes near Gobabeb. LSE estimated with algorithms based on land cover classification and vegetation cover fraction data primarily depend on correct classifications and assigned bare-ground emissivities. In contrast, the physics-based ASTER-TES and MODTES algorithms were shown to correctly estimate LSE on the gravel plains and sand dunes: consequently, split window algorithms would benefit significantly from using MODTES LSE.

(Hulley et al. 2019) illustrate temperature-based validation with examples from the ESA FRM4STS LST Field Inter-comparison Experiment (FICE) performed on the Namib gravel plains near Gobabeb (Göttsche et al. 2018). During this experiment, *in situ* LST obtained from measurements with five different TIR radiometers were compared. Furthermore, *in situ* LSE were obtained with a Fourier Transform spectrometer and an 'emissiometer', which uses oscillating TIR radiance and digital signal processing to determine LSE. For a four day radiometer inter-comparison at Gobabeb's wind tower (Figure 1b), results showed that *in-situ* LST can be retrieved with RMSEs of about 0.5 K, if the instruments are well-aligned, have narrow spectral bands and view angles, observe areas of at least 2 m^2 and accurate emissivities are available. Furthermore, (Göttsche et al. 2018) investigated spatial LST variability near Gobabeb by driving the radiometers several times about 20 km across the Namib gravel plains (Figure 3): the five in-situ LST were first averaged individually over 200 m and yielded RMSEs of about 0.6 K compared to their mean (Figure 4).

(Freitas et al. 2010) quantified the uncertainty of the operational GSW algorithm used by LSA SAF to retrieve LST from MSG/SEVIRI. They quantified the uncertainty of the LST estimations by accounting for the algorithm's error statistics for globally representative atmospheric profiles and by carefully characterizing the uncertainty of the input data, particularly surface emissivity and total water vapor content. The retrieved values were also compared with a full seasonal cycle of *in situ* observations from Gobabeb, showing good agreement with root-mean-square differences between 1°C and 2°C. (Göttsche et al. 2013) used in-situ LST from Gobabeb wind tower to validate the MSG/SEVIRI LST product operationally derived by LSA SAF, which has a target accuracy of better than 2 K. For two years of SAF LST, the magnitude of the monthly biases was generally less than 1.0 K and RMSE below 1.5 K. SAF LST and *in situ* LST obtained for three days at another location on the gravel plains were also in good agreement with each other (bias 1.0 K); the corresponding bias between the SAF LST and Gobabeb wind tower LST for this period was even smaller (0.4 K). The bias between in-situ LST obtained along a 40 km track and at Gobabeb wind tower was 0.4 K with a standard deviation of 1.2 K, showing that the Gobabeb wind tower measurements are representative for large parts of the gravel plains. Thanks to SEVIRI's high temporal resolution (15 min), there are typically thousands of monthly match-ups with in-situ LST: ignoring rainy seasons, results for 2009–2014 showed that LSA SAF LST consistently met its target accuracy (Göttsche et al. 2016). (Trigo et al. 2021) validated LST retrieved from the geostationary MSG satellites and Metop polar orbiters. The in-situ validations performed for the two LST products included measurements from Gobabeb wind tower and revealed overall accuracies of 0.13°C for SEVIRI LST and 0.32°C for AVHRR-based LST. Better matches were usually found at night-time, highlighting the influence of LST spatial and temporal variability as well as viewing geometry on satellite daytime estimates. Both LST data sets were found to be consistent and to meet high accuracy standards. Furthermore, their ensured production throughout the sensors' lifecycles makes the two LST products good candidates for long term applications and studies.

(Jimenez-Munoz et al. 2014) analyzed the feasibility of applying the TES algorithm to MSG/SEVIRI data and its potential for improving LSA SAF's LST product over arid and semiarid areas. The so-called SEVTES algorithm was validated with *in situ* measurements from five stations in Africa; due to the high spatial homogeneity of the gravel plains the data from Gobabeb were crucial for the analysis. SEVTES-derived LSE were consistent with MODIS-TES and ASTER-TES retrievals and within 1%–2% of laboratory measurements.

(Martins et al. 2019) developed the first all-weather LST product based on visible and infrared observations by combining clear-sky LST and other satellite products retrieved from MSG/SEVIRI with LST estimated with a land surface energy balance (EB) model to fill gaps caused by clouds. The new product was compared with *in situ* observations from three dedicated LST validation stations, including Gobabeb wind tower, and indicated an accuracy between -0.8 K and 1.1 K and a precision between 1.0 K and 1.4 K.

(Masiello et al. 2015) developed a Kalman filter-based approach for the physical retrieval of LST and LSE from SEVIRI data and validated it with *in situ* LST from Evora and Gobabeb stations operated by KIT. For both sites the Kalman filter yielded a root mean square accuracy of 1.5°C and over the gravel plains at Gobabeb the emissivity retrieved in SEVIRI channel 10.8 μm was in excellent agreement with *in situ* observations. Furthermore, in order to speed up emissivity retrieval, a SEVIRI hyper-fast forward model has been developed (Masiello et al. 2019).

Using single-channel LST retrieval algorithms to ensure consistency across the Meteosat satellite series, (Duguay-Tetzlaff et al. 2015) generated a 30+ year LST climate data record and validated it over various sites, including Gobabeb; they showed that Meteosat single-channel and GSW retrievals are within 0.1–0.5 K except for very moist atmospheres. (Martin et al. 2019) systematically validated satellite LST data sets from several sensors

(AATSR, GOES, MODIS, and SEVIRI) against multiple years of *in situ* data from globally distributed stations. For the large data base of standardized satellite LST provided by the European Space Agency's (ESA) GlobTemperature project average accuracies were generally within ± 2.0 K during night, and within ± 4.0 K during day; however, time series analyses over individual stations also revealed seasonal cycles.

(Duan et al. 2019) validated the C6 MODIS LST product and identified surface emissivity as the largest uncertainty in the MODIS GSW algorithm; they also showed that adjustments of the GSW algorithm, e.g. incorporating dynamic LSE retrieved with the TES algorithm, can reduce LST errors over bare soil surfaces.

Within ESA's GlobTemperature project, (Ghent et al. 2017) validated LST from the Along-Track Scanning Radiometers (ATSR). The retrieval formulation was a nadir-only, two-channel, split-window algorithm, based on biome classification, fractional vegetation, and across-track water vapor dependences. One year of AATSR LST data (2009) were validated against *in situ* LST from "gold standard reference" stations, including Gobabeb, and showed average absolute biases of 1.00 K at daytime and 1.08 K at nighttime.

(Liu et al. 2015) used in-situ observations from Gobabeb wind tower to assess the quality of the S-NPP VIIRS LST Environmental Data Record (EDR). While ground observations from more vegetated areas indicated an overall accuracy of −0.41 K, validation results over arid regions in Africa suggested that VIIRS underestimated LST by 1.57 K. It was concluded that the VIIRS retrieval algorithm strongly depends on correct land cover classifications and, more generally, that surface type dependent algorithms have difficulties with large emissivity variations within a surface type.

(Sobrino et al. 2016) made synergistic use of MERIS and AATSR as a proxy for estimating LST from ESA's Sentinel 3 (S3) satellite. The proposed methodology for retrieving LST from S3 instruments is based on the SW technique with an explicit dependence on surface emissivity. LST retrievals with different input LSE are validated against *in situ* data measured along one year (2011) at five test sites, including Gobabeb wind tower. The results show that LST is retrieved with the proposed SW algorithm typically with RMSE below 2 K.

The official SLSTR LST product is a split-window (SW) algorithm (SWA) with an implicit use of LSE: this motivated (Yang et al. 2020) to investigate alternative SWAs with an explicit use of LSE. (Yang et al. 2020) studied seventeen algorithms for estimating LST from Sentinel-3 SLSTR data: nine of these exhibited low sensitivity to uncertainties in LSE and column water vapor content and were validated against in-situ LST from six sites. Among the land sites, the lowest RMSE of 1.65-1.79 K was obtained for Gobabeb.

(Masiello et al. 2018) developed a fully physical retrieval scheme for LSE spectra, which can be applied to high spectral resolution infrared observations from satellite sensors like IASI (Infrared Atmospheric Sounder Interferometer). The methodology retrieves the LSE spectrum, LST and atmospheric parameters simultaneously and has been developed within the general framework of Optimal Estimation. Applying the scheme to IASI data, it was shown the retrieved LSE spectra are independent of background information and in good agreement with *in situ* observations from Gobabeb (Göttsche et al. 2018). (Safieddine et al. 2020) developed an artificial neural network approach to retrieve LST from IASI data and validated their results against Gobabeb *in-situ* LST.

(Ermida et al. 2020) realized that the Landsat series of satellites have the potential to provide LST estimates at a high spatial resolution, which is particularly appropriate for local or small-scale studies. However, the available Landsat LST datasets generally require the users to handle large data volumes: this can be avoided by using the online platform Google Earth Engine (GEE), which allows users to perform big data analyses without the need for large local computing resources. (Ermida et al. 2020) provide a GEE repository for computing LSTs from Landsat 4, 5, 7, and 8. The retrieved Landsat LST were validated with in-situ measurements from twelve globally distributed sites and include Gobabeb wind tower as a desert site.

(Hulley et al. 2022) used Gobabeb in-situ LST to validate and assess LST and LSE products obtained from the ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS), which currently provides the highest spatial resolution TIR data (38 m × 69 m) available from space. ECOSTRESS LST showed good agreement with ground-based measurements (fourteen sites) with an average RMSE of 1.07 K and a mean absolute error (MAE) of 0.40 K. The multispectral and high-spatial-resolution characteristics of ECOSTRESS serve as a pathfinder to NASA's Surface Biology and Geology (SBG) mission.

(Göttsche & Olesen 2009) fitted a model of the diurnal temperature cycle (DTC) to *in situ* LST from Gobabeb wind tower to obtain parameters that summarize the surface's thermal dynamics. Modelling DTC is also useful for temporal compositing and for cloud screening. (Zhou et al. 2017) used *in situ* LST from Gobabeb to test and validate a method for correcting the thermal sampling depth (TSD) of passive microwave (PMW) observations over barren land. This is required since over arid regions MW radiation penetrates deeper into the ground than TIR radiation, which results in systematic LST differences. The core of the TSD correction (TSDC) method is a new formulation of the passive MW radiation balance equation, which links MW effective physical temperature to the soil temperature at a specific depth. The validation of the TSDC method with *in situ* LSTs from Gobabeb and yielded an RMSE of about 2–3 K and a slight systematic error, i.e. a similar accuracy as many TIR LST products.

5 Discussion

In situ validation of satellite LST remains a challenging task and requires continuous, high quality radiometric measurements from sites with a large, homogenous and temporary stable land cover. It is essential that the *in situ* measurements, which are usually performed over areas between 2 m^2 and 100 m^2, are also representative on the pixel scale, e.g. 1 km^2 to 25 km^2, of the satellite LST to be validated. Therefore, the vast and homogeneous gravel plains near the Gobabeb Namib Research Institute offer ideal conditions for validating satellite LST products up to pixel sizes of about 100 km^2, while at the same time covering a large diurnal temperature range and providing frequent clear-sky observations. The station design, in particular instrumentation and location, target specifically the validation of LST satellite products derived for pixel scales over 1 km, e.g., the precision radiometers used have particularly small drift, and the landscape surrounding the sites is homogeneous at the scale of several satellite pixels. Uncertainty analysis performed for one year of Gobabeb station data yielded an *in situ* LST uncertainty of 0.80 ± 0.12°C. This value is dominated by uncertainty in land surface emissivity within the radiometer's band, which for Gobabeb is estimated as ±0.015.

Continuous *in situ* measurements of up- and downwelling TIR radiance are performed at the Gobabeb wind tower since 2008. This allows analyses of long time series of satellite LST to be performed and can reveal potential deviations as well as seasonal cycles. *In situ* LST from Gobabeb have been used to validate a variety of satellite LST products and helped researchers to develop and evaluate new LST and LSE retrieval algorithms. The results obtained at Gobabeb highlight the need to carefully consider the temporal and spatial properties of LST and LSE when using them for scientific purposes.

Currently, several new TIR satellite missions are in preparation, e.g. the high-resolution French-Indian TRISHNA mission (Thermal infraRed Imaging Satellite for High-resolution Natural resource Assessment), or close to becoming operational, e.g. EUMETSAT's Meteosat Third Generation (MTG) with its main payload, the Flexible Combined Imager (FCI). LST products from these missions are of particular interest for African countries and the *in situ* emissivity spectra collected on the Namib gravel plains will help to validate their retrieved channel-effective emissivities. The continued acquisition of high-quality *in situ* LST at Gobabeb wind tower will ensure that current and new LST products, with their unprecedented temporal and spatial resolutions, can be monitored and achieve their target accuracies over a large temperature range.

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Abbreviations

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AATSR	Advanced Along-Track Scanning Radiometer
AVHRR	Advanced Very High Resolution Radiometer
ECMWF	European Center for Medium-range Weather Forecasts
ECOSTRESS	ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station
ESA	European Space Agency
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
FVC	Fraction of Vegetation Cover
GSW	Generalized split-window
IASI	Infrared Atmospheric Sounding Interferometer
LSA SAF	Land Surface Analysis Satellite Application Facility
LSE	Land Surface Emissivity
LST	Land Surface Temperature
Metop	Meteorological Operational satellite
MODIS	Moderate Resolution Imaging Spectroradiometer
MSG	Meteosat Second Generation
MTG	Meteosat Third Generation
NASA	National Aeronautics and Space Administration
SBG	Surface Biology and Geology
SEVIRI	Spinning Enhanced Visible and Infrared Imager
SLSTR	Sea and Land Surface Temperature Radiometer
S-NPP	Suomi National Polar-orbiting Partnership
TES	Temperature-Emissivity Separation
TIR	Thermal Infra-Red
TOA	Top of Atmosphere
VIIRS	Visible Infrared Imaging Radiometer Suite

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