# Summary of All-Sky LST Calculation Workflow

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# Introduction

This document summarizes the workflow for calculating all-sky land surface temperature (LST). The experiment was carried out as a case study using data from **November 27, 2021**.

As shown in the figure 1, the process starts with computing a hypothetical clear-sky LST from ERA5 data. A machine learning model is then applied to downscale the results, and the GOES-R clear-sky LST product is used to calibrate the hypothetical clear-sky values. Next, based on the surface energy balance theory and the conventional force-restore theory, the temperature changes caused by cloud effects are estimated. Finally, the clear-sky LST and the cloud-induced temperature change are combined to obtain the all-sky LST.

It should be noted that, due to time and resource limitations, this experiment only used November 27, 2021, as a sample case. The models applied in the downscaling and calibration steps were not fully trained or validated. Therefore, the results should be considered as preliminary and for reference only.

A diagram of a software development process

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Figure 1 Flowchart for All-Sky LST Calculation

# Hypothetical clear-sky LST

The purpose of this step is to generate a baseline land surface temperature (LST) field under hypothetical clear-sky conditions. This field is then refined spatially and corrected against satellite product to serve as the foundation for all-sky LST estimation.

## Input

|  |  |  |  |
| --- | --- | --- | --- |
| **Data** | **Temporal Resolution** | **Spatial Resolution** | **Usage** |
| ERA5 clear-sky DLR and NLR | hourly | 0.25 deg | LST calculation |
| VIIRS BBE | daily | 0.009deg | LST calculation and calibration |
| NDVI | daily | 0.05 deg | Downscaling and calibration |
| DEM | \ |  | Downscaling and calibration |
| GOES-R clear-sky LST | hourly | 2km | calibration |

## LST calculation and downscaling

Clear-sky LST was derived from the Stefan–Boltzmann law:

where is the broadband emissivity from VIIRS and is the Stefan–Boltzmann constant. The result is a set of hourly ERA5-based clear-sky LST fields at low resolution.

Since ERA5 has a coarse spatial resolution, a downscaling step was applied:

**1.Training data**: Low-resolution LST values were paired with DEM and NDVI at the same resolution.

**2.Model**: An XGBoost regression model was trained to capture the relationship between surface properties (DEM, NDVI) and LST.

**3.Application**: The trained model was applied to DEM and NDVI at GOES-R resolution, producing a high-resolution clear-sky LST field that reflects finer heterogeneity due to topography and vegetation.

## Calibration and Correction

Although the hypothetical clear-sky LST derived from ERA5 radiation data provides a useful baseline, it often carries systematic biases due to the coarse resolution of ERA5 and simplifications in the radiative transfer assumptions. To improve its reliability, a calibration step was performed using the GOES-R clear-sky LST product as the reference.

The procedure was implemented as follows:

1.Preparation of training data

The difference between the ERA5-based clear-sky LST (LST\_0) and the GOES-R clear-sky LST (LST\_clear) was taken as the target variable (bias). Auxiliary predictors included albedo, BBE, NDVI, and DEM, along with the raw ERA5-based LST.

2.Model training

A Random Forest regression model was used to capture the nonlinear relationships between the predictors and the LST bias. The dataset was randomly split into training and validation subsets (80/20).Model performance was evaluated using mean absolute error (MAE) and root mean square error (RMSE). Results showed that emissivity and albedo were among the strongest predictors, followed by vegetation (NDVI) and topography (DEM), indicating that surface properties significantly influence the LST correction.

3.Bias correction application

After training, the model was applied to the full spatial domain using all available valid pixels.The estimated bias was added back to the original ERA5-based. This produced a corrected clear-sky LST field that more closely matches the GOES-R reference while retaining the spatial detail introduced by the downscaling.

A map of the south and south america

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Figure 2 Corrected hypothetical clear-sky LST

# LST difference induced by the cloud radiative effect

This section estimates the temperature perturbation caused by clouds, , which will later be added to the corrected clear-sky LST to obtain the all-sky LST.

## Theory

We start from the surface energy balance (SEB):

where is net radiation, and are net shortwave and longwave radiation, G is ground heat flux, and is the sum of sensible and latent heat fluxes.

Under a cloud perturbation, following prior work, we parameterize the flux partition using a surface-type coefficient :

Using the conventional force–restore theory, the link between G and LST gives

so that

With

* ： the ground soil thermal conductivity， W m–1 K–1
* ： depth of the subsurface layer (usually set as 0.1 m)

## Input

|  |  |  |  |
| --- | --- | --- | --- |
| **Data** | **Temporal Resolution** | **Spatial Resolution** | **Usage** |
| Goes-R Albedo | hourly | ~2km | LST calculation |
| GLASS LAI | 8 Days | 0.05deg | calculation |
| VIIRS BBE | daily | 0.009deg | CRE calculation |
| DSR | CERES | 1 deg | CRE calculation |
| DLR | CERES | 1 deg | CRE calculation |
| LST from chapter 2 | Hourly | 2km | CRE and calculation |

## Solution Methods

From 3.1 we know that

we solve the nonlinear equation with three complementary approaches and compare results.

1.Fixed-point iteration

This method starts with an initial guess of ΔT and repeatedly updates it using the governing equation until the solution stabilizes. Convergence is achieved when the change between two successive iterations is smaller than a defined tolerance. It is straightforward and stable for moderate perturbations but may converge slowly in complex cases.

2.Newton’s method

The residual equation is solved directly using an iterative Newton–Raphson approach. Each update step uses both the residual and its derivative, allowing faster convergence compared to fixed-point iteration. Safeguards such as damping and step-size clipping were included to maintain stability and prevent divergence in regions with strong nonlinearity.

3．Quartic root solver

By expanding the nonlinear term, the ΔT equation can be expressed as a quartic polynomial. All possible roots are calculated explicitly, and the most physically consistent root is selected based on predefined ranges and residual checks. This method is non-iterative and provides a useful fallback when iterative methods fail to converge.

A map of the world with different colors

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Figure 3 Comparison of

# All-sky LST

The final step of the workflow is to combine the clear-sky baseline from chapter 2 with the cloud-induced temperature correction from chapter3, producing hourly high-resolution maps for the case study day of November 27, 2021 as shown in Fig.4

A map of the world

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Figure 4 All-Sky LST Estimation Example at 18:00 UTC, 27 Nov 2021