ECOSTRESS Collection 3 Level-2 STARS NDVI & Albedo Algorithm Theoretical Basis Document

ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS)

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Introduction

Purpose

The ECOSTRESS Collection 3 Level-2 STARS (Spatial Timeseries for Automated high-Resolution multi-Sensor data fusion) product provides coincident, gap-filled NDVI and albedo estimates at 70 m ECOSTRESS standard resolution for each daytime ECOSTRESS overpass. These products are essential auxiliary data inputs for evapotranspiration (ET) algorithms and other land surface modeling applications.

NDVI and albedo are critical biophysical parameters that capture vegetation health, phenology, and surface energy balance characteristics. The STARS algorithm addresses the challenge of providing high spatial resolution (70 m), temporally complete NDVI and albedo data by fusing observations from multiple satellite instruments with complementary spatial and temporal characteristics.

Scope and Objectives

This Algorithm Theoretical Basis Document (ATBD) provides the scientific and technical foundation for the STARS algorithm. It includes:

1. A description of the NDVI and albedo parameter characteristics and requirements.
2. An overview of the STARS data fusion methodology and its theoretical foundation.
3. Mathematical formulations and statistical models.
4. Implementation details for near-real-time processing.
5. Quality assessment and uncertainty quantification approaches.

For practical information on data access, file formats, processing workflows, and applications, please refer to the companion ECOSTRESS Collection 3 Level-2 STARS NDVI & Albedo Data Product User Guide.

Parameter Description and Requirements

Attributes of STARS NDVI and Albedo Data

- Spatial resolution: 70 m x 70 m
- Temporal resolution: Diurnally varying to match ISS overpass characteristics
- Latency: Near real-time, as required by the ECOSTRESS Science Data System (SDS)
- Spatial extent: All land globally, excluding poleward ±60°

Parameter Specifications

Parameter	Description	Units	Range	Source Instruments
NDVI	Normalized Difference Vegetation Index	Dimensionless	-1.0 to 1.0	HLS 2.0, VIIRS VNP09GA
Albedo (α)	Broadband shortwave albedo	Dimensionless	0.0 to 1.0	HLS 2.0, VIIRS VNP09GA

Auxiliary Data Requirements

The STARS algorithm requires high-quality surface reflectance data from multiple satellite instruments to achieve both high spatial resolution and temporal continuity:

Primary Data Sources: - Harmonized Landsat Sentinel (HLS) 2.0: 30 m spatial resolution, 3-5 day revisit - VIIRS VNP09GA: 500 m spatial resolution for NDVI, 1 km for albedo, daily coverage

Ancillary Data: - GEOS-5 FP tavg3_2d_aer_Nx: Aerosol optical depth for BRDF correction - Solar geometry: Solar zenith angle for BRDF modeling

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STARS NDVI and Albedo Algorithm

The STARS algorithm produces coincident, gap-filled NDVI and albedo estimates at 70 m ECOSTRESS standard resolution through multi-instrument data fusion. This approach combines observations from high spatial resolution instruments (Sentinel-2A/B, Landsat-8/9) with moderate spatial but high temporal resolution instruments (VIIRS) to achieve both the spatial detail and temporal coverage required for ECOSTRESS applications.

Data Sources

The STARS algorithm utilizes complementary satellite data sources that provide different spatial-temporal trade-offs:

Resolution Category	NDVI Source	Albedo Source	Characteristics
High Spatial (<100 m)	HLS 2.0 (30 m)	HLS 2.0 (30 m)	3-5 day revisit, high spatial detail
High Temporal (daily)	VIIRS VNP09GA (500 m)	VIIRS VNP09GA (1 km)	Daily coverage, moderate resolution

BRDF Correction

Prior to data fusion, a pixelwise, lagged 16-day implementation of the VNP43 algorithm (Schaaf, 2017) is used for near-real-time bi-directional reflectance function (BRDF) correction on the VNP09GA reflectance products. This produces VIIRS nadir BRDF-adjusted red and near-infrared reflectance at 500 m resolution for NDVI calculation, and 1 km estimates of black-sky albedo (a_{black}) and white-sky albedo (a_{white}) for VIIRS M-bands 1, 2, 3, 4, 5, 7, 8, 10, and 11.

Blue-sky albedo (a_{blue}) for each band is calculated as:

$$a_{blue} = SKYL \cdot a_{white} + (1 - SKYL) \cdot a_{black}$$

where $SKYL$ is the fraction of diffuse skylight determined from a look-up table based on solar zenith angle and aerosol optical depth (AOD) retrieved from GEOS-5 FP tavg3_2d_aer_Nx.

The broadband blue-sky albedo is calculated using a weighted sum of the VIIRS M-band blue-sky albedo estimates with near-to-broadband (NTB) coefficients:

VIIRS M-band Near-to-Broadband Coefficients:

VIIRS M-Band	NTB Coefficient
1	0.2418
2	-0.201
3	0.2093
4	0.1146
5	0.1146
7	0.1348
8	0.2251
10	0.1123
11	0.0860
Offset	-0.0131

Near-to-broadband albedo is estimated from the Harmonized Landsat Sentinel (HLS) products using sensor-specific coefficients. The 30 m albedo estimates from HLS are up-sampled to the 70 m ECOSTRESS standard resolution prior to data fusion.

Sentinel-2A/B Near-to-Broadband Coefficients:

Band	NTB Coefficient
2	0.1324
3	0.1269
4	0.1051
5	0.0971
6	0.0890
7	0.0818
8	0.0722
11	0.0167
Offset	0.0002

Landsat-8 Near-to-Broadband Coefficients:

Band	NTB Coefficient
2	0.356
3	0.13
4	0.373
5	0.085
6	0.072
Offset	-0.018

Data Fusion Methodology

The data fusion is performed using the Spatial Timeseries for Automated high-Resolution multi-Sensor data fusion (STARS) methodology (Johnson et al., 2022). STARS is a statistical, state-space timeseries methodology that provides streaming data fusion and uncertainty quantification through efficient Kalman filtering.

Statistical Model

For ECOSTRESS, the STARS method is implemented separately for NDVI and albedo. Let $x_{i,t}$ represent NDVI/albedo to be estimated in the i^{th} 70 m ECOSTRESS resolution pixel on day t. Let $Y^f_{i,t}$ represent measurements from high spatial resolution instruments at the i^{th} 70 m pixel (note that $Y^f_{i,t}$ is missing if there are no high spatial resolution overpasses on day t). Let $Y^c_{j,t}$ represent the coarse spatial resolution VIIRS measurement at the j^{th} cell in the VIIRS resolution grid (~500 m for NDVI, ~1 km for albedo), and let A_j be the set of all 70 m pixels overlapped by the VIIRS pixel.

The statistical model for ECOSTRESS STARS has the following form:

Observation Equations:

$$Y_{j,t}^{c} = \frac{1}{|A_j|}\sum_{i \in A_j} x_{i,t} + \epsilon_{j,t}^{c} \quad \text{where} \quad \epsilon_{j,t}^{c} \sim \text{Normal}(0, \sigma_c^2) \quad (1a)$$

$$Y_{i,t}^{f} = x_{i,t} + \epsilon_{i,t}^{f} \quad \text{where} \quad \epsilon_{i,t}^{f} \sim \text{Normal}(0, \sigma_f^2) \quad (1b)$$

State Evolution Equation:

$$x_{i,t} = x_{i,t-1} + \omega_{i,t} \quad \text{where} \quad \omega_{i,t} \sim \text{GP}(0, \tau^2, K(\cdot)) \quad (2)$$

where:

- Equations (1a,b) describe the instrument measurements as noisy observations of the target high-resolution image values $x_{i,t}$
- VIIRS measurements (1a) represent spatial aggregates over the coarse resolution grid
- Measurement errors are mean-zero and normally distributed with standard deviations σ_c, σ_f for coarse and fine instruments, respectively
- Equation (2) describes day-to-day temporal dependence in NDVI/albedo through a first-order Markov chain
- Pixel-level changes between days ($\omega_{i,t}$) follow a Gaussian process (GP) with covariance function $K(\cdot)$, modeling spatial correlation of day-to-day changes between pixels
- The standard deviation parameter τ constrains the expected magnitude of change

To achieve scalability, STARS is implemented using a block-wise, moving window approach where blocks are defined by the coarse resolution grid plus a spatial buffer region.

Implementation

For $x_t = (\ldots, x_{i,t}, \ldots)$ the vector of the n target image pixels within a block on day t, and y_t the stacked vector of available coarse and fine measurements, the timeseries model above induces the full state space model:

State Space Formulation:

$$y_t = F_t x_t + \epsilon_t \quad \text{where} \quad \epsilon_t \sim \text{MultivariateNormal}(0, V) \quad (3)$$

$$x_t = x_{t-1} + \omega_t \quad \text{where} \quad \omega_t \sim \text{MultivariateNormal}(0, W) \quad (4)$$

where: - V is a diagonal matrix with elements σ_f^2, σ_c^2 - F_t is the aggregation matrix linking coarse and fine measurements to the target resolution grid (equations 1a,b)

The estimation of the target 70 m NDVI/albedo images on day t is inferred through the posterior distribution of x_t given all past and current measurements up to day t. This distribution is Gaussian with mean m_t and covariance C_t. The mean provides the estimated imagery, while the covariance provides quantified uncertainties characterizing uncertainty due to spatial and temporal downscaling.

Kalman Filtering:

Estimates of m_t and C_t are obtained recursively through Kalman filtering equations (Kalman, 1960). Given estimates of m_t, C_t, and new observations on day $t+1$ (y_{t+1}), the updated estimates are calculated as:

$$m_{t+1} = m_t + K_{t+1}(y_{t+1} - F_{t+1}m_t) \quad (5)$$

$$C_{t+1} = (I - K_{t+1}F_{t+1})(C_t + W) \quad (6)$$

where the Kalman gain matrix is:

$$K_{t+1} = (C_t + W)F_{t+1}^T[F_{t+1}(C_t + W)F_{t+1}^T + V]^{-1}$$

If no new measurements are available on day $t+1$, the mean estimate is propagated forward ($m_{t+1} = m_t$) but the covariance is increased ($C_{t+1} = C_t + W$), quantifying increased uncertainty in fused estimates due to lack of available data.

Key Advantages of STARS:

1. Automated spatial and temporal gap-filling: Provides complete coverage even when individual sensors have data gaps
2. Uncertainty quantification: Pixel-wise uncertainties are calculated and distributed as data layers
3. Near-real-time capability: Efficient streaming processing for operational applications
4. Multi-scale integration: Optimally combines data from different spatial and temporal scales

Near-Real-Time Processing:

STARS NDVI/albedo products corresponding to each daytime L2T_LSTE product are produced by:

1. Loading the means and covariances from the previous L2T_LSTE product day
2. Downloading available measurements (VIIRS, HLS, etc.) between overpasses
3. Kalman filtering forward the NDVI/albedo estimates to the current target day

The latency of this operation depends on the availability of input products. The coincident STARS NDVI and albedo products, along with their pixel-wise uncertainties, are recorded in the

L2T_STARS product.

Mask/Flag Derivation

Quality flags and masks are derived from multiple sources to ensure reliable NDVI and albedo estimates:

Input Data Quality Assessment: - HLS quality flags: Cloud, cirrus, snow/ice, and water masks from HLS QA bands - VIIRS quality flags: Pixel quality indicators from VNP09GA QF bands - BRDF quality: Assessment of BRDF model fit quality and availability

STARS-Specific Quality Indicators: - Fusion confidence: Based on number and quality of input observations - Temporal consistency: Flags for unusual temporal changes that may indicate errors - Spatial coherence: Assessment of spatial consistency in fused estimates - Uncertainty thresholds: Quality levels based on estimated uncertainty magnitudes

Quality Flag Structure: - Level 1 (Best): High-quality inputs with low uncertainty - Level 2 (Good): Adequate inputs with moderate uncertainty
- Level 3 (Fair): Limited inputs or higher uncertainty - Level 4 (Poor): Heavily gap-filled with high uncertainty

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Metadata

NDVI Specifications

- Unit of measurement: Dimensionless
- Range of measurement: -1.0 to 1.0
- Data type: Float32
- No data value: -9999
- Valid range: -1.0 to 1.0

Albedo Specifications

- Unit of measurement: Dimensionless
- Range of measurement: 0.0 to 1.0
- Data type: Float32
- No data value: -9999
- Valid range: 0.0 to 1.0

Common Attributes

- Projection: ECOSTRESS swath (L2T_LSTE grid)

- Spatial resolution: 70 m x 70 m
- Temporal resolution: Dynamically varying with precessing ISS overpass
- Spatial extent: All land globally, excluding poleward ±60°
- Processing level: Level-2 (L2T)
- Latency: Near real-time
- Quality flags: 4-level system (1=best, 4=worst)

Uncertainty Layers

- NDVI uncertainty: Standard deviation of NDVI estimate
- Albedo uncertainty: Standard deviation of albedo estimate
- Data type: Float32
- Units: Same as corresponding parameter

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