

Surface air temperature from satellite LST for a better understanding of climate change

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Introduction

- The quantification of the global climate feedback and the climate sensitivity is crucial to estimating the response of the climate to anthropogenic GHG emissions.
- The MOTECUSOMA (Monitoring The Energy Cycle For A Better Understanding Of Climate Change) project is estimating the Earth Energy Imbalance (EEI) and surface air temperature (TAS) over the last three decades.
- TAS is critical because on monthly scales it is closely coupled surface heat fluxes, and, through convection, to the tropospheric temperature, atmospheric humidity and water vapour feedbacks.
- Air temperatures predicted from satellite observations form part of the input to the MOTECUSOMA TAS analysis along with in situ observations. Estimates from satellite are made separately over the land, ocean, and cryosphere domains. This poster describes the estimation of TAS over land.

Estimation method

The method of estimation of TAS over land builds on the work of Good(2015) developed in the EUSTACE (EU Surface Temperatures for All Corners of Earth) project (Rayner et al., 2020). Multiple linear regression of station air temperatures onto a set of predictors is used to infer the relationship between TAS and these predictors. The relationships are then used to predict TAS wherever the predictor data are available. The predictor set comprised descending and ascending swath Land Surface Temperatures (LSTs), surface wind speed (sh2m) and surface humidity (sh2m) at the LST observation times, daily fractional vegetation cover (FVC), daily snow presence (snow), and elevation).

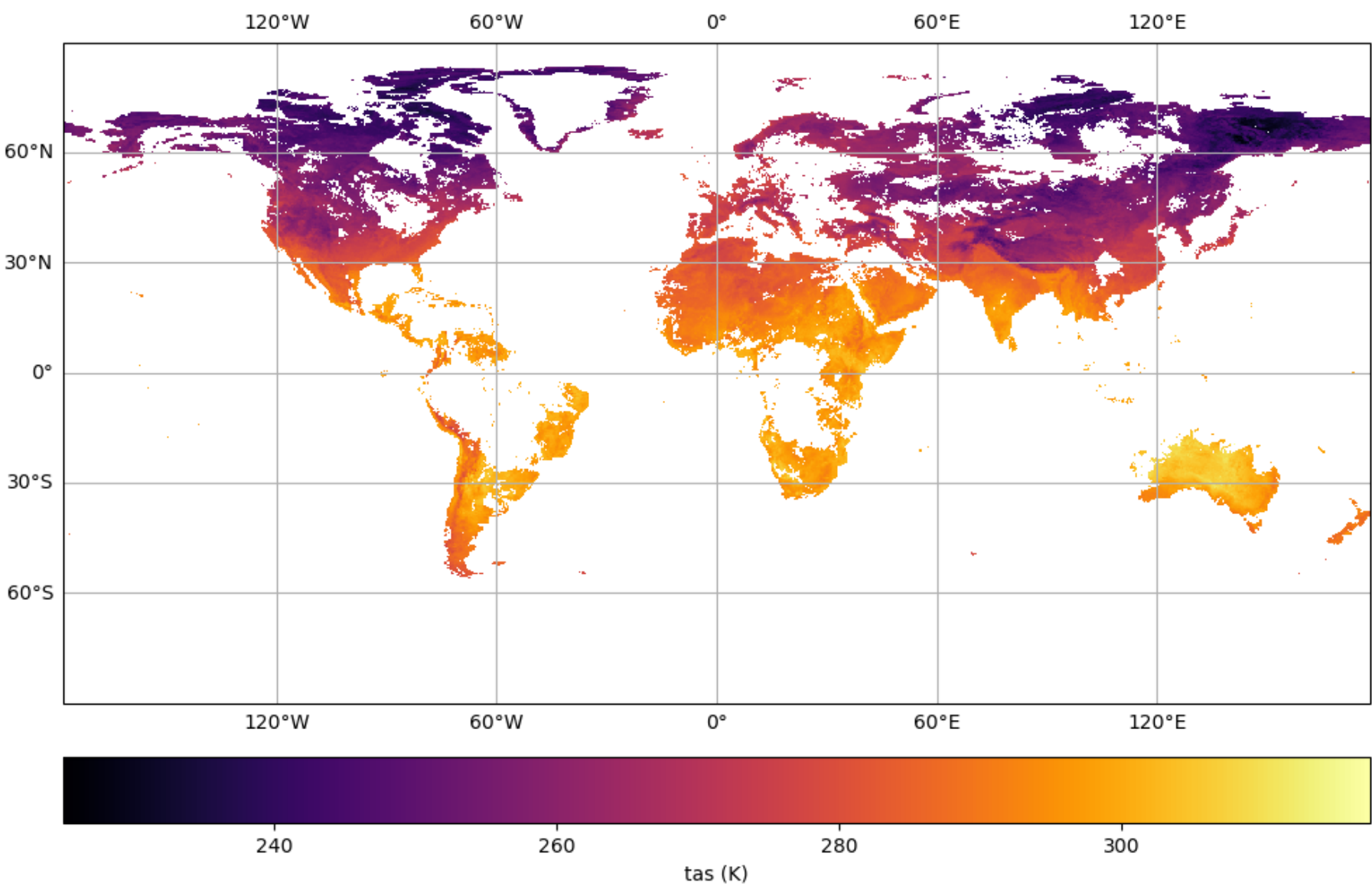
Since the relationship between TAS and LST depends on emissivity and vegetation cover and type, coefficients are generated for each of 22 land cover classes. Air temperatures are taken from the GHCN-D (Global Historical Climate Network - Daily). The input LST dataset is the LST CCI Multisensor Infra-Red Climate Data Record V3.5 (1996-2025).

The model for each land cover class takes the form:

$$TAS = a_0 + a_1 LST_{desc} + a_2 sh2m_{desc} + a_3 ws2m_{desc} + a_4 LST_{asc} + a_5 sh2m_{asc} + a_6 ws2m_{asc} + a_7 FVC + a_8 elevation + a_9 snow$$

where a_i are the coefficients obtained from the regression. The input data sets are given in the table below.

Predictor	Data set
LST	LST_cci Multisensor Infra-Red Climate Data Record V3.5 (1996-2025)
FVC	Copernicus Land Monitoring Service FCover 10 day 300m
sh2m	ECMWF Reanalysis V5 (ERA 5)
ws2m	ECMWF Reanalysis V5 (ERA 5)
elevation	USGS GMTED2010 30 arc seconds
snow	NSIDC Interactive Mapping Service



- Figure 1 (Above): 0.25° TAS field for 1st January 2008
- Figure 2 (Right): Uncertainty budget for 0.25° TAS on 1st January 2008: (a) total uncertainty, (b) uncertainty from uncorrelated errors, (c) uncertainty from errors correlated on atmospheric scales, (d) uncertainty from model coefficient errors.

Ongoing work

- Production of a time series of land TAS for 1996 to 2025
- Validation of the TAS uncertainties and their correlation lengths by comparison of TAS with in situ station air temperatures

Uncertainty model

The analysis system combines data (direct in situ measurements and satellite derived TAS) by weighting with respect to uncertainty across length scales. Thus, it is critical that a realistic estimation is made of the uncertainties and their respective length scales.

The land TAS is estimated at the resolution of the LST product (0.01°) and then averaged to 0.25° for input to the analysis system. The table below gives the error effects to be considered in the prediction and subsequent spatial averaging of TAS.

Error effects are grouped by their correlation length scales for propagation through spatial averaging. LST product has uncertainty budget components broken down by correlation length. The other predictors, except the snow mask, have uncertainty information with the products and correlation lengths are assigned. The snow mask uncertainty is estimated from the fraction of surrounding pixels that agree with the pixel value.

The output land TAS product at 0.25° includes the uncertainty budget broken down by error correlation length into components, uncertainties from: uncorrelated errors, errors correlated on atmospheric scales, systematic errors, errors correlated between models.

Error effects for day-night model				
Error effect	Uncertainty information	Correlation length	0.01 to 0.25	0.25 output
1 uncorrelated errors in daytime LST	lst_unc_ran_day	Uncorrelated	1	1
2 errors in daytime LST correlated on surface scales	lst_unc_loc_sfc_day	5km	3	1
3 errors in daytime LST correlated on atmospheric scales	lst_unc_loc_atm_day	100km	4	4
4 large scale correlated errors in daytime LST	lst_unc_sys_day	Global	2	2
5 errors in time correction of daytime LST	lst_unc_time_correction_day	5km	3	1
6 uncorrelated errors in nighttime LST	lst_unc_ran_night	Uncorrelated	1	1
7 errors in nighttime LST correlated on surface scales	lst_unc_loc_sfc_night	5km	3	1
8 errors in nighttime LST correlated on atmospheric	lst_unc_loc_atm_night	100km	4	4
9 large scale correlated errors in nighttime LST	lst_unc_sys_night	Global	2	2
10 errors in time correction of nighttime LST	lst_unc_time_correction_night	5km	3	1
11 errors in daytime specific humidity at 2 m	ERA5 ensemble spread	100 km	4	4
12 errors in nighttime specific humidity at 2 m	ERA5 ensemble spread	100 km	4	4
13 errors in daytime windspeed at 2 m	ERA5 ensemble spread	100 km	4	4
14 errors in nighttime windspeed at 2 m	ERA5 ensemble spread	100 km	4	4
15 errors in fractional vegetation	SD of 10 day aggregation	5 km	3	1
16 error in elevation	neglected			
17 error in snow mask	from surrounding pixels	5 km	3	1
18 model coefficient error a_1	covariance matrix output from OLS regression (will vary with model)		5	5
19 model coefficient error a_2			5	5
20 model coefficient error a_3			5	5
21 model coefficient error a_4			5	5
22 model coefficient error a_5			5	5
23 model coefficient error a_6			5	5
24 model coefficient error a_7			5	5
25 model coefficient error a_8			5	5
26 model coefficient error a_9			5	5
27 model coefficient error a_{10}			5	5
28 model residual error	output from OLS regression	Uncorrelated	1	1
29 spatial sampling	scaled variance	Uncorrelated	1	1

1 uncorrelated; 2 systematic; 3 surface scales; 4 atmospheric scales; 5 model type.

