ARIES DATASET DOCUMENTATION

AUGUST, 2025

Dataset documentation – Thermal and Ecological spatiotemporal trends to assess extreme heat hazard in Euskadi

COMPILED BY SUDESHNA KUMAR (BC3) WITH SUPPORT FROM CATERINA GILLI (BC3)

Contents

1 Datasets generated for Euskadi 3
1.1 Mean Land Surface Temperature and Normalized Difference Vegetation Index 3

2 Urban Thermal Field Variance Index (UTFVI) 4
2.1 Threshold UTFVI value for ecological evaluation and thermal comfort 5

3 Application 5

Land surface temperature (LST) is obtained from Landsat images using the widely used radiative transfer equation. The thermal and ecological conditions are evaluated by computing urban heat island (UHI) and urban thermal field variance index (UTFVI) from LST data. The influence of vegetation, built area, presence of waterbody, and bare soil on LST is examined using land cover indices through pixel-level multivariate linear regression analysis (Abir et al., 2021). Land surface temperature (LST) is frequently used as an indicator for UHI and shows a positive correlation with the density of sealed surfaces while displaying a negative association with UGS (Aznarez et al., 2024; Rodríguez-Gómez et al., 2022). LST is used to quantify the extent and size of surface heat. LST is an integral variable in quantifying thermal hazard levels across cityscapes. Local topography, human activity, and specific urban heat island effects influence cities' dynamics and green spaces.

1 Datasets generated for Euskadi

1.1 Mean Land Surface Temperature and Normalized Difference Vegetation Index

The LST data generation process was commenced by adapting a NASA ARSET (2022) open-source code in Google Earth Engine (GEE). The initial script provided a foundational approach to retrieving daytime LST spatial data at 30 m pixels for the entire Euskadi region. Building upon this, the methodology was refined, incorporating robust techniques and additional parameters based on Kafy et al. (2021), enhancing the accuracy and applicability of the analysis to the Euskadi region. The LST data were obtained from Landsat 8 level 2 Surface Reflectance (SR) and Surface Temperature (ST) imagery (Collection 2 Tier 1), covering the hottest months (June, July, August, September) (Aznarez et al., 2024; Marquez-Torres et al., 2025) from 2020–2024. To ensure reliability, images considering minimal cloud cover ($< 10\%$) were selected Abir et al. (2021), and cloud/shadow pixels were masked using the QA_PIXEL band Abir et al., 2021; NASA ARSET, 2022. The spatial context was defined using OpenStreetMap (OSM) within the administrative boundary of Euskadi.

Vegetation-based emissivity correction was applied to improve LST estimation, following methods adapted from Sobrino et al. (2004) and Kafy et al. (2021). The Normalized Difference Vegetation Index (NDVI) was first calculated using the red (SR_B4) and near-infrared (SR_B5) bands from Landsat for the summer period (June 1st–September 30th) of 2020–2024 at 30 m of spatial resolution.

NDVI is calculated using Equation (1):

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \tag{1}$$

where: NIR (Near-Infrared, band SR_B5) implies high reflectance in healthy vegetation, and band RED (Red, SR_B4) implies High absorption in healthy vegetation.

With NDVI mapping, we can identify and prioritize vegetation-poor, heat-exposed areas for greening interventions.

LST is derived from the thermal band (ST_B10) using Equation (2), which is derived from Equation (3):

$$LST = \frac{T_B}{1 + \left(\frac{\lambda \cdot T_B}{\rho}\right) \ln \varepsilon} \tag{2}$$

where:

- $\lambda = 11.5\ \mu$m: central wavelength of Landsat TIR band

- $\rho = 1.438 \times 10^4$ μm·K: Planck's radiation constant
- T_B: brightness temperature from band ST_B10
- ε: surface emissivity estimated from NDVI

T_B (Brightness Temperature) implies raw thermal readings from Landsat. ε (Emissivity) implies estimation based on NDVI, indicating surface heat retention.

Vegetation proportion (P_v) was derived using min-max normalization of NDVI values across the study area. Where, P_v = proportion of vegetation is calculated using Equation (3).

Surface emissivity (ε) is computed as a linear function of P_v:

$$\varepsilon = 0.004 \cdot P_v + 0.986 \tag{3}$$

Simultaneously, NDVI was also evaluated independently to assess vegetation distribution and its relation to urban temperature patterns across the Euskadi region. NDVI is crucial in estimating urban heat exposure because areas with higher vegetation cover tend to have lower surface temperatures due to evapotranspiration and shading effects.

2 Urban Thermal Field Variance Index (UTFVI)

The urban thermal field variance index (UTFVI), derived from Land Surface Temperature (LST), is a suitable indicator for assessing urban heat stress and eco-environmental conditions. It is another widely used indicator derived from LST to evaluate the urban environment's eco-environmental quality or thermal well-being. The urban thermal field variance index (UTFVI) is widely used to describe the UHI effect (Tomlinson et al., 2011). It can be quantified using Equation (4), calculated using Zhang's equation (Zhang, 2006).

$$\text{UTFVI} = \frac{T_s - T_m}{T_s} \tag{4}$$

T_s = LST value of pixels and T_m = the Mean LST of the area.

2.1 Threshold UTFVI value for ecological evaluation and thermal comfort

UTFVI range	UHI presence	Ecological evaluation index
< 0	None	Excellent
$0 - 0.005$	Weak	Good
$0.005 - 0.010$	Middle	Normal
$0.010 - 0.015$	Strong	Bad
$0.015 - 0.020$	Stronger	Worse
> 0.020	Strongest	Worst

Table 1: UTFVI classification thresholds

These hotspots have altered microclimates, including stagnant air flow, high humidity, and increased pollution (Ge et al., 2010; Sejati et al., 2019). UTFVI also increases convection, which leads to increased thunderstorms (Singh et al., 2017).

3 Application

Urban designers and planners can use UTFVI to identify thermally sensitive zones, which opens the door to green infrastructure, shaded pedestrian paths, and cooling centers. Also, forecasting UTFVI patterns in the future can aid cities to devise climate-adaptation policy and reduce heat-related health hazards (Wang et al., 2017). Therefore, UTFVI is an effective tool in planning heat-resilient as well as human-sensitive urban composition.

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