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DATA DESCRIPTOR

Four decades of circumpolar super-resolved satellite land surface temperature data

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Land surface temperature (LST) is an essential climate variable (ECV) crucial for understanding land-atmosphere energy exchange and monitoring climate change, especially in the rapidly warming Arctic. Long-term satellite-based LST records, such as those derived from the Advanced Very High Resolution Radiometer (AVHRR), are essential for detecting climate trends. However, the coarse spatial resolution of AVHRR's global area coverage (GAC) data limit their utility for analyzing fine-scale permafrost dynamics and other surface processes in the Arctic. This paper presents a new 42 years pan-Arctic LST dataset, downscaled from AVHRR GAC to 1 km with a super-resolution algorithm based on a deep anisotropic diffusion model. The model is trained on MODIS LST data, using coarsened inputs and native-resolution outputs, guided by high-resolution land cover, digital elevation, and vegetation height maps. The resulting dataset provides twice-daily, 1 km LST observations for the entire pan-Arctic region over four decades. This enhanced dataset enables improved modelling of permafrost, reconstruction of near-surface air temperature, and assessment of surface mass balance of the Greenland Ice Sheet. Additionally, it supports climate monitoring efforts in the pre-MODIS era and offers a framework adaptable to future satellite missions for thermal infrared observation and climate data record continuity.

Background & Summary

Land surface temperature (LST) is an important variable in the energy exchange between the land surface and the atmosphere. LST plays a key role in determining Earth's surface radiative energy budget and has been recognized as an Essential Climate Variable (ECV) by the Global Climate Observing System (GCOS)¹ due to its relevance for climate change monitoring^{2–4}. Satellite-based retrievals from thermal infrared (TIR) observations have enabled the characterization of LST at high spatiotemporal resolution, providing an indispensable metric for a wide range of environmental applications⁴. In the pan-Arctic region, LST is especially important for understanding the consequences of Arctic amplification, which over recent decades has driven rapid warming^{5–7}. Notably, permafrost temperatures across the northern high latitudes are responding to these warming trends⁸. LST can be used to model the thermal state of the ground and derive permafrost fractions^{9–11}, reconstruct two-meter air temperatures (T2M)¹² and provide input for surface mass balance models of the Greenland Ice Sheet¹³. Warming trends of LST are also associated with glacier ice retreat¹⁴.

To detect statistically significant trends in ECVs, such as LST, a time series spanning at least 30 years is required¹⁵. The considered period has to be sufficiently long to account for interannual variability¹⁶. Long-term LST time series, of more than four decades of data (1980 to present), have been generated based on the heritage Advanced Very High Resolution Radiometer (AVHRR) mission^{17,18}. A pan-Arctic AVHRR LST dataset based on EUMETSAT's global area coverage (GAC) fundamental data record (FDR)¹⁹ covering 1981–2020 has been specifically computed for the northern high latitudes²⁰. To accurately capture small-scale variations in the ground thermal regime, studies suggest that a spatial resolution of 1 km or finer is necessary^{11,21}; such LST data provide important information about ecosystems responses when exposed to extreme temperature²². In addition, the understanding of Arctic winter warming events would benefit from the availability of circumpolar high-resolution temperature datasets²³. The permafrost ECV products generated by the ESA Climate Change Initiative (CCI) Permafrost project are based on Moderate Resolution Imaging Spectroradiometer (MODIS)

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LST data, as they meet most user requirements, e.g. extensive geographical coverage, high spatial resolution (target resolution 1 km), sufficiently high temporal resolution (monthly data) and multi-decadal temporal coverage (2000 - present)²⁴. However, the MODIS timeseries is less than the required 30 years. Therefore, a generated pan-Arctic AVHRR LST dataset with GAC resolution (called hereafter ‘pan-Arctic AVHRR GAC LST’), extended to 2023, will be spatially enhanced to a spatial resolution of 1 km. In addition to offering four decades of data, the pan-Arctic LST AVHRR product provides up to eight overpasses per 24 hours in the later years of operations.

The most common approach for downscaling satellite-derived LST data is to perform spatiotemporal fusion (STF) on multiple sensors, such as Landsat or Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and MODIS^{25,26}. STF generates a fine-spatial-resolution image by deriving conversion relationships from pairs of coarse-resolution and fine-resolution images, using either weighted function-based methods or learning-based methods²⁵. Common architectures for STF include among others: autoencoders²⁷, generative adversarial networks^{28,29} and vision-transformers^{30,31}. Other common methods include thermal sharpening and spectral unmixing-based algorithms^{32,33}. The main drawback of fusion methods are inconsistencies that arise from differences in solar geometry, viewing angle and observation time and issues with non-homogeneous pixels for the thermal sharpening and unmixing methods^{25,34}. Spatial downscaling is also a common task in the computer vision domain, where advanced deep-learning architectures have been exploited for image super-resolution (SR) or STF learning-based methods³⁵. Guided SR takes a low-resolution source image of some target quantity as input, e.g., perspective depth acquired with a time-of-flight camera and a high-resolution guide image from a different domain, such as a greyscale image from a conventional camera^{36,37}. The target output is a high-resolution version of the source image. In Earth observation, guided super-resolution has been used to map above ground biomass or vegetation height with high-resolution satellite imagery as a guide^{38,39}. Previous work⁴⁰ compared three strategies for downscaling AVHRR GAC LST data: a classical weight-based STF method, a learning-based STF method, and a guided super-resolution approach based on the deep anisotropic diffusion-adjustment (DADA) algorithm introduced by Metzger *et al.* (2023)⁴¹. The DADA algorithm is an edge-preserving filtering algorithm based on anisotropic diffusion⁴² and guided by a separate guide image⁴³. The DADA method yielded the best results for downscaling AVHRR LST data. Building on these findings, the present study applies DADA to enhance the spatial resolution of the pan-Arctic AVHRR GAC LST dataset to 1 km. The deep learning model is trained on MODIS LST data, where coarsened MODIS LST serve as low-resolution input, and native-resolution MODIS LST provide the target. A three-channel guide image — composed of land cover data, a digital elevation model (DEM), and a vegetation height map — is used to inform the model. The main advantage of relying on static predictors is the ability to train a model at the circumpolar scale and to infer high-resolution LST across a long time-frame. During inference, the trained model downscales AVHRR GAC LST using the 1 km resolution guide, yielding a high-resolution pan-Arctic LST dataset suitable for permafrost modelling and Arctic climate analysis.

The objective is to deliver a twice-daily 1 km spatial resolution LST time series for the entire pan-Arctic region covering more than four decades (1981–2023). These data form a unique and highly valuable dataset for monitoring the high northern latitudes, which are particularly sensitive to climate change due to Arctic amplification. The dataset provides valuable and so far missing information about LST dynamics in the pre-MODIS era (before 2000). Furthermore, alongside the LST product, the associated data used for the training of the super-resolution algorithm are also provided. The DADA super-resolution algorithm and its training data can be reemployed for similar tasks, which will be crucial for the upcoming thermal infrared missions to ensure sensor interoperability and the creation of long-term fundamental climate data records.

Methods

The downscaling of the pan-Arctic AVHRR GAC LST dataset involves five main steps (Fig. 1): (1) the computation of LST from AVHRR GAC brightness temperature²⁰, (2) compilation of guide and MODIS datasets for the (3) training of the DADA deep learning model, (4) inference on AVHRR GAC data and (5) the validation and intercomparison of the final LST product.

pan-Arctic AVHRR GAC LST dataset. The pan-Arctic AVHRR GAC LST dataset is based on the EUMETSAT AVHRR GAC brightness temperature data for the period 1981–2023²⁰. The main difference with the previously generated LST GAC dataset⁴⁴ is that the snow cover information has been updated to version 3.1 for the snow water equivalent (SWE) data⁴⁵ and to version 4.0 for the fractional snow cover (FSC)⁴⁶. The cloud mask applied to the pan-Arctic AVHRR LST product is a probabilistic cloud mask called CMAPROB⁴⁷. Cloud probabilities range from 0% to 100% and pixels that have a cloud probability higher than 10% are removed²⁰. The pan-Arctic AVHRR GAC LST dataset is a gridded product with extent (−180, 90, 180, 50°) distributed in the Network Common Data Form (NetCDF) format and has a spatial resolution of 0.05°. Data from NOAA-7, 9, 11, 12, 14, 16, 17, 18 and 19, as well as the EUMETSAT MetOp satellites series (MetOp-A, MetOp-B and MetOp-C), are available. Twice daily data (day and night observations) are available for each satellite. NOAA-15 has been discarded due to data quality issues.

Datasets for DADA model training. This study uses the multisensor LST IRCDR L3S (“MULTISENSOR_IRCDR_L3S_0.01”)⁴⁸ and the Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) LST L3C (“AQUA_MODIS_L3C_0.01”)⁴⁹ datasets developed by the ESA LST CCI project, as well as auxiliary datasets such as a land cover from the ESA CCI on land cover⁵⁰, digital elevation model from Copernicus⁵¹ and a canopy height dataset developed at the ETHZ⁵². The ESA CCI LST datasets and the auxiliary dataset are used to train the deep learning neural network for the super-resolution task, as input source data and guide data respectively.

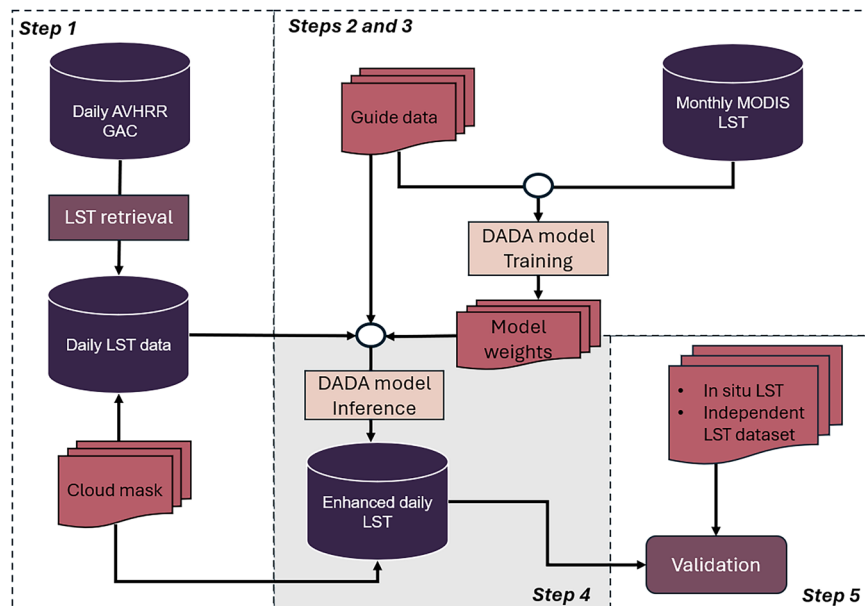


Fig. 1 Downscaling workflow of the pan-Arctic AVHRR LST dataset.

ESA CCI LST datasets. The ESA CCI project on LST provides LST ECV products globally for the past 25 years^{53,54}. Products based on different sensors are available, such as thermal infrared sensors and passive microwave sensors. All products follow strict validation procedures and are distributed as level 3 (L3) products with daily and monthly temporal frequency. The products are accessed through the python toolbox *ESA CCI Toolbox*, which provides directly access to the relevant data stores (<https://climate.esa.int/en/data/toolbox/>, last accessed: 15.09.2025). These datasets all have a spatial resolution of 0.01° and are distributed as latitude-longitude gridded products.

The selected LST datasets for this study are based on Aqua-MODIS (hereafter 'MODISA') with observation time at approximately 1:30 pm and 1:30 am (local solar time) and the multi-sensor climate data record (CDR) constructed from the ATSR-2, AATSR, Terra-MODIS and Sentinel-3 Sea and Land Surface Temperature Radiometer (SLSTR) instruments. These instrument series all have observation times at roughly 10:30 am and 10:30 pm (local solar time). The LST retrieval is performed with the University of Leicester (UOL) algorithm for the IRCDR dataset and the generalized split-window (GSW) algorithm⁵⁵ for the MODISA dataset⁵³. The UOL algorithm introduces a dependence on land cover: land surface emissivity (LSE) is implied in the retrieval coefficients⁵⁶. The GSW algorithm, on the other hand, assumes that LSE is known a priori. The LST datasets from the ESA CCI project on LST use a semi-Bayesian algorithm for cloud masking⁵³.

Guide data. The super-resolution of the pan-Arctic AVHRR GAC LST dataset requires auxiliary datasets. The following datasets are included in the guide:

- The Copernicus digital elevation model (DEM) GLO-90, coarsened to 0.01° spatial resolution (<https://doi.org/10.5270/ESA-c5d3d65>⁵¹, last accessed: 15.09.2025). This dataset represents the elevation of the Earth's surface and is derived from interferometric synthetic aperture radar (InSAR) data acquired during the TanDEM-X Mission⁵⁷.
- ESA CCI Land Cover for the year 2005: The land cover data comes from the ESA CCI Land Cover project, which provides global land cover maps derived from MERIS global surface reflectance and SPOT vegetation datasets. Each pixel in the land cover map corresponds to a land cover class labelled according to the UN Land Cover Classification System (LCCS), which includes 22 global land cover categories. The LCCS classifiers also enable the conversion to Plant Functional Types (PFTs), which are used in Earth System Models (<https://www.esa-landcover-cci.org>, last access: 28 July 2025). The spatial resolution of the original data was coarsened to 0.01° to match the MODIS LST datasets. This coarsening was achieved by selecting the most frequent land cover class within each coarsened pixel, ensuring consistency with the original land cover distribution.
- A high-resolution canopy height model derived from the global ecosystem dynamics investigation (GED) space-borne LiDAR mission and satellite data from Sentinel-2⁵². The spatial resolution was decreased to match the spatial resolution of the MODIS LST datasets (0.01°).

Data sampling. To avoid the persistent cloud cover in the Arctic, monthly mean LST scenes with as little cloud cover as possible are selected from the ESA CCI LST datasets across the pan-Arctic region, Europe and the United States of America (USA). For the model training, 198 scenes with a size ranging from 1600×1600 pixels to 400×700 pixels are selected. The size varies to avoid as many missing pixels as possible due to inland water bodies and coastal zones, as water bodies are masked out in the LST CCI datasets. These different scenes

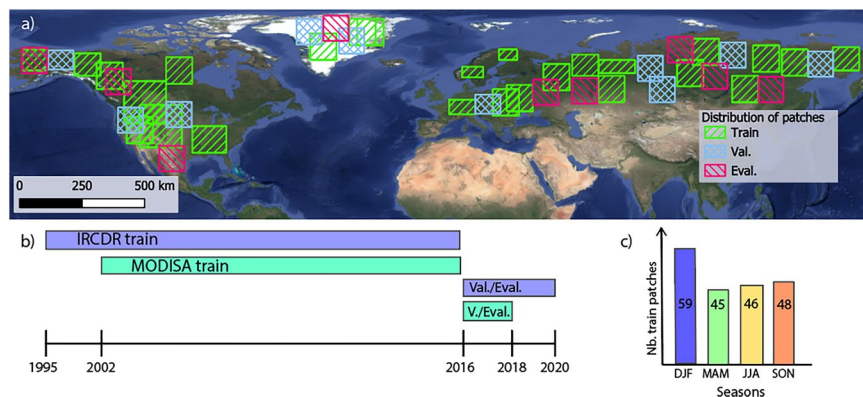


Fig. 2 Overview of selected scenes for the training of the super-resolution algorithm. The spatial distribution of training, validation and evaluation scenes are shown in (a), the temporal span of all sets for both LST datasets is shown in (b) and the count per season for the scenes belonging to the training set are shown in (c).

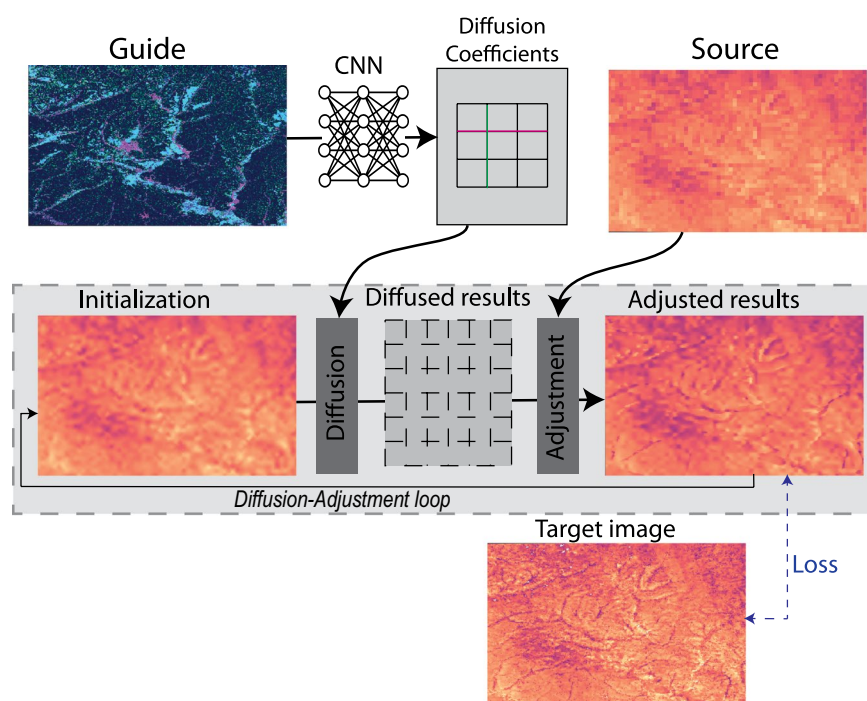


Fig. 3 Overview of the algorithm. The source represents coarsened MODIS data, and the target image is the original MODIS monthly mean LST information. Adapted from Metzger *et al.*, (2023)⁴¹.

have been selected to cover diverse topographic features, diverse types of land cover and a diverse temperature range, which is obtained by sampling different Köppen-Geiger climate classes⁵⁸ separately. Additionally, the scenes were sampled to cover day and night times as well as different seasons and different years. The training data covers the period from 1995 to 2015 for the IRCDR and 2002 to 2015 for the MODISA dataset, and the validation and evaluation sets cover the years 2016 to 2018, or 2020 for the IRCDR dataset. The validation set contains 20 scenes, and the evaluation set contains 8 scenes. The validation scenes have a size of 960×960 pixels, and the evaluation scenes all have a size of 1000×1000 pixels. Patches of size 240×240 pixels are extracted in all splits. In summary, among all available training scenes, there are 3064 non-overlapping patches that can be extracted. In the validation split, there are 320 non-overlapping patches and in the evaluation split, 200 patches with overlap are extracted. An overview of the data sampling is presented in Figure 2. Additionally, the sampled LST scenes as well as the auxiliary data are available from Zenodo: <https://zenodo.org/records/17341544>.

DADA model training. The guided super-resolution framework proposed by Metzger *et al.* (2023)⁴¹, originally implemented in PyTorch⁵⁹, has been adapted to integrate the TorchGeo python library⁶⁰ for handling geo-spatial data. An overview of the DADA model training is shown in Figure 3. The neural feature extractor is, as in

Run	MAE (mean $\pm$ std) [°C]	RMSE (mean $\pm$ std) [°C]
Default (ResNet-50, lr_step=150)		
All data	1.150 $\pm$ 1.028	1.669 $\pm$ 1.478
IRCDR data only	1.159 $\pm$ 1.049	1.675 $\pm$ 1.594
MODISA data only	1.173 $\pm$ 1.069	1.689 $\pm$ 1.614
NIGHT data only	1.174 $\pm$ 1.067	1.692 $\pm$ 1.612
DAY data only	1.168 $\pm$ 1.060	1.684 $\pm$ 1.606
Bicubic	1.244 $\pm$ 1.092	1.768 $\pm$ 1.619
Source (coarse MODIS)	1.283 $\pm$ 1.115	1.816 $\pm$ 1.629
ResNet Variants		
ResNet-18, lr_step=150	1.160 $\pm$ 1.047	1.677 $\pm$ 1.592
ResNet-34, lr_step=150	1.158 $\pm$ 1.044	1.674 $\pm$ 1.591
ResNet-50, lr_step=100	1.158 $\pm$ 1.048	1.674 $\pm$ 1.594
ResNet-50, lr_step=300	1.156 $\pm$ 1.051	1.675 $\pm$ 1.603
sampler_length = 800	1.157 $\pm$ 1.048	1.675 $\pm$ 1.599

Table 1. Mean MAE and MSE of the eight evaluation scenes (Fig. 5) for selected runs. Unless otherwise stated, results are obtained with ResNet-50, lr_step=150 and sampler_length=400.

the original work, a U-Net with a ResNet-50 backbone⁴¹. ResNets with different depths (18 and 34 layers) were tested but ResNet-50 presented better performances on the evaluation dataset (see Table 1).

All sampled scenes contained in the training, validation and evaluation sets were extracted from the NetCDF data cubes, available from the *ESA CCI Toolbox* and saved as separate GeoTIFF files to ensure seamless integration with TorchGeo. Before the actual training of the model, the guide dataset is created by taking the intersection of the land cover, DEM and vegetation height datasets. Then, the newly created 3-channel guide is intersected with the selected LST scenes. This ensures that for each LST scene, a corresponding guide scene is assigned and that only LST scenes with valid guide data are selected. In addition to the 3 channels composing the guide, the upsampled low-resolution LST is concatenated as a fourth channel before applying the neural feature extractor.

During the training phase, data augmentation in the form of random horizontal and vertical flipping is applied. Both LST and guide data are previously scaled with a min-max scaler. In addition, random Planckian color jittering is applied to the guide⁶¹. During training, each epoch consists of 400 randomly sampled patches of size 240×240 pixels, drawn from the training dataset. With a batch size of 8, this corresponds to 50 iterations per epoch. The model converges after approximately 3000 such epochs (i.e., 150,000 total iterations, see Fig. 4), which takes approximately 24h on a single NVIDIA RTX3090 GPU. The training of the model is stopped when the validation loss starts to increase. At each epoch, the model weights corresponding to the best validation results and last model iteration are saved. The original hyperparameters from Metzger *et al.*, (2023)⁴¹ have been kept, with exception of the learning rate scheduler step size (lr_step), which is set to 150. Performances for a selection of alternative settings are shown in Table 1. The ESA CCI LST data is coarsened $\times 5$ during training with NaN-aware average pooling, and these coarsened patches represent the source image and the original ESA CCI LST data is the target image. The scaling factor is $\times 5$ to downscale the AVHRR scenes, with 0.05° spatial resolution, to the 0.01° resolution of MODIS LST. Lakes, rivers and smaller inland water bodies are masked out in the ESA CCI LST datasets, therefore a few holes are present in the patches. The algorithm is able to handle gaps due to clouds and missing pixels⁴¹. The source is generated by ignoring missing values and a pixel validity mask is generated for both the target and the source³⁶, so that invalid pixels are ignored during training, validation, testing and inference.

During the validation phase, the same scaling is applied to the datasets. This time, the scenes from the validation dataset are sampled systematically by extracting patches of 240×240 pixels in a grid-like fashion for the entire area of interest. Exactly 16 patches of 240×240 pixels are fed into the model for each image. During the model evaluation, only inference is performed, and patches are again selected systematically with a smaller stride parameter. The smaller stride parameter allows an overlap in the output evaluation patches that are merged for the analysis. This overlap avoids stitching issues in the final product⁶². The final product is obtained by computing the mean LST value for all pixels presenting overlapping patches.

DADA model evaluation. The performance of the model was evaluated using independent geographical patches (Fig. 2) that capture both daytime and nighttime temperature dynamics across the pan-Arctic region. The spatial distribution of residuals and their corresponding error histograms are shown in Figures 5 and 6. The error distribution is centred around 0°C for all regions with a standard deviation ranging from 0.914°C to 1.331°C . Residuals exceeding a few degrees can be attributed to boundary effects at sharp transitions, such as the edges of water bodies or small gaps caused by cloud coverage. These effects are particularly visible near the bottom in the Krasnoyarsk panel in Figure 5. Larger residuals ($>5^\circ\text{C}$) occur very rarely and are mainly associated with artefacts in the satellite imagery. In general, abrupt temperature gradients that are not well represented by the guide features tend to produce higher errors. For instance, due to its spatial homogeneity in the guide features the Greenland Ice Sheet (Greenland panel, Fig. 5) exhibits larger discrepancies, which cannot reproduce fine-scale temperature variations in the target data.

The overall model performance, quantified by the mean absolute error (MAE) and root mean square error (RMSE), is summarized in Table 1. The values show the overall results, averaging all eight evaluation scenes. The

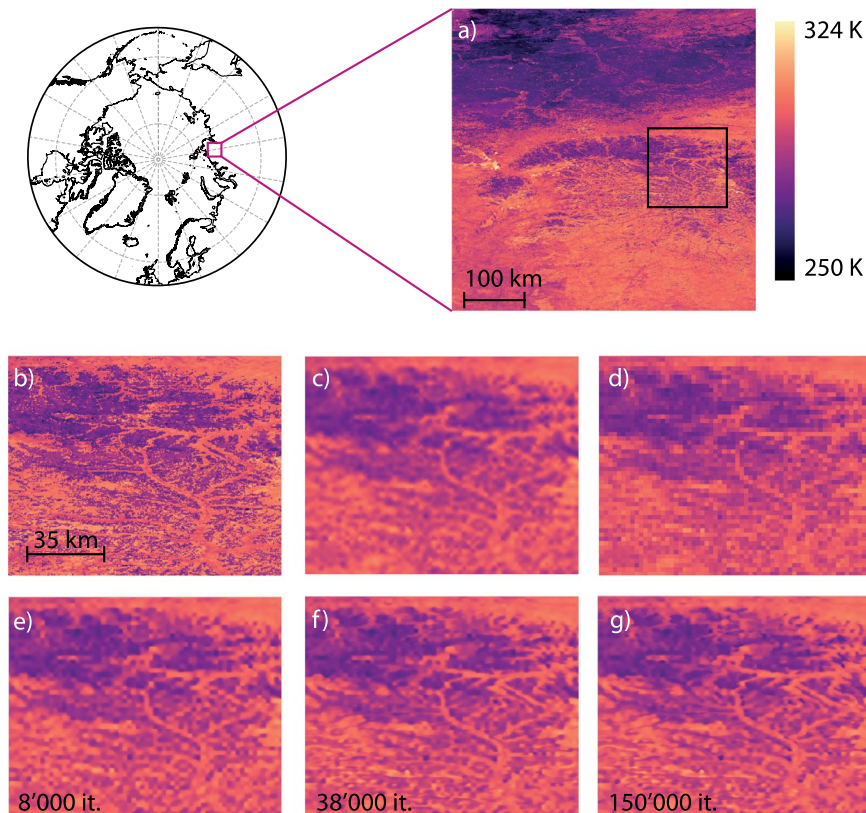


Fig. 4 Evaluation example for an evaluation scene in Northern Siberia in June 2018 (local equatorial crossing time = 10:30 am). (a) Shows the entire evaluation scene (original MODIS LST) with a spatial subset indicated by a black box, that is used in subsets (b) to (g). (b) presents the original MODIS LST scene (the target). (c) represents the bicubic interpolation and (d) the coarsened MODIS scene (the source). (e), (f) and (g) represent the evaluation results at 8000, 38000 and 150000 iterations, respectively.

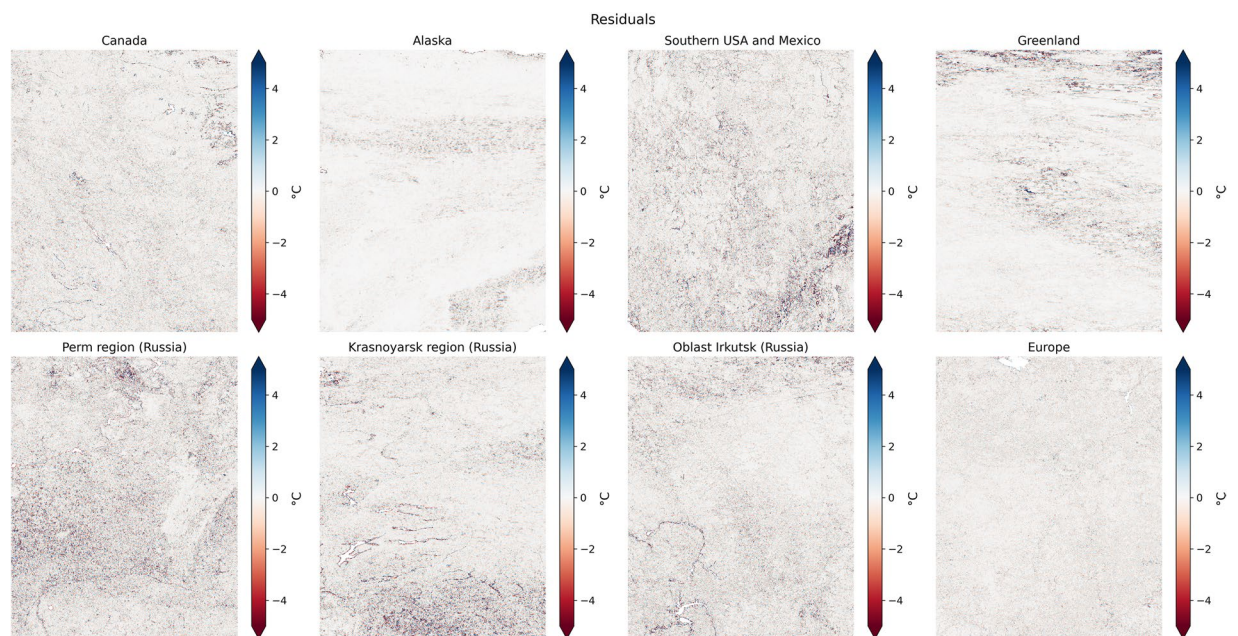


Fig. 5 Difference maps for the eight evaluation scenes (original MODIS LST - inferred MODIS LST). Blue denotes underestimation and red overestimation of the LST.

final configuration employs both ESA LST CCI datasets for training, a ResNet-50 backbone, a sampler length of 400, and `lr_step` of 150. To further assess the influence of different training datasets (MODISA and IRCDR),

Residual Differences Histograms

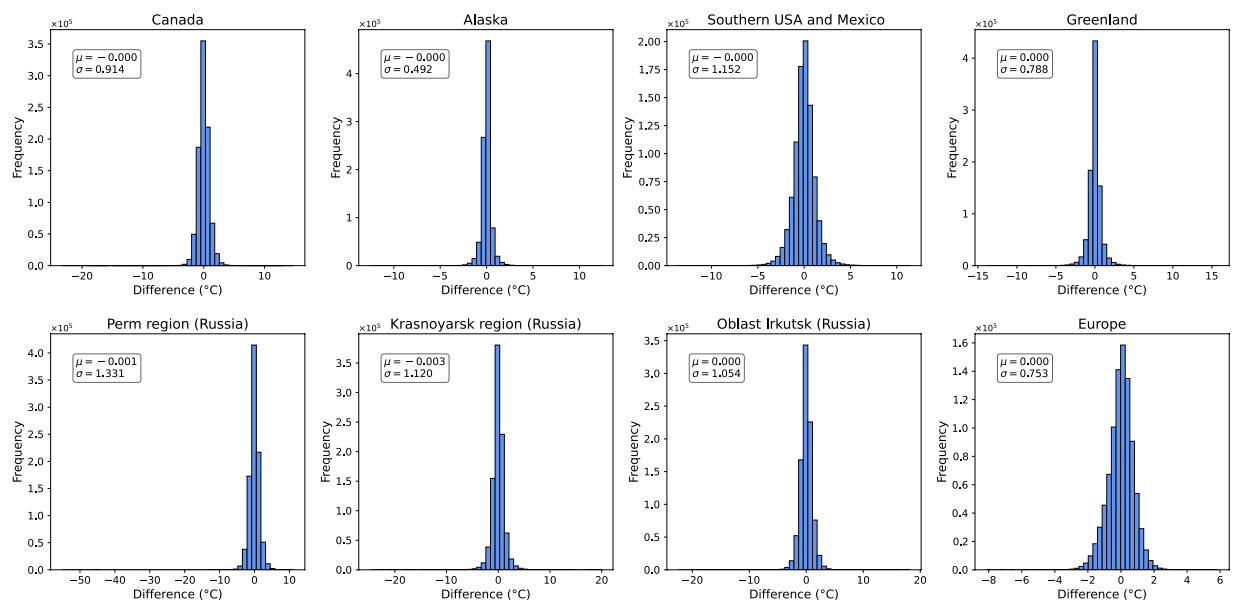


Fig. 6 Histograms of residuals (original MODIS LST - inferred MODIS LST) for geographical patches used for model evaluation (see Fig. 5).

Year	MAE (mean ± std)	RMSE (mean ± std)
1992	1.151 ± 1.029	1.670 ± 1.478
2005	1.150 ± 1.028	1.669 ± 1.478
2020	1.149 ± 1.028	1.668 ± 1.477

Table 2. MAE and RMSE for selected land covers from the ESA CCI land cover project. Values are given as mean ± standard deviation.

additional experiments were conducted using each dataset independently, as well as with daytime-only and nighttime-only subsets. Figure 4 illustrates the evaluation results for a monthly mean daytime Terra-MODIS LST scene in Northern Siberia, including the target image, the source input, bicubic interpolation results, and model outputs across several training iterations until convergence.

The MAE and RMSE values reported in Table 1 are very similar, differing only by fractions of a degree. This consistency, over an extensive evaluation dataset (8 million pixels) that covers many local temperature patterns and variations, demonstrates the robustness of the model to architectural and training changes. STF models often do not generalize well across regions due to uncertainties of spatial, temporal, and spectral patterns inherent to thermal imaging⁶³. However, the spatial residual patterns (Fig. 5) show no major discrepancies between regions with contrasting topography and climate. The final MAE and RMSE values are consistent with the accuracy levels of the pan-Arctic AVHRR LST GAC and ESA LST CCI datasets when compared to insitu observations^{40,64}. Furthermore, we evaluated the sensitivity of the model to land cover changes across years. Table 2 presents the MAE and RMSE values on the evaluation set for different land covers from the ESA CCI land cover project. Three different land covers were used, 2005 represents the one used as a default setting. The differences in MAE and RMSE are very small. The year 2020 shows slightly better performance, which can be explained by the fact that evaluation data are sampled for the period 2016–2020. The proposed final dataset has an increased spatial resolution of 5, which allows to reconstruct missing details in narrow valleys and along coastlines, for example. In comparison to fusion methods⁶⁵, the scaling factor is limited. However, the DADA methodology allows complete fidelity to the input data, thanks to the adjustment step of the algorithm. Finally, the DADA algorithm was compared against a broad range of guided super-resolution methods, both learning-based and learning-free, and showed to have the best performance on different depth-RGB benchmark datasets⁴¹. In addition, DADA also outperformed two different LST fusion algorithm in almost all test cases for the Arctic and obtained on average, the lowest MAE and MSE⁴⁰.

Inference on AVHRR data. The pan-Arctic AVHRR GAC LST dataset with 4 km spatial resolution (GAC format) is stored in NetCDF-4 format. Therefore, the inference workflow for the AVHRR data has been built with the Python package Xarray^{66,67}, to read in labelled multi-dimensional arrays in the NetCDF format. Before inference, cloud masking is applied to the AVHRR GAC LST scenes. The downscaled LST scenes are then computed as patches of 1920 × 1920 pixels with a stride of 1480 vertically and 1792 horizontally. Different stride sizes for the

Instrument	Satellite	Data start	Data end	Node: Daytime overpass time
AVHRR/2	NOAA-7	1981-08-24	1985-01-31	Ascending: PM
AVHRR/2	NOAA-9	1985-02-25	1988-11-07	Ascending: PM
AVHRR/2	NOAA-11	1988-11-08	1994-09-13	Ascending: PM
AVHRR/2	NOAA-12	1991-09-16	1998-11-26	Descending: PM
AVHRR/2	NOAA-14	1995-01-20	2002-08-01	Ascending: PM
AVHRR/3	NOAA-16	2001-01-01	2009-12-31	Ascending: PM
AVHRR/3	NOAA-17	2002-07-10	2010-02-28	Descending: AM
AVHRR/3	NOAA-18	2005-06-05	2016-12-31	Ascending: PM
AVHRR/3	NOAA-19	2009-02-22	2019-12-31	Ascending: PM
AVHRR/3	MetOp-A	2007-06-29	2021-11-27	Descending: AM
AVHRR/3	MetOp-B	2013-01-01	2023-12-31	Descending: AM
AVHRR/3	MetOp-C	2019-07-01	2020-12-31	Descending: AM

Table 3. Data coverage of the pan-Arctic AVHRR LST dataset per satellite.

horizontal and vertical strides were chosen in order to cover the entire pan-Arctic region and allow for overlap between patches to avoid stitching issues while producing the final product. For each AVHRR scene covering the pan-Arctic, defined as the part of the globe north of 50°, 40 patches are computed. The patches are stitched together for each timestamp by taking the average value in the presence of overlapping pixels, the same cloud mask is applied as for the corresponding LST GAC images, and performance and quality indicators from the LST GAC images are applied to the downscaled images. The production of one day of super-resolved LST for the entire pan-Arctic takes approximately 1 minute, which comprises the in and out reading of the data, the inference and the stitching process. The entire pipeline is run on the University of Bern Linux Cluster (UBELIX), which allows for efficient parallel processing. The final data are stored in NetCDF-4 format with accompanying metadata. The file-name and the metadata of each NetCDF file contain the timestamp, the satellite name and the processing version.

Data Record

The downscaled version of the pan-Arctic AVHRR GAC LST dataset⁶⁸ (hereafter ‘AVHRR SR LST’) is accessible from the IEEE Data Portal (DataPort): <https://doi.org/10.21227/ghmz-f132>. The original AVHRR GAC dataset and the downscaled version are distributed in the same dataset, under different variables. The entire dataset is called hereafter ‘pan-Arctic AVHRR LST dataset’. The ESA CCI LST scenes and auxiliary data⁶⁹ used to train the DADA model are available from Zenodo: <https://doi.org/10.5281/zenodo.17341544>. The AVHRR SR LST are stored in NetCDF-4 format files and provide twice daily clear-sky LST (at day and night time) for each satellite, covering a total of 42 years (1982 to 2023) at 0.01° spatial resolution. Clouds are masked out from the data and are replaced with NaN values. Water bodies have not been masked out, due to the high classification uncertainty of water bodies in the high Arctic⁷⁰, and to let users choose the right water mask for their purpose. The data are provided as a gridded latitude-longitude product, in WGS84 projection (EPSG:4326) with extent –180°–180° longitude and 50°–90° latitude. Files containing large gaps due to scanline failures or other data outages have been filtered out. The dataset is organized by year and satellite, each folder containing 730 NetCDF files for a complete year (732 for leap years). An overview of the available data is provided in Table 3.

Filenames are encoded with the timestamp, satellite name, version name and a DAY or NIGHT tag. The files can easily be opened in Python with the Xarray package, either separately or directly in a data cube, by reading a whole folder simultaneously. Each NetCDF file contains distinct data arrays for LST, acquisition time, satellite zenith angle, performances of the GSW algorithm as well as sun zenith angle. The key variables, stored as data arrays in NetCDF-4 format, are listed in the Table 4. All data arrays have associated metadata. The AVHRR SR LST data are stored under the variable ‘LST’ and the original LST data at GAC resolution are stored under the variable ‘LST-GAC’. Cloudy pixels are masked out in the AVHRR SR LST dataset and are assigned the value 110 in the GAC dataset. Satellite overpass time is saved in variable ‘scanline time’ as fractional hours of the day and satellite and sun zenith angle information are also available. ‘Test MAE’ and R^2 values reflect the performances of the GSW algorithm and can be used as proxies for data quality.

The files are stored in a compressed format using a scale factor and an offset value. Most GIS tools and geo-data packages automatically apply these formatting values at data opening. However, they have to be applied manually when creating custom parsing routines.

Technical Validation

Validation against in situ measurements. The most conventional and reliable method to validate satellite-derived LST is the ‘T-based’ validation, which directly compares in situ and satellite LST at the satellite overpass^{4,54,71}. In situ LST obtained from the Surface Radiation Budget (SURFRAD) network⁷², the Karlsruhe Institute of Technology (KIT) network^{71,73,74}, the Atmospheric Radiation Measurement Climate Research Facility US Department of Energy (ARM) site at the North Slope of Alaska (NSA)⁷⁵, the “Copernicus Space Component Validation for Land Surface Temperature, Aerosol Optical Depth and Water Vapor Sentinel-3 Products Project” (LAW project, <https://law.acri-st.fr/home>, last accessed: 20-09.2025) and the Baseline Surface Radiation Network (BSRN, <https://bsrn.awi.de/stations/maps/>, last accessed: 01-03.2026) are used for validation. KIT stations are equipped with KT15.85 IIP (KT15) infrared radiometers, detailed description on calibration and accuracy of the

Variable name	Long name	Standard name	Units	Valid range	Scale factor	Offset
LST	enhanced daytime land surface temperature (0.01° GSD)	lst	K	200-360	0.01	273.15
LST_GAC	daytime land surface temperature (0.05° GSD)	lst_gac	K	200-360	0.01	273.15
scanline_time	scanline time as fractional hours of the day	time	h	0-24000	0.01	0.0
satzen	Satellite Zenith Angle	sensor_zenith_angle	degrees	0-18000	0.01	0.0
sunzen	Sun Zenith Angle	solar_zenith_angle	degrees	0-7500	0.01	0.0
test_mae	Mean Absolute Error (MAE) value of GSW algorithm performances - evaluation on test set	test_mae	K	—	0.01	0.0
r2	R ² value of GSW algorithm performances - evaluation on test set	R ²	—	—	0.01	0.0

Table 4. NetCDF data variables in the pan-Arctic AVHRR LST product files.

measurement device and set up are exposed in Martin *et al.*, (2019)⁷³ and Götsche *et al.*, (2016)⁷¹. SURFRAD sites measure broadband radiances, and the associated broadband emissivity (BBE) must be estimated first and is determined as shown in Martin *et al.*, (2019)⁷³. The uncertainty associated with BBE and upwelling and downwelling measurements are computed as explained in Martin *et al.*, (2019)⁷³. The emissivity assignment of the LAW stations is done according to their ATSR land site classification, as described in the LAW Validation Protocol dedicated to LST products⁷⁶. The emissivity is assumed to be static, as dense forests and snow cover, both have high values of emissivity⁷⁷. For the BSRN stations, BBE is obtained from channel effective emissivity data provided in the ASTER Global Emissivity Database (GED)⁷⁸ with the linear equation described in Cheng *et al.*, (2013)⁷⁹. In addition, three-sigma (3σ) filtering was employed to remove the samples contaminated by undetected clouds^{18,71}, and for removing outliers due to problems of the radiometer optics. Table 5 lists the stations: the KIT stations, which are part of LSA SAF's validation effort and supported by EUMETSAT, are located in different climate zones, such as Mediterranean, marine west coast and humid continental climates^{71,72,74,75}. In situ LST is computed from measured radiation components as in Martin *et al.*, (2019)⁷³. BSRN stations in Alert⁸⁰, Ny-Ålesund⁸¹ and Tiksi⁸² presented a sufficiently long data record for validation and have been chosen to complement the coverage of in situ stations in the Arctic.

Figures 7 and 8 show the validation results for NOAA-14, 16, 17, 18 and 19, and MetOP-A, B and C against in situ LST from the validation sites in Table 5. The validation is separated for daytime (represented in red) and nighttime (blue) observations. For each validation site, the median deviation (MD), RMSE and robust standard deviation (RSD), as computed in Pérez-Planells *et al.* (2023)⁸³ are shown. The match-up with the SURFRAD stations covers the period from 1985 to 2023, the match-up period for KIT station in EVORA (EVO) starts in 2009 and ends in 2023, the match-up period for Lake Constance starts in 2016 and ends in 2020, and the match-up period for the ARM site North Slope of Alaska (NSA) covers 2007-2014 and 2020-2023. Regarding the BSRN data, the match-up period for station Alert (ALE) starts in 2004 and ends in 2014, Ny-Ålesund (NYA) starts in 2006 and ends in 2020 and Tiksi (TIK) starts in 2010 and ends in 2018. The LAW stations (KIT, HYY and SVA) cover the period 2021 to 2023. The obtained results are very similar to the results obtained with the GAC product²⁰, the present results are very similar. This can be attributed to the fact that the chosen SURFRAD stations are located in relatively homogeneous areas, i.e. regions where land surface properties such as vegetation, topography, and land cover vary little across space. As a result, the difference in spatial resolution between the 4 km and 1 km products has limited impact. Compared to previous studies on AVHRR LST^{17,18,84}, the present dataset shows similar accuracy and precision.

Intercomparison with EDLST from LSA SAF. Due to differences in satellite equatorial crossing times, which would lead to large differences in LST or diverging compositing strategies, such as mean daily composites versus selection of the scene nearest to nadir, only qualitative comparisons against other LST satellite products with a spatial resolution of 0.01° are possible.

The satellite application facility on land surface analysis (LSA SAF), as part of the EUMETSAT application ground segment, delivers products and services for land surface monitoring, such as albedo, LST and emissivity, surface radiation, vegetation and wildfires. The LSA SAF generates and distributes a LST product derived from AVHRR onboard the EUMETSAT polar system satellites, the MetOp series. This EUMETSAT Polar System (EPS) daily LST product (EDLST; LSA-002), is available from 2015 until the present and disseminated in a global grid in sinusoidal projection with a spatial resolution of 0.01°⁸⁵. The EDLST product is generated with the GSW algorithm⁵⁵, which is calibrated with data from the SeaWiFS database⁸⁶ and the radiative transfer simulations using the MODerate spectral resolution atmospheric TRANsmittance algorithm (MODTRAN4) software⁸⁷.

The EDLST product consists of daily composites of mean LST values and the cloud mask is obtained from the Nowcasting and Very Short Range Forecasting Satellite Application Facility (NWC) SAF. The pan-Arctic AVHRR LST GAC product has been generated by always selecting the pixel closest to the nadir and uses the cloud mask from the CLARA-A3 product⁴⁷. Figures 9 and 10 show a comparison of the EDLST product and the AVHRR SR LST product for four areas of interest across the pan-Arctic during day and night respectively. The comparison uses the Metop-A satellite at the daytime and Metop-B satellite at nighttime. The two LST products use different cloud masks: therefore in Figures 9 and 10, the cloud mask used for the pan-Arctic product (CLARA-A3 cloud mask) is additionally applied to the already masked EDLST product. The EDLST product includes a water mask, therefore for the purpose of this comparison, the AVHRR SR LST dataset uses the ESA CCI land cover dataset for water masking. For the daytime comparison, both LST products show good agreement in all four regions (see Fig. 9). The sharp temperature changes from the Greenland Ice Sheet to contiguous land is well represented in both datasets, and generally small structures are well visible in the downscaled dataset. In a few places, next to gaps due to clouds, the EDLST seems to be slightly cooler than the AVHRR SR LST e.g. a) and b) from Figure 9. The nighttime comparison (Fig. 10) presents small differences in temperature textures

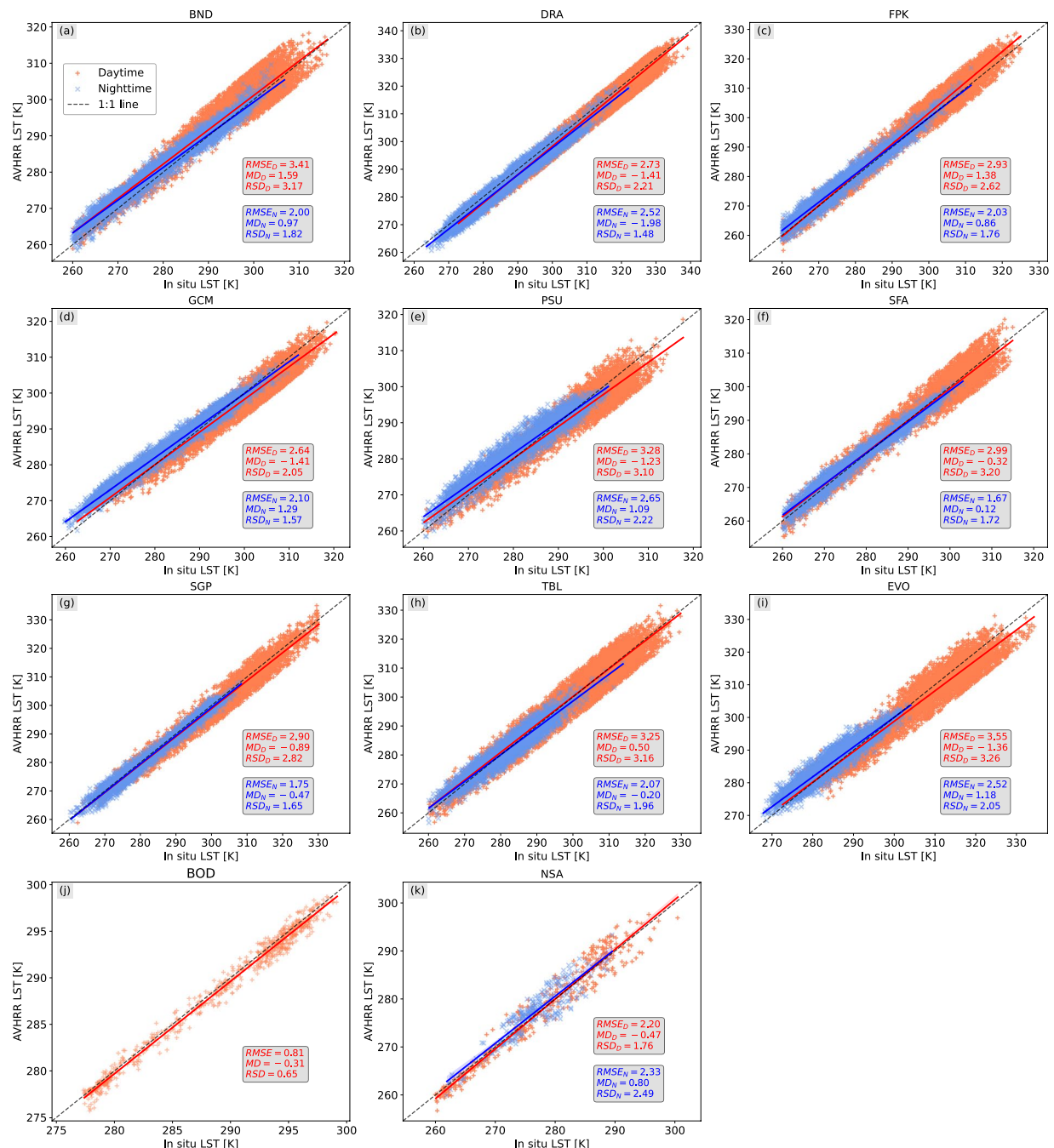


Fig. 7 Enhanced (1 km) AVHRR LST versus in situ LST at (a) Bondville (BND), (b) Desert Rock (DRA), (c) Fort Peck (FPK), (d) Goodwin Creek (GCM), (e) Penn. State Univ (PSU), (f) Sioux Falls (SFA), (g) Southern Great Plains (SGP), (h) Table Mountain (TBL), (i) Evora (EVO), (j) Lake Constance (BOD) and (k) North Slope of Alaska (NSA). Red represents daytime and blue nighttime measurements. Match-up periods differ and are provided in the text.

in Northern Siberia and the Greenland area, which could be attributed to differences in compositing as the GAC and the downscaled version are coherent. In addition, Figure 11 shows the distribution of differences between the EDLST product and the Metop-A AVHRR SR LST dataset for the same four areas of interest during daytime for the entire year 2020. The differences are computed as $EDLST - pan_Arctic_AVHRR_LST(MetOpA)$.

The differences are centered around 0 °C and in three areas of interest. No cold or warm bias is visible from the distribution. East Siberia has a mean value of 1.13 °C, which indicates slightly warmer values in the EDLST product than in the AVHRR SR LST product. Rare, very large deviations can be attributed to differences in cloud and water masking and to cloud contamination in one or the other dataset.

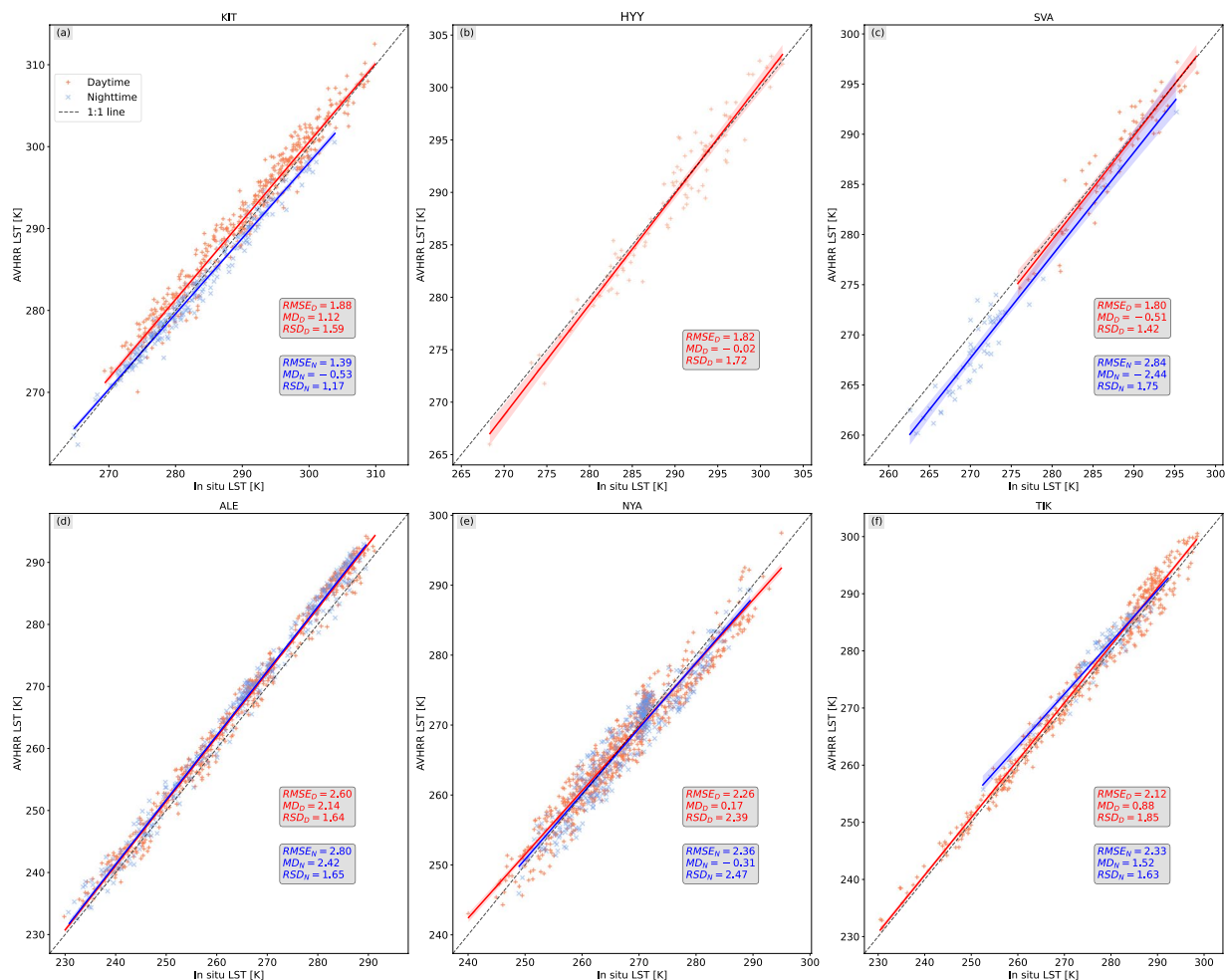


Fig. 8 Enhanced (1 km) AVHRR LST versus in situ LST at (a) the KIT Campus Nord (Germany), (b) Hyttiälä, (c) Svartberget (Sweden), (d) Alert (Canada), (e) Ny-Ålesund (Norway) and (f) Tiksi (Russia). Red represents daytime and blue nighttime measurements. Match-up periods differ and are provided in the text.

Station name (ID)	Network	Latitude [°]	Longitude [°]	Elevation [m]	LCCS
Bondville, Illinois (BND)	SURFRAD	40.0519	-88.3731	230	Cropland
Desert Rock, Nevada (DRA)	SURFRAD	36.6237	-116.0195	1007	Open Shrubland
Fort Peck, Montana (FPK)	SURFRAD	48.3078	-105.1017	634	Grassland
Goodwin Creek, Mississippi (GCM)	SURFRAD	34.2547	-89.8729	98	Wooded Grassland
Penn. State Univ., Pennsylvania (PSU)	SURFRAD	40.7201	-77.9309	376	Deciduous Broadleaf Forest
Sioux Falls, South Dakota (SFA)	SURFRAD	43.73403	-96.62328	1689	Cropland
ARM Southern Great Plains, Oklahoma (SGP)	SURFRAD	36.60406	-97.48525	314	Cropland
Table Mountain, Boulder, Colorado (TBL)	SURFRAD	40.1250	-105.2368	1689	Cropland
Lake Constance, Germany (BOD)	KIT	47.58	9.57	396	Water
Evora, Portugal (EVO)	KIT	38.54	-8.003	300	Mosaic Tree and Shrubs
North Slope of Alaska, USA (NSA)	ARM	71.323	-156.609	8	Lichens and Mosses
Alert, Canada (ALE)	BSRN	82.49	-62.42	127	Bare Soil
Ny-Ålesund, Norway (NYA)	BSRN	78.9227	11.9273	11	Bare soil
Tiksi, Russia (TIK)	BSRN	71.5862	128.9188	48	Shrubland
Svartberget, Sweden (SVA)	LAW	64.26	19.77	269	Mixed Forest
Hyttiälä, Finland (HYY)	LAW	61.85	24.29	181	Mixed Forest
KIT Forest, Germany (KIT)	LAW	49.09	8.43	115	Deciduous Broadleaf Forest

Table 5. Measurement stations used for LST validation. Station name and ID, network the station belongs to, latitude, longitude, elevation above sea level and the dominant land cover type.

Comparison of EDLST LSASAF, downscaled AVHRR and GAC AVHRR LST datasets

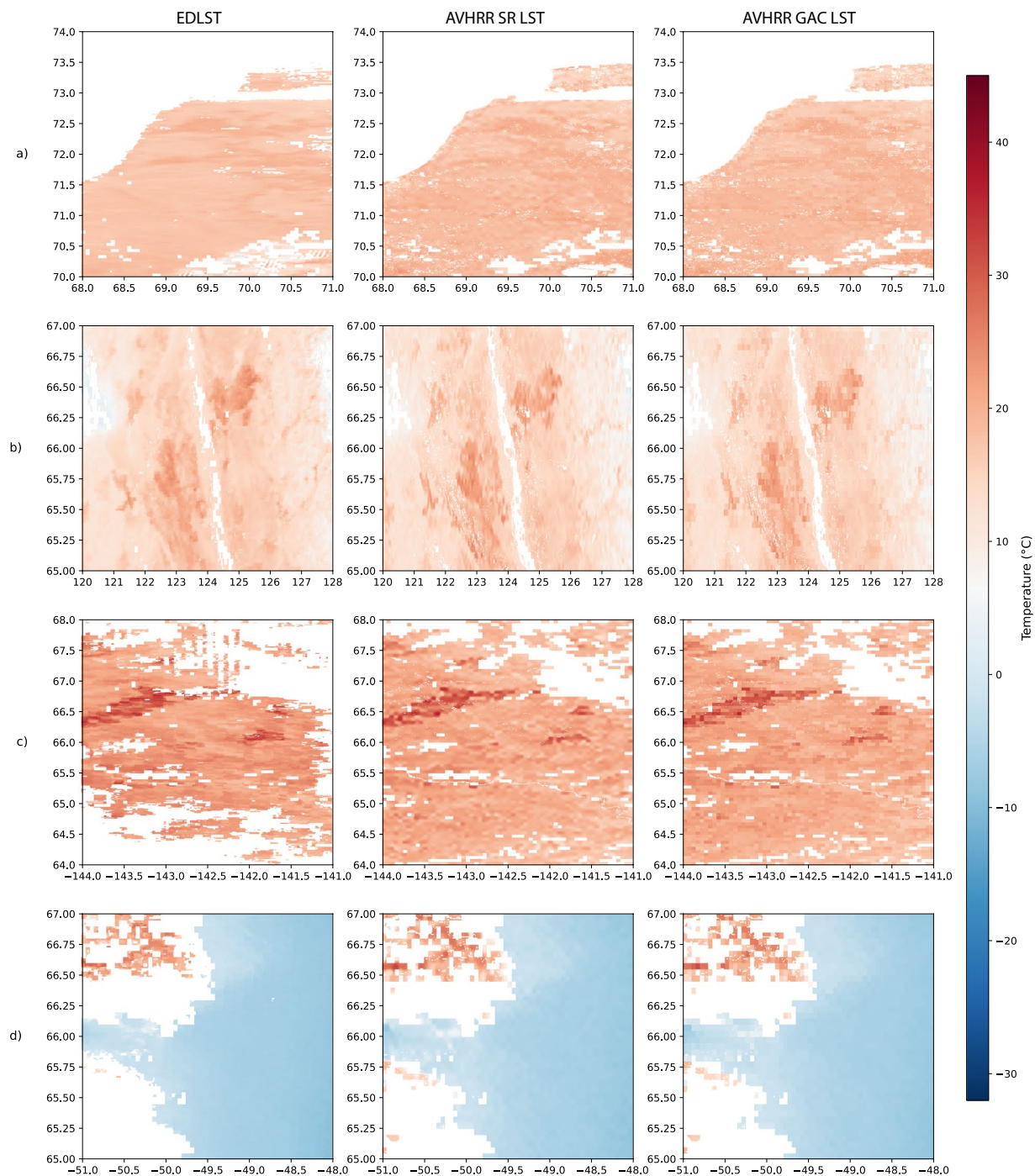


Fig. 9 Comparison of the EDLST product and the AVHRR SR LST dataset from the Metop-A satellite during daytime. **(a)** On the 20.08.2020, in Northern Siberia, **(b)** on the 20.08.2020 in East Siberia, **(c)** on the 10.06.2020 in Alaska and **(d)** on the 20.05.2020 in Greenland. The cloud mask of the pan-Arctic LST dataset in GAC format has been applied to both datasets for comparison purposes.

Usage Notes

The presented 1 km AVHRR LST product, obtained from 40 years GAC LST with static high-resolution guide images and a guided super-resolution algorithm from computer vision provides long-term pan-Arctic LST observations at a hemispheric scale. It complements the existing LST time series derived from MODIS, which is only available after 2000 and provides a valuable resource for assessing LST trends and dynamics over four decades. In addition, the proposed methodology and the dataset used to train the model can be reused for other

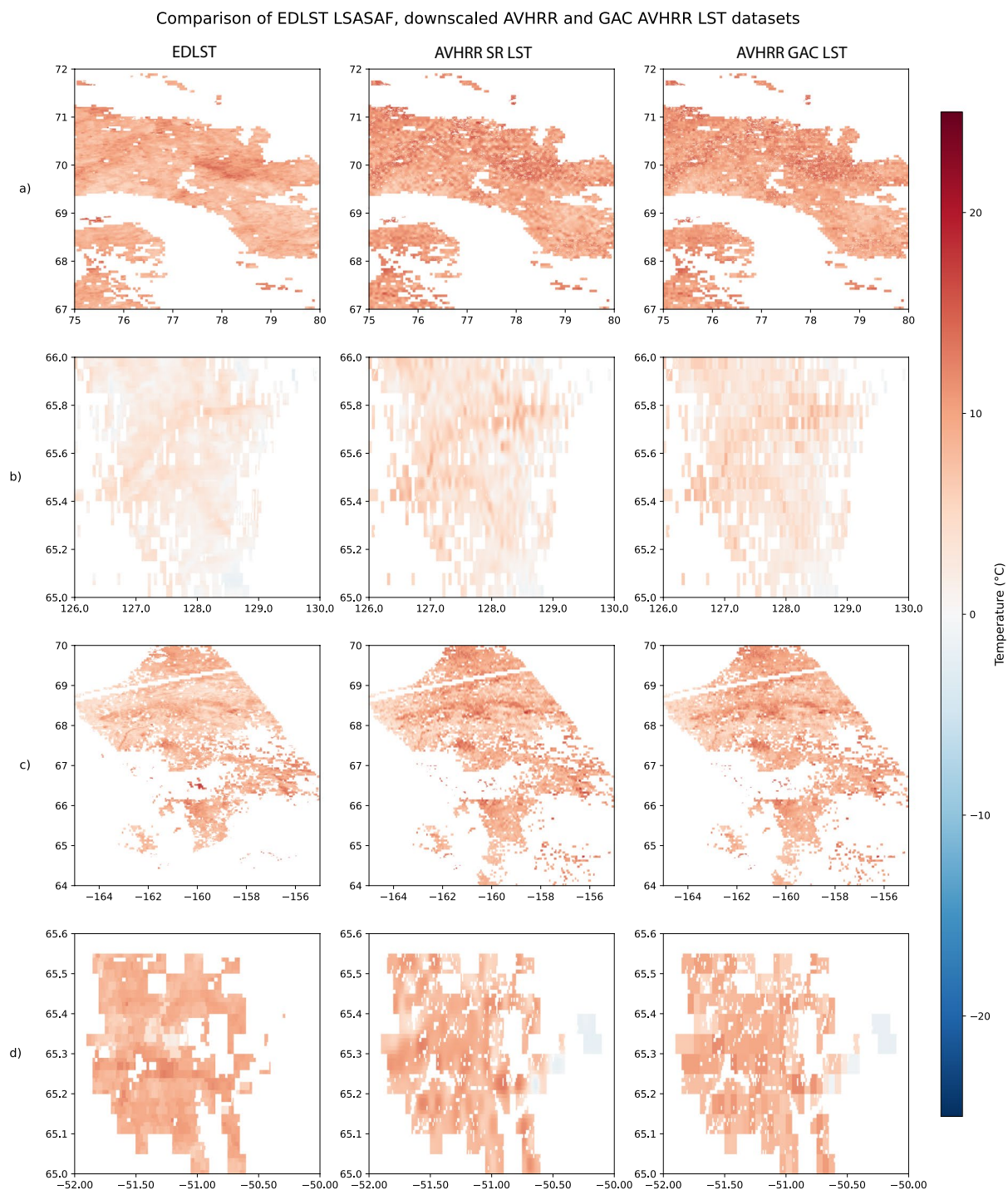


Fig. 10 Comparison of the EDLST product and the AVHRR SR LST dataset from the Metop-B satellite during nighttime. **(a)** On the 28.08.2020, in Northern Siberia, **(b)** on the 09.08.2020 in East Siberia, **(c)** on the 22.08.2020 in Alaska and **(d)** on the 17.08.2020 in Greenland. The cloud mask of the pan-Arctic LST dataset in GAC format has been applied to both datasets for comparison purposes.

similar use cases. The data are stored in NetCDF-4 format and follow the Climate-Forecast (CF) metadata conventions⁸⁸. Python tools such as Xarray or Netcdf4 for example can be used to read the data.

The dataset contains only clear-sky observations and even though a conservative cloud mask has been applied, studies of LST trends or comparisons with other temperature records may be affected by a potential clear-sky bias. As shown by Good *et al.* (2022)⁸⁹, this bias should be considered when interpreting LST variability and trends. The performance and long-term stability of the cloud mask directly influence the stability of LST records, as the proportion of missed clear-sky cases and falsely flagged clouds can vary both spatially and temporally, thereby affecting the uncertainty of calculated LST trends⁹⁰. Cloud masking is particularly challenging during

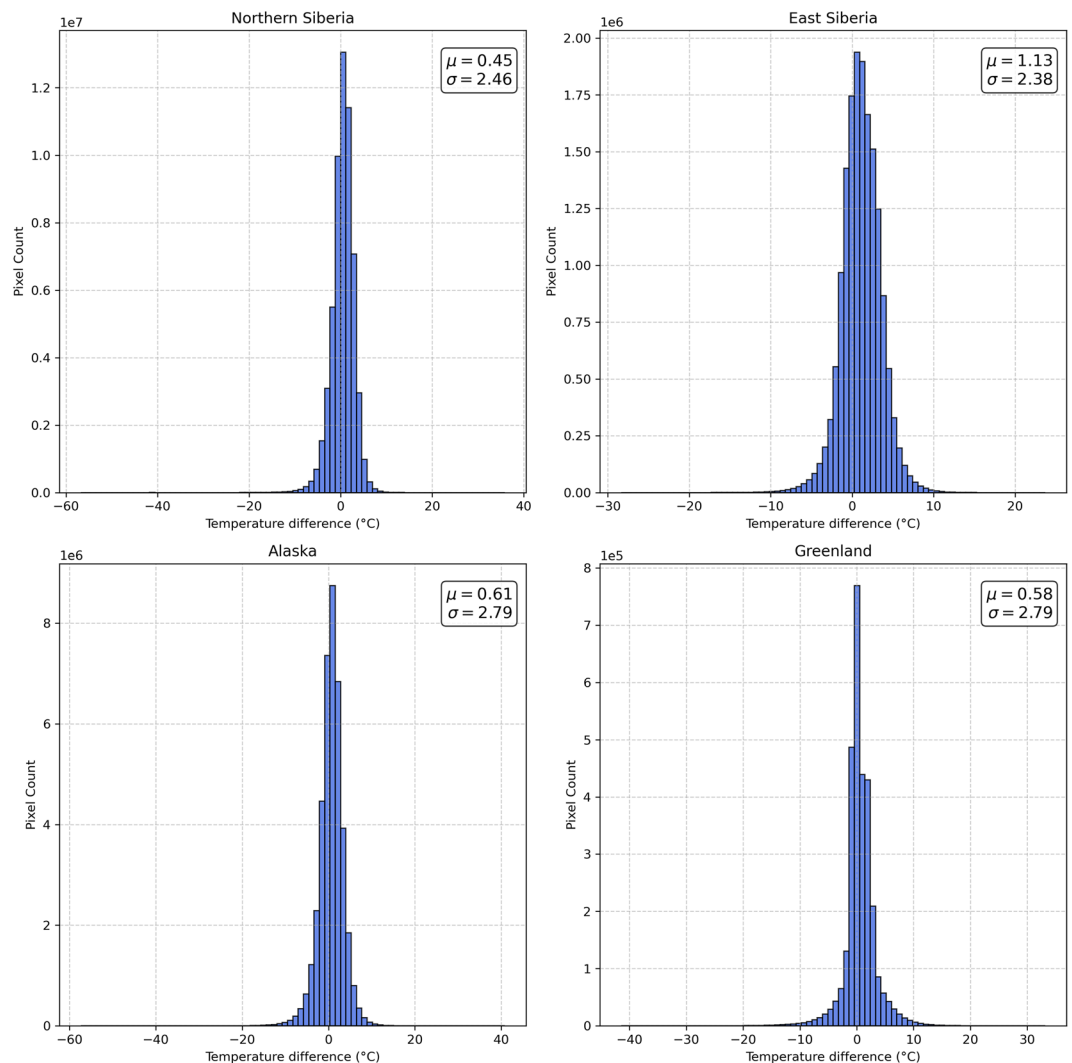


Fig. 11 Histograms of differences of Land SAF EDLST product minus the AVHRR SR LST from the Metop-A satellite during daytime for four areas of interest (see Fig. 9) for the entire year 2020.

winter, leading to increased uncertainties and greater variability in retrieved temperatures^{91,92}. In Arctic winter conditions, cold surface temperatures are typically associated with clear-sky situations, which can lead to an over-representation of cold temperatures in satellite-derived LST compared with station measurements⁹³. Conversely, a warm bias in summer has been observed over the Arctic-boreal region⁹⁴. Differences between LST anomalies derived from thermal infrared observations and air temperature anomalies therefore show a pronounced seasonal cycle, unlike LST anomalies derived from passive microwave observations⁸⁹. Despite these potential biases, further analyses suggest that their influence on long-term LST trends is limited. For example, Good *et al.* (2022)⁸⁹ found no clear evidence that clear-sky bias significantly affects trend estimates. Similar conclusions have been reported for the pan-Arctic AVHRR LST record, where only a limited impact on trend analysis was identified²⁰.

The land cover map used for the downscaling is static and does not account for the land cover changes over time. Furthermore, in areas that are permanently covered by ice, such as the Greenland Ice Sheet, the downscaling algorithm lacks guiding information as the land cover, the vegetation height, and the DEM will mostly be homogeneous. Users interested in downscaling LST over ice sheets are encouraged to use other more fine-grained predictors. The training algorithm can be used seamlessly with different predictors. Finally, in regions where AVHRR local area coverage (LAC) data with higher spatial resolution (1.1 km) are available, such as Europe, additional sensor-derived predictors, including solar and satellite zenith angles, could be incorporated. The algorithm could also be trained directly on AVHRR LAC data instead of MODIS. However, AVHRR LAC data are only available on a regional basis, which limits their applicability for large-scale analyses.

Data availability

The pan-Arctic AVHRR LST dataset (Dupuis *et al.*, 2026) is accessible from the IEEE Data Portal (DataPort): <https://doi.org/10.21227/ghmz-f132>. The GAC and the downscaled LST product are packaged in different variables: 'LST' and 'LST_GAC'. The ESA CCI LST scenes and auxiliary data (Dupuis *et al.*, 2025) used to train the DADA model are available from Zenodo: <https://doi.org/10.5281/zenodo.17341544>.

Code availability

The downscaling algorithm is written in the Python (v3.12.3) programming language, relying on the PyTorch framework, as well as TorchGeo for handling geospatial data. The Xarray and RioXarray packages have also been used for the analysis of the data in the NetCDF format. The entire code used is freely available on GitHub (https://github.com/soniajdupuis/Enhanced_pan_Arctic_LST).

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Author contributions

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Competing interests

The authors declare no competing interests.

Additional information

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