# NASA Multi-Source Land Imaging (MuSLI)

# Multi-Source Land Surface Phenology (MS-LSP) Product User Guide

## Version 1.1

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## Science Team

**Principal Investigator: Mark Friedl**
**Principal Investigator: Doug Bolton**
**Principal Investigator: Minkyu Moon**
**Co-Investigator: Josh M Gray**
**Collaborator: Lars Eklundh**
**Collaborator: Thomas Maiersperger**

## Document History

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# 1. Dataset Overview

## 1.1. General Description

The Multi-Source Land Surface Phenology (MS-LSP) product (Bolton et al., 2020) is designed to provide the land and ecological science community with open access to operational moderate spatial resolution land surface phenology data sets at continental scale. More specifically, the MS-LSP product is designed to include information related to: (1) the timing of phenological events; (2) reduced dimension image data sets that maximize multispectral information and minimize temporal correlation in image time series; and (3) identify in-season anomalies in near real-time. To achieve this goal, the MS-LSP product is generated at 30-meter spatial resolution for North America and is delivered in a Universal Transverse Mercator (UTM) projection on a Military Grid Reference System (MGRS). The MS-LSP product includes three categories of Science Data Sets (SDSs):

*(i) MS-LSP Timing Metrics* are traditional LSP metrics that indicate the timing of seasonality at each pixel, and include the day-of-year corresponding to 15 percent, 50 percent and 90 percent of Enhanced Vegetation Index-2 (EVI2) amplitude during the green-up and green-down period; an additional metric included in this group ("*integrated greenness*") corresponds to the sum of daily interpolated EVI2 values during each growth cycle.

*(ii) MS-LSP Reflectance Metrics* provide the modeled reflectance value in each of the six Harmonized Landsat-Sentinel 2 (HLS) bands corresponding to each MS-LSP timing metric.

*(iii) MS-LSP Mean and Anomaly Metrics* provide the mean and anomaly in weekly EVI2, along with the cumulative growing season anomaly in EVI2 at each pixel, and are designed to measure in-season departures from normal conditions associated with disturbance, drought, land cover change, and other sources of change in surface conditions.

A key feature of the full MS-LSP product is that it includes three distinct types of information that complement each other. SDSs included in category (i) provide traditional LSP metrics that characterize the timing of seasonality in land surface "greenness" at each pixel. SDSs included in category (ii) provide surface reflectances in each HLS band based on daily interpolated values estimated by the MS-LSP algorithm. These SDSs provide users with six gap-free HLS images that capture seasonal dynamics in surface reflectances, while at the same time dramatically reducing temporal correlation and data dimensionality relative to the raw HLS data. SDSs included in these first two categories of require a full seasonal cycle before they can be created. SDSs included in category (iii), on the other hand, will be generated in-season and are designed to provide near real-time data regarding anomalies in weekly EVI2 values relative to longer-term average conditions. These SDSs will support the needs of users who require timely information related to ecosystem health and disturbances for whom retrospective data products are less useful.

## 1.2. Science Context and Background

Land surface phenology (LSP) measurements provide critical information related to land surface properties and ecosystem function (De Beurs and Henebry, 2004; Melaas et al., 2016; Morisette et al., 2009). In natural ecosystems, the timing of phenological events has been used to quantify the impact of climate change on growing seasons (Körner and Basler, 2010; Peñuelas, 2009; Piao et al., 2019; Richardson et al., 2013), to distinguish among vegetation communities with different phenological triggers (Møller et al., 2008; Sherry et al., 2007), and to characterize the sensitivity of ecosystem processes to climate change (Friedl et al., 2014; Keenan et al., 2014b). In agro-ecosystems, phenology is diagnostic of management practices (e.g., sowing and harvest dates, irrigation), crop types, and crop yields (Bolton and Friedl, 2013; Kucharik, 2006; Sacks et al., 2010). More generally, the nature, magnitude, and timing of LSP dynamics provide a wealth of useful information that is increasingly being used for mapping land cover, land use, and land cover change (Kennedy et al., 2014; Zhu and Woodcock, 2014a).

The earliest studies leveraging LSP information were focused on agriculture and used time series of Landsat imagery (e.g., Badhwar, 1984). However, because Landsat data acquisitions are relatively infrequent, most LSP studies have used data from coarse spatial resolution instruments such as AVHRR, SPOT Vegetation, MERIS, and MODIS (de Beurs and Henebry, 2005; Delbart et al., 2008; Justice et al., 1985; Reed et al., 1994; White et al., 1997; Zhang et al., 2017). Over the last two decades, as data from coarse spatial resolution instruments in general, and from MODIS in particular, have become more available and easier to process, LSP algorithms, data products, and applications have rapidly expanded and matured (e.g., Ganguly et al., 2010; Jönsson and Eklundh, 2002; Zhang et al., 2003). For many applications, however, information is required at finer spatial resolutions than is afforded by MODIS. Newly available imagery from Sentinel-2A and -2B, in combination with data from Landsat 8, largely resolves this constraint. The data products described in this User Guide are designed to fill this gap.

In the current context, information related to land surface phenology is recognized to be important for three main reasons. First, phenology "is perhaps the simplest process in which to track changes in the ecology of species in response to climate change" (Parry et al., 2007). Reflecting this, a large and growing literature has documented how the phenology of ecosystems is changing (Cleland et al., 2007; Parmesan and Yohe, 2003; Richardson et al., 2013). Second, because phenological dynamics affect numerous ecosystem functions, improved information related to phenology is critical to understanding how changes in phenology impact and propagate through the diverse array of ecosystem processes that are linked to phenology. For example, phenology is known to strongly influence water, carbon, and energy fluxes (Keenan et al., 2014b; Richardson et al., 2012; Wolfe et al., 2016), and there is increasing evidence that changes in phenology arising from climate change are cascading across trophic levels, leading to complex and poorly understood ecosystem changes (Beard et al., 2019; Møller et al., 2008; Sherry et al., 2007; Thackeray et al., 2010). Third, information related to phenology is increasingly being used in applied ecosystem science and in land cover, land use, and land cover change applications (Miller and Morisette, 2014). In particular, information related to stand-level phenology is important to ecologists and land managers for whom phenology provides important diagnostics related to species composition, forest health, invasive species, and other ecosystem processes (Morisette et al., 2009). In agricultural systems, a diverse array of applications ranging from crop yield prediction to monitoring and mapping rangelands are affected by phenology (Butt et al., 2011; Funk and Budde, 2009; Kumar and Goh, 1999; Sankey et al., 2013). As a result, information related to phenology is identified as a critical variable required for the UN's Global Climate Observing System (GCOS, 2016), the IPCC’s Fifth Assessment Report (Cramer et al., 2014), and the United States National Climate Assessment (Melillo et al., 2014).

A key limitation of traditionally available phenology data sets is that they are only available at two very different spatial scales and resolutions. Specifically, ground-based observations from networks such as the National Phenology Network (USA-NPN) and the PhenoCam Network (Richardson et al., 2018; Seyednasrollah et al., 2019) provide point-based measurements at local scale (https://phenocam.sr.unh.edu/webcam/). At the other extreme, coarse spatial resolution remote sensing provides information at continental to global scales (e.g., Ganguly et al., 2010), but does not resolve ecologically important processes at landscape scale (Elmore et al., 2012; Fisher et al., 2006). Further, a variety of studies have demonstrated that land surface phenology metrics derived from coarse spatial resolution remote sensing and in situ observations of phenology collected at local scale provide different information. Most of this inconsistency can be attributed to mismatch between the spatial resolution of available remote sensing data products (i.e., 500-m MODIS) and the scale(s) of processes captured by ground-based measurements. In particular, the timing of local-scale phenological events, especially in landscapes that are topographically complex, fragmented, or affected by human management, is not resolved in coarse spatial resolution land surface phenology products. This issue limits the utility of such products for applications focused on questions and processes occurring at landscape scale, and points to the need for land surface phenology information at spatial resolutions capable of resolving landscape-scale properties and processes.

To address this need, the LSP community has increasingly focused on moderate spatial resolution imagery from Landsat for mapping and monitoring phenology. Fisher et al. (2006) and Elmore et al. (2012) demonstrated that long term average land surface phenology can be accurately estimated from multi-year time series of Landsat imagery, and established that landscape-scale patterns in phenology (which cannot be detected in coarse spatial resolution instruments such as MODIS) are clearly discernible in Landsat imagery. More recently, Melaas et al. (2013, 2016) developed a method that estimates the timing of leaf emergence and fall senescence at annual time steps from Landsat, and used data from several data sources to demonstrate the accuracy and realism of their Landsat-based LSP retrievals across a range of sites. A key limitation of the approach described by Melaas et al. (2013), however, is that it requires long time series (i.e., >10 years) and is best suited for retrospective analysis in “side-lap” regions between adjacent Landsat scenes where data density high. Recently, Jonsson et al. (2018) demonstrated the feasibility of retrieving interannual variation in phenology from Sentinel-2, thereby overcoming limitations imposed by Landsat’s 16-day repeat period. Building on this, the data sets described in this User Guide build upon the legacy of existing LSP algorithms developed for MODIS and Landsat to provide continental-scale estimates of LSP metrics from a combination Landsat 8 and Sentinel 2 imagery at 30-meter spatial resolution.

# 2. Dataset Characteristics

## 2.1. Description and Format of SDS

Table 1. MS-LSP product table

| Layer Name | Description | Units | Scale Factor | Valid Range | Fill value |
|---|---|---|---|---|---|
| NumCycles | Number of phenological cycles detected in target year | Number of cycles | 1 | 0 – 6 | 32767 |
| **First Vegetation Cycle: Largest EVI2 amplitude cycle** | | | | | |
| **Phenology Timing Metrics** | | | | | |
| OGI | Onset Greenness Increase (Date of 15% greenness increase) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| 50PCGI | 50 Percent Greenness Increase (Date of 50% greenness increase) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| OGMx | Onset Greenness Maximum (Date of 90% greenness increase) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| Peak | Date of Cycle Peak | Day of year (January 1 of target year = 1) | 1 | 1-366 | 32767 |
| OGD | Onset Greenness Decrease (Date of 10% greenness decrease) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| 50PCGD | 50 Percent Greenness Decrease (Date of 50% greenness decrease) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| OGMn | Onset Greenness Minimum (Date of 85% greenness decrease) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| **Vegetation Indices** | | | | | |
| EVImax | Maximum EVI2 during vegetation cycle | - | 0.0001 | 0–10000 | 32767 |
| EVIamp | EVI2 Amplitude during vegetation cycle | - | 0.0001 | 0–10000 | 32767 |
| EVIarea | Integrated EVI2 during vegetation cycle | - | 0.01 | 0–32766 | 32767 |
| **Second Vegetation Cycle: Second Largest EVI2 amplitude cycle** | | | | | |
| **Phenology Timing Metrics** | | | | | |
| OGI_2 | Onset Greenness Increase (Date of 15% greenness increase) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| 50PCGI_2 | 50 Percent Greenness Increase (Date of 50% greenness increase) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| OGMx_2 | Onset Greenness Maximum (Date of 90% greenness increase) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| Peak_2 | Date of Cycle Peak | Day of year (January 1 of target year = 1) | 1 | 1-366 | 32767 |
| OGD_2 | Onset Greenness Decrease (Date of 10% greenness decrease) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| 50PCGD_2 | 50 Percent Greenness Decrease (Date of 50% greenness decrease) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| OGMn_2 | Onset Greenness Minimum (Date of 85% greenness decrease) | Day of year (January 1 of target year = 1) | 1 | -181–548 | 32767 |
| **Vegetation Indices** | | | | | |
| EVImax_2 | EVI2 maximum during vegetation cycle | - | 0.0001 | 0–10000 | 32767 |
| EVIamp_2 | EVI2 Amplitude during vegetation cycle | - | 0.0001 | 0–10000 | 32767 |
| EVIarea_2 | EVI2 area during vegetation cycle | - | 0.01 | 0–32766 | 32767 |
| numObs | Number of days with clear observations in calendar year | Days | 1 | 0-366 | 32767 |
| **Quality Assurance (QA)** | | | | | |
| gupQA | Quality Assurance for Greenup Segment | - | 1 | 1–10 | - |
| gdownQA | Quality Assurance for Greendown Segment | - | 1 | 1–10 | - |
| gupQA_2 | Quality Assurance for Second Greenup Segment | - | 1 | 1–10 | - |
| gdownQA_2 | Quality Assurance for Second Greendown Segment | - | 1 | 1–10 | - |

### 2.2. QA Layers

Table 2. MS-LSP quality assurance values

| Quality Assurance Values | |
|---|---|
| **QA value** | **Description** |
| 1 | High quality |
| 2 | Moderate quality |
| 3 | Moderate quality with snow filled values |
| 4 | Moderate quality with snow filled values and fills from alternate years |
| 5 | Phenology detected, but poor quality |
| 6 | No cycles detected |
| 9 | Border pixels masked in 2016 due to HLS processing issue |
| 10 | Water, algorithm not run |

Note that a QA value of 6 can arise for multiple reasons including insufficient observation density, insufficient amplitude, or errors from pre-processing that lead to unrealistic EVI2 values or amplitudes.

## 3. Dataset knowledge

### 3.1. FAQ's

### 3.2. Known Issues

1. The algorithm is designed to capture seasonal phenology in vegetation indices. Hence, by definition, uncertainty in MS-LSP data is higher in areas with lower seasonality in vegetation, such as evergreen forests or arid and semi-arid systems. These effects should be captured by the QA data.
2. In regions where data density is low, due to for e.g., cloud cover, the quality of MS-LSP data will be lower. This is compounded by the fact that gap filling based on historical imagery tends to be more challenging in these regions. As the time series of HLS data becomes longer, this latter issue will be mitigated. These effects should be captured by the QA data.
3. Areas with disturbance, e.g., from fires, may result in low quality MS-LSP data. These effects should be captured by the QA data.
4. The MS-LSP product only allows for 2 cycles per year. While locations with more than two cycles are rare, they do exist (e.g., alfalfa) but are not capture in the product. Note however, that these locations are flagged in the number of cycles SDS layer.
5. Regions with seasonal snow are likely to have lower quality values because of challenges associated with screening for and removing the effects of snow contamination on EVI2 values. These effects should be captured by the QA data.

### 3.3. Changes made for V1.1

1. Spline fitting: Modest changes were made to the spline fitting algorithm use to estimate the MSLSP30NA product in V011. Specifically, in V001, we filled all gaps using observations from the outside of the target year (i.e., from "alternate years"), irrespective of gap duration. In V011, to reduce the computational burden, we only fill the gaps that are greater than 20 days. Sensitivity analyses demonstrated that this change had negligible impact on product results.
2. Changes to QA fields: the QA fields was updated to reflect the changes in the gap-filling described above.
3. Added "Peak" and "numObs" layers: Two new data layers were added to the product: (1) Peak, which identifies date corresponding to the maximum EVI2 value in a growth cycle and (2) numObs, which provides the number of days with clear observations in each calendar year at each pixel. Please see the revised product table below.

## 4. Dataset Access

The following tools offer options to search the LP DAAC data holdings and provide access to the Multi-Source Land Imaging Land Surface Phenology Yearly North America 30 meter (MSLSP30NA) data:

Bulk download: LP DAAC Data Pool and DAAC2Disk
Search and Browse: NASA Earthdata Search

## 5. Contact Information

LP DAAC User Services
U.S. Geological Survey (USGS)
Center for Earth Resources Observation and Science (EROS)
47914 252nd Street
Sioux Falls, SD 57198-0001

Phone Number: 605-594-6116
Toll Free: 866-573-3222 (866-LPE-DAAC)
Fax: 605-594-6963
Email: LPDAAC@usgs.gov
Web: https://lpdaac.usgs.gov

For the Principal Investigators, please contact Mark Friedl at friedl@bu.edu or Minkyu Moon at mkmoon@bu.edu.

Project web site: MS-LSP

## 6. Data Citation

The recommended citation in APA or Chicago style is available on the Digital Object Identifier (DOI) Landing page (https://doi.org/10.5067/Community/MuSLI/MSLSP30NA.001).

An example of a citation using the Chicago style format for the MS-LSP dataset is provided below.

Bolton, D.K, Gray, J.M, Melaas, E.K., and M. Moon, *MuSLI Multi-Source Land Surface Phenology Yearly North America 30 m V011*. 2020, distributed by NASA EOSDIS Land Processes DAAC, https://doi.org/10.5067/Community/MuSLI/MSLSP30NA.011. Accessed YYYY-MM-DD.

## 7. Publications

Bolton, D. K., Gray, J.M, Melaas, E.K., Moon, M., Eklundh, L. and M.A. Friedl (2020). Continental-scale land surface phenology from harmonized Landsat 8 and Sentinel-2 imagery, *Remote Sensing of Environment*, 240, https://doi.org/10.1016/j.rse.2020.111685.

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