Recent Advances in Land Surface Phenology Estimation with Multispectral Sensing

Irini Soubry[1][a], Ioannis Manakos[2][b] and Chariton Kalaitzidis[3][c]

[1]*Department of Geography and Planning, University of Saskatchewan, SK S7N 5C8, Canada*

[2]*Information Technologies Institute, Centre for Research and Technology Hellas, Thessaloniki 57001, Greece*

[3]*Department of Geoinformation in Environmental Management, Mediterranean Agronomic Institute of Chania, 73100 Crete, Greece*

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Abstract: Vegetation phenology refers to changes in seasonal patterns of vegetation cycles, such as flowering and leaf fall, influenced by annual and seasonal fluctuations of biotic and abiotic drivers. Information about phenology is crucial for unravelling the underlying biological processes across vegetation communities in space and time. It is also important for ecosystem and resources management, conservation, restoration, policy and decision-making on local, national, and global scales. Numerous approaches to register Land Surface Phenology (LSP) appeared since Earth Observation from space became possible a few decades ago. This paper attempts to capture current progress and new capacities that arose with the advent of the free data policy, the Sentinel-era, new multispectral satellite sensors, cloud computing, and machine learning in LSP for natural and semi-natural environments. Spaceborne sensors' capacity to capture LSP, data fusion, and synergies are discussed. Information about retrieval methods through open-source tools and global LSP products and phenology networks are presented.

1 INTRODUCTION

Vegetation phenology refers to the changes in seasonal patterns of natural phenomena on the land, e.g. leaf out, flowering, leaf browning and fall, influenced by annual and seasonal fluctuations of biotic and abiotic (e.g. temperature, day length, precipitation) drivers (Gerstmann et al., 2016; Lieth, 1974; USA-NPN, 2020). On the other hand, Land Surface Phenology (LSP) is the study of the spatio-temporal vegetation development of the land surface as measured by satellite sensors, and is different from species-specific phenology observed on the ground (de Beurs & Henebry, 2004, 2005). Vegetation phenology has a pivotal function in delineating the structure and function of ecosystems. The main drivers of vegetation phenology are related to climate and vary across ecoregions (Munson & Long, 2017; Zhang et al., 2007).

Phenology is studied in various frameworks, such as assessing urban heat islands effects on vegetation phenology (Ding et al., 2020; Zhang et al., 2004), vegetation phenology detection in urban areas (Granero-Belinchon et al., 2020), and crop growth stages detection (Gao et al., 2020). Nevertheless, this paper focuses on its applications in natural and semi-natural vegetation. By semi-natural vegetation, one means vegetation that includes "extensively managed grasslands, agro-forestry areas and all vegetated features that are not used for crop production" (García-Feced et al., 2014).

Knowledge of phenological cycles contributes to the development of protection measures and management practices to sustain ecosystems and their services (Buisson et al., 2017). The importance of phenology monitoring is acknowledged by the Group on Earth Observations (GEO) (GEO-BON, 2019), the UN (United Nations) Sustainable Development Goals

[a] https://orcid.org/0000-0001-7937-5726
[b] https://orcid.org/0000-0001-6833-294X
[c] https://orcid.org/0000-0001-5217-7164

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(SDGs) -towards goals 13 (climate action) and 15 (life on land) (Trondheim Conference, 2019; UN, 2019)-, and the Convention on Biological Diversity (CBD); which has set the Aichi Biodiversity Targets (ABTs) (target 15 – ecosystem resilience and biodiversity contribution to carbon stocks – needs phenological data to be resolved) (CBD, 2019).

Phenology cycles can be approximated from spaceborne time series of vegetation indices (VIs) (Kuenzer et al., 2015). Towards this purpose, there exist global spaceborne phenology products (GLOBE, 2019; NEON, 2019; PEP725, 2019; USA-NPN, 2019), which are based on LSP. Different remote sensors can approximate LSP, i.e. LiDAR (see the review of Salas (2020)), SAR (Synthetic Aperture Radar) mainly related to crop phenology (Cota et al., 2015; Mascolo et al., 2016), and passive microwave remote sensing systems (Alemu & Henebry, 2013;. Alemu et al., 2019; Dannenberg et al., 2020; Tong et al., 2019). Optical remote sensing remains the common approach in LSP estimation, since vegetation pigments detected with multispectral sensors relate to different phenological stages. Lastly, a recent direction in LSP estimation is fluorescence remote sensing; in particular the use of satellite-derived Solar-Induced Cholophyll Fluorescence (SIF) (Joiner et al., 2014). The coarse spatial (0.5-1°) and temporal resolution of such systems still pose a large barrier towards detailed monitoring of seasonal vegetation changes (Springer et al., 2017). Recently employed and future satellite SIF missions have higher spatial and temporal resolutions; and will be able to alleviate some of the current problems. One example includes the future Fluorescence Explorer (FLEX) (to be launched in 2022), which could provide more accurate estimations of phenology in heterogeneous landscapes (ESA, 2020).

Advances in sensor technology, coupled with increasing demand for frequent, spectrally rich, and spatially detailed satellite data, have led to the launch of multiple satellite missions and new image processing technologies. These allow for increased spatial and temporal resolution of data individually, or through fusions and synergies (Claverie et al., 2018; Li et al., 2017; Pouliot et al., 2018). As the science of LSP has grown dramatically over the past two decades, there is a pressing need to report the advances in this field. Several reviews have been made; tackling separately LSP methods and their limitations (de Beurs & Henebry, 2010; Zeng et al., 2020), LSP products (Henebry & de Beurs, 2013; Reed et al., 2009), phenology networks (Morisette et al., 2009; Reed et al., 2009), and challenges that arise in LSP of optical remote sensing (Helman, 2018; Henebry & de Beurs, 2013; Morisette et al., 2009; Reed et al., 2009). This paper reviews recent and future trend developments for LSP retrieval of natural and semi-natural vegetation with multispectral sensors during the Sentinel-era; including sensors, data fusion, synergies, workflows, products, and networks. Towards this purpose, recent papers (up until December 2020) from the last 5 to10 years and heavily cited papers that fall within the aforementioned topic were selected.

2 CURRENT AND FUTURE PROGRES IN LSP ESTIMATION THROUGH MULTISPECTRAL REMOTE SENSING

Since earth observation from space became possible, several satellite sensors have been used for LSP estimation. An overview of sensors and LSP example applications is presented in Table 1. The VIIRS LSP product follows-up the mission of the MODIS product (Moon et al., 2019). The Project for On-Board Autonomy-Vegetation (PROBA-V) was developed as an improved smaller version of SPOT-VGT to provide continuity of its 10-year archive and to fill the gap until the launch of Sentinel-3 (in 2016 and 2018) (eoPortal Directory, 2020). As of July 2020, it can be used for experimental monitoring over Europe and Africa up until its orbit will go into darkness in October 2021 (eoPortal Directory, 2020). Since its data is freely available, its use in LSP studies becomes even easier. Upcoming plans for 2021 include the addition of a small satellite with the same type of sensor on PROBA-V, which will look at the same targets from a different viewing angle so as to generate fused images (VITO, 2020). LSP has also been estimated from geostationary satellites. More recently, the Advanced Himawari Imager (AHI) on the geostationary Himawari-8 satellite was used to enhance LSP estimation over the Asian-Pacific region (Miura et al., 2019; Yan et al., 2019), and to study the sun-angle effects on LSP (Ma et al., 2020).

When Landsat imagery became freely available in 2008, numerous land imaging applications and studies were conducted. Landsat's spatial resolution enhances the way in which LSP variations set by micro-climatic and topographic effects are registered. Additionally, the heterogeneity in land cover classes within each pixel is reduced, and a more detailed matching with field- Landsat's long-term continuity provides tremendous opportunities for LSP time series development, especially at present, when cloud-computing and machine learning have set the stage for current and future trends in image processing (see Section 2.2).

Table 1: Multispectral satellite sensor characteristics for LSP studies and example applications (spat. res.= spatial resolution; temp. res.=temporal resolution; sun-synchr.=sun-synchronous; geostat.=geostationary).

Satellite sensor	Orbit-type	Operation timespan	Spat. res.	Temp. res.	Example LSP applications	Relevant studies	Data Source
AVHRR	Sun-synchr.	1978-Present	1.1 km at nadir	Daily	global LSP trends	(Bradley et al., 2007; Wang et al., 2012)	(Wunderle & Neuhaus, 2020)
MODIS	Sun-synchr.	1999-Present	250 m, 500 m, 1 km	Daily	global LSP trends	(Cai et al., 2017; Cui et al., 2019, 2020; Henebry & de Beurs, 2013; Karkauskaite et al., 2017; Misra et al., 2016; Wu et al., 2017)	(ESA, 2020)
VIIRS	Sun-synchr.	2011-Present	375 m, 250m, 750 m	Daily	global LSP trends; comparison of global products; comparison with ground phenology	(Moon et al., 2019; Zhang et al., 2017; Zhang, Jayavelu, et al., 2018; Zhang, Liu, et al., 2018)	(NASA EARTHDATA, 2020)
SPOT-VGT	Sun-synchr.	1988-2014	1.15 km at nadir	Daily	regional LSP trends; global baseline LSP product; comparison with ground phenology	(Meroni et al., 2014; Verhegghen et al., 2014; Wu et al., 2017)	(Wolters et al., 2016)
PROBA-V	Sun-synchr.	2013-2020	100 m, 300 m, 1 km	Daily	regional LSP trends; comparison with ground phenology	(Bórnez, Richardson, et al., 2020; Guzmán et al., 2019)	(eoPortal Directory, 2020)
SEVIRI	Geostat.	2002-Present	1 km, 3 km	15 min.	regional LSP trends	(Sobrino et al., 2013; Yan et al., 2017)	(Aminou, 2002)
AHI	Geostat.	2014-Present	500 m, 1 km, 2 km	10 min.	regional LSP trends	(Ma et al., 2020; Miura et al., 2019; Yan et al., 2019)	(eoPortal Directory, 2020)
Landsat	Sun-synchr.	1972-Present	30 m, 80 m	16-days, 18-days	LSP trends; comparison with ground phenology; land cover characterization	(Dethier et al., 1973; Fisher et al., 2006; Liu et al., 2016; Melaas et al., 2013)	(eoPortal Directory, 2020)
Sentinel-2	Sun-synchr.	2015-Present	10 m, 20 m, 60 m	5-days, 10-days	LSP trends; comparison with ground phenology	(Cai, 2019; Löw & Koukal, 2020; Solano-Correa et al., 2018; Vrieling et al., 2018)	(eoPortal Directory, 2020)
PlanetScope	Sun-synchr.	2009-Present	3.7 m at nadir	Daily	LSP trends in agriculture	(Chen et al., 2019; Cheng et al., 2020; Myers et al., 2019; Sadeh et al., 2019)	(eoPortal Directory, 2020; ESA, 2020)
VENμS	Sun-synchr.	2017-Present	3 m, 5.3 m	2-days	LSP trends in agriculture	(Gao et al., 2020; Herrmann et al., 2020; Manivasagam et al., 2019)	(eoPortal Directory, 2020)

The Sentinel-2 MultiSpectral Instrument (MSI) improves the temporal and spatial coverage of existing satellite sensors and has recently been used for LSP extraction (Cai, 2019; Löw & Koukal, 2020; Vrieling et al., 2018). Sentinel-2 data have spatial and spectral complementarity with Landsat data, which could enable integration (Storey et al., 2016), allowing for an average temporal overpass of 2.9 days (Li & Roy, 2017), providing higher chances of cloud-free surface data use for LSP studies.

LSP can also been retrieved with the use of very high spatial (<10 m) and temporal resolution data. The potential use of PlanetScope for phenology estimation in semi-arid rangelands showed promising results (Cheng et al., 2020). Additionally, Vegetation and Environment monitoring on a New Micro-Satellite (VENµS) has also been used for LSP studies (Gao et al., 2020; Herrmann et al., 2020), and transformation functions between Sentinel-2 and VENµS surface reflectance have been developed in order to combine these data into one dense time-series for vegetation monitoring (Manivasagam et al., 2019).

Upcoming satellite generations will be able to support data continuity for LSP monitoring through optical remote sensing and improve data quality. More specifically, the JPSS mission, carrying -among others- the VIIRS instrument, is scheduled to launch three spacecrafts between 2021 and 2031 (Trenkle & Driggers, 2019). Furthermore, commercial solutions, such as the Planetscope nanosatellite constellation, with continuous launches every three to six months, will eventually allow for daily imaging of the entire globe at very high spatial resolution (3m approximately) (eoPortal Directory, 2020; ESA, 2020). Lastly, UrtheDaily will be launched by UrtheCast in 2022, providing daily medium resolution global images with 9 spectral bands that will be cross calibrated to Sentinel-2 and will be analysis ready through a constellation of six satellites (UrtheCast, 2020).

2.1 Multi-Source Satellite Data Integration Methods for LSP Estimation

The use of composite images has been frequently applied for AVHRR, MODIS, and SPOT data in order to account for cloud cover. However, this technique reduces the temporal frequency of the data, which is important for LSP. Data fusion or blending of satellite data from different sensors to create synthetic information of high spatio-temporal resolution has introduced a way that optimizes the capacity to monitor land surface changes (Zhu et al., 2010). Similarly, synergies between satellite products (e.g. Sentinel-2 and Landsat-8) are used to densify time series; here the individual products that make up the synergy remain the same. These methods are particularly important for LSP estimations, since both high temporal and high spatial resolution are needed to derive detailed phenology cycles. Examples of recent types of data integration methods are provided in Table 2.

Table 2: Examples of satellite data integration methods (i.e. data fusion & synergies) that are useful for LSP estimation.

Method	Sensor combination	Details	Source
FORCE ImproPhe	MODIS, Landsat, Sentinel	Uses local pixel neighborhood, denoises LSP, preserves sharp edges	(Frantz, 2019)
Automatic co-registration	Landsat, Sentinel	Co-registration of Landsat-8 to Sentinel-2A & Sentinel-2A to Sentinel-2B	(Skakun et al., 2017)
Assisted downscaling	Landsat, Sentinel	Downscales Landsat-8 to Sentinel-2 resolution	(Li & Roy, 2017)
Super-resolution enhancement	Landsat, Sentinel	Uses convolution neural networks trained with Sentinel-2 data	(Pouliot et al., 2018)
HLS	Landsat, Sentinel	A combined Landsat/Sentinel product	(Claverie et al., 2018)

Scientists of the NASA Multi-source Land Imaging (MuSLI) program combined Sentinel-2 and Landsat-8 data (Li et al., 2017) towards the production of the Harmonized Landsat Sentinel-2 (HLS) dataset. This currently covers the entire North America and other globally distributed test sites. Version 1.4 is available for 120 pilot regions, which correspond to 4090 MGRS (Military Grid Reference System) tiles (Masek, 2018; Skakun et al., 2018). This data is tested for several applications, including LSP (Claverie et al., 2018). A project targeting an enhanced LSP product was created (Melaas et al., 2017), and further developed towards an operational LSP product (Bolton et al., 2020; Friedl et al., 2020). The integration and combined use of these satellite sensors provide a chance of developing time series with unprecedented frequency. Nevertheless, the combined use of different constellations introduces various theoretical and technical hurdles.

2.2 New Trends in LSP Retrieval and Recent Discoveries

The twinned potential of cloud computing (CC) and machine learning provides new pathways for enhanced LSP retrieval. The current big volume of satellite data requires high-performance processing methods, which are hard to obtain through just a single computer. CC represents a paradigm shift to next-generation studies of plant phenology, since it allows for processing and analysis of previously unmanageable volumes of data, shifting the processing burden from a scientist's personal computer to an external server that is accessed through the cloud. Since Landsat data have long-term data continuity, CC has made it possible to assemble time series from all available Landsat scenes. Cloud solutions for data storage and LSP processing include freely accessible platforms, such as Google Earth Engine, Amazon Web Services (AWS) Open Data, TerraScope Virtual Machine, and the 'Phenology Metrics' algorithm (see Section 3.1). For instance, Google Earth Engine (GEE) has allowed for online LSP calculation and analysis in recent studies (Bórnez et al., 2020a; Li et al., 2019; Venkatappa et al., 2019; Workie & Debella, 2018), facilitating processing burden.

Moreover, data cube technologies are gaining popularity in the earth observation society for remote sensing data processing. Image data cubes are defined as "large collections of temporal, multivariate datasets typically consisting of analysis ready multispectral Earth observation data" (Kopp et al., 2019). The Committee of Earth Observation Satellites (CEOS) created Open Data Cube to facilitate the creation of such cubes. LSP processing can hugely benefit from such technology. For instance, Li et al. (2020) used data cube processing to analyse changes in vegetation green-up dates over various dimensions to reveal greater spatiotemporal discrimination. Overall, researchers can incorporate all available imagery over much larger extents, leading to phenology results that are either temporally detailed, geographically expansive, or both.

Similarly, machine-learning techniques deserve a mention, given that the large volume of available data has made it possible to apply increasing sophisticated analysis approaches that depend on massive data inputs. Machine learning could be applied to data cubes and multi-source earth observation data. For now, it has been used to predict ground-based phenophases or LSP from daily pheno-tower data. Examples include its use to learn phenological patterns and detect them in a large number of ground digital imagery (Almeida et al., 2014; Ryu et al., 2018), or in filling spatiotemporal ground-based LSP observations and forecasting phenophases with remote sensing and meteorological data (Czernecki et al., 2018). Recently, the DATimeS software was launched to specifically incorporate twelve different machine learning fitting algorithms for time series analysis of phenology data (see Section 3.1). Overall, the use of machine learning techniques to enhance phenological models has not been fully explored until now.

Lastly, many studies note that LSP of end of season (EOS) is more difficult to estimate because canopy greenness of plants changes gradually during autumn. To avoid being based on just one method for EOS estimation, Yuan et al. (2020) recently calculated EOS by taking the average of two methods (i.e. the midpoint and double logistical fitting). Furthermore, recent studies revealed that the estimat-ion of autumn phenology is a gradual process that requires a combination of sensors and satellite data for accurate depiction. Lu et al. (2018) found that autumn phenology defined by fluorescence satellite data agreed better with gross primary production (GPP) autumn phenology than that derived from VIs. Their findings agree with those of Wang et al. (2020). They support that photosynthetic activity senesces before changes in leaf color, and that the decrease in vegetation water content occurs at the end. This was consistent globally, providing a better understanding of the underlying structural and functional processes behind autumn senescence, being a longer and more gradual process than start of season (SOS).

3 LSP SOFTWARE TOOLS, GLOBAL PRODUCTS & NETWORKS

3.1 Open-source LSP Software Tools

There is an abundance of LSP data processing and extraction software from Earth observation time-series. All of these use a variety of fitting functions to extract a number of LSP metrics. Exemplary open-source tools are presented in Table 3. They all provide the advantage of being freely available, but might have limitations regarding the nature of the time series, algorithm verification, lack of a graphical user interface, or demand for advanced knowledge. The use of cloud processing with an online workflow for "Estimation of phenology metrics" by the Centre for Research and Technology - Hellas (CERTH), and the incorporation of next-generation machine learning regression algorithms for LSP time series by DATimeS are promising.

Table 3: Open-source software tools for LSP extraction.

Software tool	Source
TIMESAT	(Eklundh, 2017)
PhenoSat	(Rodrigues et al., 2013)
BFAST	(Verbesselt et al., 2010)
SpliTS	(Frantz et al., 2016; Mader, 2012)
SPIRITS	(Eerens & Dominique, 2013; Rembold et al., 2013)
'greenbrown' R package	(Forkel et al., 2013, 2015; Forkel & Wutzler, 2015)
'phenex' R package	(Lange & Doktor, 2017)
"Estimation of phenology metrics" by CERTH	(Guigoz, 2017; Nativi et al., 2016)
DATimeS	(Belda et al., 2020)

3.2 Global LSP Products

Some of the most important global LSP product are listed in Table 4. One of the benefits of the MCD12Q2 product is that it can be used for regions that have two growing seasons (Henebry & de Beurs, 2013). Similarly, the VIIRS GLSP product can separate phenological phases in a wide variety of vegetation types and climate systems, with high quality (Zhang et al., 2018). The MEaSUREs VIP product has the advantage of combining AVHRR and MODIS data and provides 26-year LSP metrics. Lastly, the HLS surface reflectance dataset (Bolton et al., 2020), which currently covers several pilot sites around the world, can be used to derive LSP time series, and should also be mentioned here, as future plans envision for it to have global cover.

Table 4: Global LSP products: MODIS Land Cover Dynamics product (MCD12Q2), VIIRS Global Land Surface Phenology product (GLSP), Making Earth System Data Records for Use in Research Environments (MEaSUREs) Vegetation Index and Phenology (VIP) global dataset. Information retrieved from Gray et al. (2019), USGS (2019), and Zhang et al. (2018).

Global LSP products	Duration	Source	Spatial Resolution
MCD12Q2	2001-2017	EVI2 from MODIS BRDF Adjusted Reflectance (NBAR)	500 m
VIIRS GLSP	2012-Present	EVI2 from daily VIIRS BRDF NBAR	500 m
MEaSUREs VIP	1981-2014	NDVI and EVI2 from AVHRR 1981-1999; MODIS MOD09 2000-2014	5600 m

3.3 Ground Phenology Networks for LSP Validation

To link LSP estimations with ground phenology observations, it is advised to gain complete understanding of the species composition in the study area (Misra et al., 2016). Therefore, simultaneous field-based and remote sensing data has to be obtained along various stages of multiple growing seasons. The downside of *in situ* phenological data collection is that it is labor-intensive, localized, and includes only a small sample of species (Misra et al., 2016). Therefore, many countries operate ground phenology based on crowd-sourced information and transboundary networks. It has been suggested by the Society of Biometeorology Phenology Commission (ISB-PC) and the World Meteorological Organization Commission for Agricultural Meteorology (WMO-CAgM) to build a Global Alliance of Phenological Observation Networks (GAPON) (USA-NPN, 2020). The phenology networks that are included into this alliance are up to date 52 in number, and include –among others- nationwide approaches. Examples of some major phenological networks are provided in Table 5.

4 CONCLUSIONS

It has become obvious that a new era with time series at higher spatial and temporal resolution brings enormous opportunities and challenges to LSP research. The big volume of data requires high-performance processing methods. To tackle this issue, cloud solutions for data storage and processing are freely accessible along with machine learning workflows; and data cube processing techniques are being developed. All of this will facilitate the role that phenology has to play in the UN SDGs and ABTs together with the development of EBVs (essential biodiversity variables) in line with the GEO initiatives. Through this review it is made clear that the use of satellite constellations might reduce the problems associated with the spatial and temporal resolution of LSP data (e.g. HLS product). Lastly, the variety of open-source tools, global products, and ground phenology networks gives opportunity for LSP estimation by diverse science teams and capacities.

Table 5: Major existing phenology networks. Information retrieved from GLOBE (2019), Nasahara & Nagai (2015), NEON (2019), PEN (2020), PEP725 (2019), Templ et al. (2018), USA-NPN (2019), PHENOCAM (2020).

Phenology Networks	Purpose	Users	Collaborations	Extra information
USA-NPN	Collect, store, distribute phenology data	Researchers, natural resource managers, policy-makers, educators, citizen scientists, NGO's	-NEON; -Nature's Notebook	Standardized plant & animal observation protocols
NEON	Collect ecological data: in situ measurements/ observations & airborne remote sensing surveys	Researchers	-81 field sites in US	175 open access products
PEP725	Open access database to facilitate phenological research, education, environmental monitoring	Researchers, educators	-7 phenology network partners; -32 European meteorological services	-Volunteer data collected from 1868 to present; -12 million records
GLOBE	International science and education program to promote teaching and learning of science	Students, educators	-NASA, NSF, NOAA; -121 countries	Over 150 million ground biophysical measurements
PEN	Validate terrestrial RS products of ecology, phenology changes	Ecologists, remote sensing specialists, scientists, citizens	-FluxNet, ILTER, AsiaFlux -38 sites worldwide, most in Japan	Some sites measure environmental ecophysiological properties
PhenoCam	For phenological model validation, evaluation of satellite RS products, studies of climate change impacts on terrestial ecosystems	Researchers, remote sensing specialists	-750 sites across North America	Data derived from visible-wavelength digital camera imagery

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