Remote sensing of temperate and boreal forest phenology: A review of progress, challenges and opportunities in the intercomparison of in-situ and satellite phenological metrics.

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Abstract

Vegetation phenology is the study of recurring plant life cycle stages, seasonality which is linked to many ecosystem processes and is an important proxy of climate and environmental change. Remote sensing has been playing an important and increasing role in the monitoring and assessment of vegetation phenology. The aim of this review is to critically examine key studies related to remote sensing of vegetation phenology, with a special focus on temperate and boreal forests. Specifically, we focus on how the latest ground, near-surface and aerial data have been used to assess the satellite-derived Land Surface Phenology (LSP) metrics and the agreements that has been achieved in the last 15 years. Results demonstrated that the timing of satellite-derived LSP events can be detected, in the best-case scenarios, with a certainty of around half-week for spring metrics (e.g. Day of Year -DOY- of start of growing season) and around one week for autumn metrics (e.g. DOY of end of growing season). With expected shifts in plant phenology averaging less than 1 day per decade, such LSP uncertainties (in terms of absolute phenological dates) could greatly over- or under-estimate these species-level

shifts; but the spatial variation in phenology can be consistently monitored. An increasing number of studies have investigated autumn phenology in the last decade, but autumn phenological dates continue to be more challenging to retrieve and interpret than spring dates. Emerging opportunities to further advance remote sensing of forest phenology is presented that includes synergetic use of multiple orbital sensors and its LSP evaluation with data from new sensors at a ground, near-surface and airborne level; yet traditional ground-based observations will continue to be highly useful to accurately record the timing of species-specific phenological events. This review might provide a guide for planning and managing remote sensing of forest phenology.

Keywords: Satellite data; land surface phenology; phenometrics; ground observations; SOS; EOS; validation.

1 Introduction

Vegetation phenology is the study of recurring plant life cycle stages (e.g. budburst, flowering) (Lieth, 1974) and is an important proxy of climate and environmental change (Polgar and Primack, 2011; Chen *et al.*, 2019). Variations in vegetation phenology are related to carbon, energy, nutrient and water cycles within terrestrial ecosystems (Garrity *et al.*, 2011; Mizunuma *et al.*, 2013; Estiarte and Peñuelas, 2015), operating from local to global scales, as around 55% of the Earth's land surface is covered by grasslands, shrub lands and forests (Bartholomé and Belward, 2005). Therefore, many important feedbacks to the climate system are affected by the seasonality of vegetation (Richardson *et al.*, 2013a). While vegetation phenology is a general term, it can be studied from a plant phenology or Land Surface Phenology (LSP) perspective and these different approaches are described here.

Traditionally, the monitoring of phenological changes has been by direct observations of plants (plant phenology), with phenological records dating back the 9th

century (e.g. of Japanese cherry tree) (Richardson *et al.*, 2013a). Visual assessments are usually carried out by scientists (Menzel *et al.*, 2006; Liang *et al.*, 2011; Schwartz, 2013), but also by people (volunteers) interested in nature (Kosmala *et al.*, 2016). This consists of observing the plant and recording its phenological phase (e.g. the date when the first bud or flower appears) according to a defined protocol or guideline (Templ *et al.*, 2018), as exemplified in Table 1. Please see Fitchett *et al.* (2015) for a comprehensive discussion on the effects of different definitions of individual phenological events.

Table 1. Examples of phenological phases observed from the ground (plant phenology). The phenophases are recorded as occurring in a specific DOY.

Season (Location)	Observed phenophases	Authors
All seasons (Europe)*	Beginning of flowering Fruits ripe for picking Leaf unfolding First leaves separated Autumn leaf coloration (50%) Start of harvest First ripe fruits Sowing Full flowering End of flowering	Templ <i>et al.</i> (2018)
Autumn (USA)	Leaf colouration [0-10; 10-50; 50-90; 90-100 %] Leaf fall [0-10; 10-50; 50-90; 90-100 %]	Liu <i>et al.</i> (2015)
Spring (USA)	No buds visible Buds visible [<10; 10-50; 50-90; >90 %] Buds swollen [<10; 10-50; 50-90; >90 %] Bud open-leaf visible [<10; 10-50; 50-90; >90 %] Leaf out-not fully unfolded [<10; 10-50; 50-90; >90 %], Full leaf unfolded [<10; 10-50; 50-90; >90 %] Leaf expansion [<10; 10-50; 50-90; >90 %]	Schwartz <i>et al.</i> (2013)
Spring (Switzerland)	Leaf unfolding Full flowering Needle appearance	Studer <i>et al.</i> (2005)
Spring & Autumn (Siberia)	First leaves Beginning of leaf coloring	Delbart <i>et al.</i> (2005)
Spring (UK)	First flowering date	Fitter <i>et al.</i> (1995)

*These were the most commonly surveyed/used phenological phases of the Pan European Phenological database (PEP725), accordingly to the meta-analysis of Templ *et al.* (2018), but up to 287 different phases are listed in the PEP725 website (http://www.pep725.eu/pep725_phase.php; access on 20/07/2020).

Plant phenology has received increasing public and scientific attention (Bajocco *et al.*, 2019) due to the growing evidence that the timing of developmental stages is indeed largely dependent on environmental cues (Chuine and Regniere, 2017). Particularly, as plant phenology events are highly sensitive to climate fluctuations, the timing of these events has been used as an independent indicator of climate change (Menzel *et al.*, 2006; Thackeray *et al.*, 2010) mainly in temperate environments with deciduous species (Fisher and Mustard, 2007). Studies have reported shifts in plant phenology due, overall, to warming temperatures (in England (Thompson and Clark, 2008), Europe (Menzel *et al.*, 2006), China (Ge *et al.*, 2015) and Japan (Ibáñez *et al.*, 2010)), leading to earlier spring and later autumn phenology. Therefore, a changing climate can drive shifts in plant phenology (e.g. timing and length of growing season), with potential impacts on atmospheric processes, ecosystem services, ecosystem dynamics, plant-based economies, trophic interactions and species ranges (Morissette *et al.*, 2009; White *et al.*, 2009; Campoy *et al.*, 2011; Sparks, 2014; Forkel *et al.*, 2016). Modelling, assessing and monitoring phenological dynamics are therefore key requirements to improve understanding of how plants respond to a changing world and how this influences vegetated ecosystems (Fitter *et al.*, 1995; Penuelas and Filella, 2001; Morissette *et al.*, 2009; Moore *et al.*, 2016).

Visual observations only demand a person to observe and record the phenological phase of interest, providing detailed plant phenology information at species-scale or individual plant scale (Fitter *et al.*, 1995). Additionally, such observations can capture subtle transitions from one phenophase to another (Donnelly *et al.*, 2017) and they

(should) hold an explicit description of a plant growth stage (e.g. ‘leaf unfolding’ (Templ *et al.*, 2018)) on a specific date. However, observations can be time consuming and labour intensive, hampering the acquisition of a large volume of good quality data (Morellato *et al.*, 2016), facts which may constrain studies to small areas and to a few species (Liang *et al.*, 2011). But see Kudo (2020) and Templ *et al.* (2018) for examples of how citizen volunteer data can increase statistical representativeness.

To measure phenological events over a larger spatial extent, satellite remote sensing has emerged as valuable new tool (Tucker, 1979; Polgar and Primack, 2013). Phenology derived from a satellite is often called LSP (de Beurs and Henebry, 2005) because the satellite sensor integrates a mixture of signals coming not only from trees but also from all the objects visible within the pixel’s instantaneous field of view (Friedl *et al.*, 2006). Therefore, LSP metrics (e.g. start of greening/growing season) detect the general spatio-temporal dynamics of the vegetated surface, from local to global scales, rather than specific plant phenological events. This mismatch in scale and specificity of observations can bring difficulties in interpreting LSP metrics (Fisher and Mustard, 2007; White *et al.*, 2009). In this context, many studies have been devoted to efforts to developing approaches to consistently intercompare and evaluate satellite-derived LSP metrics against plant phenology and, more recently, against ground, near-surface and aerial sensors (Table 2).

Ground and near-surface sensors have been increasingly used, over the past decade, to collect data for LSP assessment purposes in place of or in complement to traditional plant phenology (accordingly to our survey in Table 2). This level of observation generally includes commercial-off-the-shelf Red-Green-Blue (RGB) digital cameras sensing visible-light wavelengths (Moore *et al.*, 2016), spectral radiometers detecting reflected radiance (Hmimina *et al.*, 2013), continuous carbon flux

measurements (Wu *et al.*, 2017) and, more recently, cameras carried by Unmanned Aerial Vehicles (UAV) (Berra *et al.*, 2019). Near-surface digital cameras for phenology applications are usually referred to as “phenocams” (Richardson *et al.*, 2009). Overall, imaging and radiometric sensors such as these can provide high temporal resolution of phenological time series, providing species-specific and/or site-level measurements (Hmimina *et al.*, 2013; Klosterman *et al.*, 2014; Brown *et al.*, 2016) and bridging the scale between traditional visual observations and satellite LSP (Sonnentag *et al.*, 2012).

Therefore, vegetation phenology monitoring by remote sensing can be performed by an array of ground, near-surface and orbital sensors; each with its advantages and disadvantages. Whilst an unprecedented variety of sensing systems, coupled with ever increasing computing capacity, makes this a golden era for researchers to investigate forest phenology, it also makes it challenging to understand the relative merits of the different remote sensing technologies available and what results they might achieve.

A broad and comprehensive overview of vegetation and animal phenology across the diverse biomes is given in the book edited by Schwartz (2013), including the advances of LSP up to 2013. Richardson *et al.* (2013a) reviewed the interconnections of phenology and climate system feedbacks, with a focus on forests and carbon/water cycling. This topic was later on complemented and expanded by Tang *et al.* (2016), whose review focused in the mechanisms and major drivers of plant phenology. Helman (2018) discussed the limitations of drawing interpretations from LSP, focusing on the effect of the many methodological choices (also thoroughly investigated by White *et al.* (2009)); more recently, Zeng *et al.* (2020) provide an updated discussion on the advantages and drawbacks of the different phenological metrics (or phenometrics) extraction methods. Bajocco *et al.* (2019) provided a bibliometric overview of what was explored up to 2018 in terms of remote sensing phenology at a global level. Some authors focused on

reviewing the advances of ground and remote sensing phenology within specific regions, such as Australia (Moore *et al.*, 2016), Japan (Nagai *et al.*, 2015), Africa (Adole *et al.*, 2016) and South and Central America (Morellato *et al.*, 2013).

The aim of this paper is to critically examine key studies related to remote sensing of vegetation phenology, with a special focus on temperate and boreal forests. Specifically, we focus on how the latest ground, near-surface and aerial data have been used to evaluate, intercompare and interpret satellite-derived LSP, the agreements that has been achieved, and what new insights on phenology understanding these data have brought. Throughout the text, challenges of current data sets and techniques used to monitor phenology are outlined, highlighting opportunities for future research. We seek to address the critical question 'what degree of agreement can be achieved between phenological transition dates estimated on the ground (and near to it) and as seen from space, across temperate and boreal forests?', providing a guide for ecologists and other researchers in developing measurement protocols.

The article is composed of 9 sections. Following this introductory section, section 2 explains the survey methodology. Section 3 provides an overview of satellite data for forest phenology applications, section 5 provides an overview on how phenological metrics are derived from time series of remote sensing data; together, these two sections provide a general introduction of phenology remote sensing. Recent figures for observed phenology shifts are presented in section 4 and the uncertainties of estimated phenological events from time series of remote sensing data is presented in section 6. Section 7 presents the potential of microwave wavelength satellite data for forest phenology detection. Future trends as well needs for improved monitoring of vegetation phenology is illustrated in section 8, following by key conclusions in section 9.

2 Survey methodology

We focus this review on published papers that intercompared and assessed satellite-derived phenometric dates against *in situ* phenology, across temperate and boreal forests in the last 15 years. For the studies that were found to meet this criteria, we report a summary table containing the degree of agreement achieved in the estimates of satellite phenological metrics dates (Table 2). For simplicity, we used the term '*in situ*' hereafter to refer to any (or all) of the data sets used as reference to evaluate satellite LSP, which are visual observations of plant phenology, CO₂ flux tower, and ground, near-surface and aerial remote sensing observations.

Initially, we used the ISI Web of Science as the search engine, using the 'Advanced Search' tool with the following expression (timespan: 2005 to 2020 (March)):

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[(TS = ("Land Surface Phenology" OR "satellite pheno*") AND
(*compar* OR validat* OR evaluat* OR link* OR assess* OR field*)
AND forest* AND satellite*)) AND LANGUAGE:(English) AND
DOCUMENT TYPES: (Article)]
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A candidate list of 82 papers returned from this initial search and was checked for evidence that fitted our criteria: 1) study area = temperate or boreal forest; and 2) satellite phenometric dates assessed against *in-situ* dates. A total of 34 studies were retained after this check. By examining cited references in these 34 studies, and based on our experience, additional papers were identified and added to Table 2, totalling 56 studies.

Results from studies comparing time series data, but not phenodates (e.g. Mizunuma *et al.* (2013) compared time series of carbon flux vs. satellite VI), are discussed throughout the text but not included in Table 2. Additionally, for studies presenting comparisons across diverse land cover types (e.g. forest, agriculture and grasslands (Moon *et al.*, 2019)), only the forest-related results are presented in Table 2; however, this was not always possible in some studies due to a lack of explicit statistical

measures for each land cover type (e.g. Peng *et al.* (2017b)). For simplicity, only one metric for the spring and one for the autumn season are presented in Table 2, but overall results are commented on throughout the paper.

There are numerous nomenclatures to characterize metrics derived from times series of remote sensing data including spring (e.g. greenup and maturity date (Xie and Wilson, 2020); start of the greenness rising (Richardson *et al.*, 2018)) and autumn (e.g. senescence and dormancy date (Xie and Wilson, 2020); end of the greenness falling (Richardson *et al.*, 2018)). Here, we adapted the nomenclature and definitions of phenometrics proposed by Klosterman *et al.* (2014) and Zeng *et al.* (2020) to simplify and guide our discussion throughout the manuscript. They consist of 3 metrics for the spring season, namely Start (SOS), Middle (MOS) and Peak (POS) of Season, and 3 metrics for the autumn season, namely Start of Fall (SOF), End of Fall (EOF) and End of Season (EOS), which are illustrated in Figure 1. However, it is important to stress that the definitions of phenological metrics are subjected to the specific approaches (as we discuss in section 5) chosen by the different researchers. Different metrics used by the original authors have been assigned to our common nomenclature according to the similar stage of the phenological transitions they capture. For example, Bolton *et al.* (2020) extracted the phenometric ‘start of greenup’ as corresponding to 15% of the VI amplitude; in Table 2, this metric is assigned to SOS.

Figure 1 shows an example of time series data for one Moderate Resolution Imaging Spectroradiometer (MODIS) 250 m pixel located in a temperate forest in Oxford, UK, data which represents a typical deciduous NDVI temporal trend. In this example, the phenological transition dates were identified by using local extremes in the rate of change in the curvature of the fitted models (Zhang *et al.*, 2003). Figure 1 is referred to throughout

the text to illustrate the key concepts of LSP. But it does not necessarily mean that the approach presented in Figure 1 was used by the authors we discuss in the text.

Figure 1: An example time series of MODIS NDVI data (product MOD13Q1) and estimated phenological transition dates for a mixed forest pixel in Oxford, England (51°46'33.66"N; 1°20'5.63"W), illustrating the nomenclature of metrics adopted in the review. The series span from 01/01/2018 to 02/02/2019. A second-order Savitzky-Golay filter (window size=5) was applied to the original time series of NDVI data in order to diminish the influence of noise in the series. The smoothed data were fitted by two logistic models (Zhang *et al.*, 2003). Phenological transitions dates (vertical dotted lines) correspond to the times at which the rate of change in curvature (blue line) exhibits local minima or maxima (Zhang *et al.*, 2003). Start (SOS), middle (MOS), Peak (POS) and end (EOS) of growing season. Start (SOF) and middle (MOF) of fall season.

237 Table 2. Degree of agreement in estimating phenological dates with satellite remote sensing across temperate and boreal forests in the last 15 years. The agreement
238 refers to the intercomparisons between satellite vs. *in situ* data and is presented in three ways: i) Average: when the authors present an overall average; ii) Best:
239 when the authors test a combination of different methods, the best results are provided; iii) Range: when the authors provide the full range of agreements achieved.
240 Root Mean Square Error (RMSE), bias and Mean Absolute Error (MAE) are in units of days (rounded to the nearest integer); r = correlation coefficient.

Authors	(Period ¹) Region	Satellite data	In situ data	Metric	Agreements		
					Average	Best	Range
Bornez <i>et al.</i> (2020)	(M) USA and Europe ^{Mix}	[SPOT-Veg. + PROBA-V] 1km	Visual obs _{vol} ⁴	SOS EOS	-	RMSE = 10 RMSE = 25	-
Bolton <i>et al.</i> (2020)	(M) North America ^{Mix}	HLS ³ 30m	Phenocam ⁵	SOS EOS	-	-	RMSE=6-22; R ² =0.15-0.9 RMSE=18-28; R ² =0.42- 0.53
Zhang <i>et al.</i> (2020)	(S) USA ^{Mix}	Fused [HLS- VIIRS] 30m	Phenocam	SOS	MAE =8	-	-
Kowalski <i>et al.</i> (2020)	(S) Germany ^{Mix}	HLS 30m	Visual obs _{vol}	SOS	-	-	RMSE=6-8; r=0.42-0.51
Xie and Wilson (2020)	(M) USA ^{Mix}	MODIS 500m	Visual obs _{vol}	SOS EOS	-	RMSE =4; MAE =3 RMSE =7; MAE =5	RMSE =4-29; MAE =3-24 RMSE =7-37; MAE =5-31
Zhao <i>et al.</i> (2020)	(M) USA ^{Mix}	MODIS 250m	Visual obs.	SOF EOS	-	-	bias =-4 to 56 bias =0 to 14
Yan <i>et al.</i> (2019)	(M) Japan ^{Mix}	MODIS 500m	Phenocam	SOS EOS	-	-	bias=-22 to 12 bias=-8 to 31
		AHI 500m		SOS EOS	-	-	bias=-4 to 2 bias=7 to 45
Moon <i>et al.</i> (2019)	(M) North America ^{Mix}	MODIS 500m	Phenocam	SOS EOS	-	-	RMSE =6-24 RMSE =11-37
		VIRSS 500m		SOS EOS	-	-	RMSE =8-28 RMSE =14-42
Stanimirova <i>et al.</i> (2019)	(M) North America ^{Mix}	MODIS 500m	Phenocam	SOS EOS	-	-	r=0-0.76 r=0-0.76
Khare <i>et al.</i> (2019)	(M) Canada ^{Home}	MODIS 250m	Visual obs.	SOS	RMSE = 13; R ² = 0.87	-	-
Berra <i>et al.</i> (2019)	(S) England ^{Mix}	Landsat	UAV	SOS	-	R ² = 0.83; RMSE = 8	-

		30m					
Liu <i>et al.</i> (2019)	(M) China ^{HetD}	MODIS 500m	Radiometer	EOS	-	R ² = 0.67; MAE =3	R ² =0.38-0.67; MAE = 3-7
			Litterfall	EOS	-	R ² =0.44; MAE =4	R ² =0.34-0.44; MAE =3-11
Donnelly <i>et al.</i> (2019)	(M) USA ^{Mix}	MODIS 500m	Visual obs.	SOS	R ² = 0.70	-	-
			Carbon flux	SOS	R ² = 0.44	-	-
Klosterman <i>et al.</i> (2018)	(S) USA ^{Mix}	MODIS 250 m	UAV ²	SOS MOF	-	-	MAE =0-1 MAE =0-3
Ruetschi <i>et al.</i> (2018)	(M) Switzerland ^{Mix}	Sentinel-1 10m	Visual obs _{vol}	SOS SOF	-	-	MAE =3-43 MAE =1-12
Zhang <i>et al.</i> (2018a)	(M) USA ^{Mix}	VIIRS 500m	Phenocam	SOS EOS	-	R ² =0.89; MAE =7 R ² =0.79; MAE =10	R ² =0.87-0.89; MAE =7-8 R ² =0.48-0.79; MAE =10-16
Zhang <i>et al.</i> (2018b)	(M) USA ^{Mix}	VIIRS 500m	Visual obs _{vol}	SOS	MAE=5	-	r =0.5-0.65; MAE =0-15
Richardson <i>et al.</i> (2018)	(M) USA ^{Mix}	MODIS 500m	Phenocam	SOS EOS	-	-	MAE =8-23 MAE =8-29
Wang <i>et al.</i> (2018)	(M) Pan-Arctic ^{HomeE}	MODIS 500m	Carbon flux	SOS EOS	-	-	R ² =0-0.3; RMSE=13-83 R ² =0-0.28; RMSE=7-55
		GOME-2 0.5°		SOS EOS	R ² =0.34; RMSE=18 R ² =0.24; RMSE=23	-	-
Lu <i>et al.</i> (2018)	(M) North Hemisphere ^{Mix}	MODIS 500m	Carbon flux	SOS EOS	-	-	RMSE=16-19; R ² =0.2-0.46 RMSE=14-17; R ² =0-0.32
		GOME-2 0.5°; OCO-2 1.3x2.25km		SOS EOS	RMSE=12; R ² =0.68 RMSE=12; R ² =0.52	-	-
Peng <i>et al.</i> (2018)	(M) USA ^{Mix}	MODIS 500m	Visual obs _{vol}	SOS	r=0.61; RMSE=17	-	-
Testa <i>et al.</i> (2018)	(M) France ^{HetD}	MODIS 250m	Visual obs.	SOS EOS	-	RMSE =10 RMSE =22	-
Wang <i>et al.</i> (2017a)	(M) China ^{Mix}	MODIS 500m	Visual obs.	SOS EOS	-	-	bias=4 to 40 bias=14 to 34
		MODIS 1km		SOS EOS	-	-	bias=4 to 26 bias=17 to 26
Jin <i>et al.</i> (2017)	(M) Northern Europe ^{Mix}	MODIS 500m	Visual obs _{vol}	SOS EOS	-	-	RMSE= 12-35 RMSE= 14-50
			Carbon flux	SOS	RMSE=13	-	-

				EOS	RMSE=16		
Liu <i>et al.</i> (2017a)	(S) North America ^{Mix}	VIRSS 750m	Phenocam	SOS	RMSE=6; R ² =0.97	-	-
Peng <i>et al.</i> (2017a)	(M) USA ^{Mix}	MODIS 230m	Carbon flux	SOS	-	-	RMSE=15-32; r=(-0.31)-0.81
			Visual obs _{vol}	SOS	-	-	RMSE=12-52; r=0-074
Peng <i>et al.</i> (2017c)	(M) USA ^{Mix}	MODIS 230m	Carbon flux	SOS	-	r =0.56; RMSE =12	r =0-0.74; RMSE =12-68
Baumann <i>et al.</i> (2017)	USA ^{HetD}	Landsat 30m	Phenocam	SOS EOS	r=0.94; MAE =4 r =0.80; MAE =3		
		MODIS 500m	Phenocam	SOS EOS	r =0.84; MAE =12 r =0.78; MAE =2		
Wu <i>et al.</i> (2017)	(M) North Hemisphere ^{Mix}	MODIS 1km	Carbon flux	SOS EOS	R ² =0.24; RMSE =33 R ² =0.1; RMSE =49	-	R ² =0.13-0.28; RMSE=27-33 R ² =0.10-0.15; RMSE=32-37
		SPOT-Veg. 1km	Carbon flux	SOS EOS	R ² =0.21; RMSE =32 R ² =0.20; RMSE =44	-	R ² =0.12-0.26; RMSE=31-36 R ² =0.13-0.2; RMSE =41-46
Melaas <i>et al.</i> (2016b)	(M) North America ^{HetD}	Landsat 30m	Phenocam	SOS EOS	R ² =0.86; RMSE =6 R ² =0.25; RMSE =10	-	R ² =0.2-0.97; RMSE =3-8 R ² =0.0-0.98; RMSE =1-18
			Carbon flux	SOS EOS	R ² =0.88; RMSE =8 R ² =0.57; RMSE =15	-	R ² =0.54-0.78; RMSE =5-9 R ² =0.12-0.64; RMSE =13-17
Verger <i>et al.</i> (2016)	(M) Europe ^{HetD}	MODIS 500m	Visual obs _{vol}	SOS EOS	RMSE=18; r=0.84 RMSE=60; r=0.12	-	-
		SPOT-VEGETATION 1km		SOS EOS	-	-	RMSE=7-28; r=0.58-0.95 RMSE=15-45; r=0.28-0.81
Chen <i>et al.</i> (2016)	(M) USA and China ^{HetD}	MODIS 250m	Visual obs.	SOS	-	-	MAE=2-58
Verma <i>et al.</i> (2016)	(M) USA ^{HetD}	MODIS 463m	Visual obs.	SOS EOS	-	-	MAE=3-6 MAE=11-15
Balzarolo <i>et al.</i> (2016)		MODIS 500m	Carbon flux	SOS	-	-	R ² =0.23-0.74; RMSE=8-22

	(M) Canada, Germany, Finland, Japan, Netherlands, USA ^{Mix}		Radiometer	SOS	-	-	$R^2 = 0-0.51$; RMSE=9-17
D'Odorico <i>et al.</i> (2015)	(M) North Hemisphere ^{HetD}	MODIS 500m	Carbon flux	SOS EOS	-	-	$R^2 = 0-0.36$; RMSE=17-31 $R^2 = 0-0.19$; RMSE=21-23
			phenocam	SOS EOS	-	-	$R^2 = 0-0.65$; RMSE=10-20 $R^2 = 0.25-0.98$; RMSE=5-14
Liu <i>et al.</i> (2015)	(S) USA ^{HetD}	MODIS 250m	Visual obs.	EOS	MAE=5	-	MAE=0-12
Rodriguez-Galiano <i>et al.</i> (2015b)	(M) Europe ^{HetD}	MERIS 1km	Visual obs _{vol}	SOS EOS	$R^2 = 0.70$; RMSE =6 $R^2 = 0.71$; RMSE =8	-	-
Wu <i>et al.</i> (2014)	(M) North America ^{Mix}	MODIS 500m	Carbon flux	SOS EOS	-	$R^2 = 0.86$; RMSE =6 $R^2 = 0.95$; RMSE =3	-
Liang <i>et al.</i> (2014)	(M) USA ^{Mix}	MODIS 500m	Visual Obs.	SOS	MAE=5	-	-
		fused [MODIS-Landsat] 30m	Visual Obs.	SOS	MAE=4	-	-
White <i>et al.</i> (2014)	(M) USA ^{HetD}	Landsat 30m	Visual Obs.	SOS	MAE = 12	-	MAE =11-58
Klosterman <i>et al.</i> (2014)	(M) USA ^{Mix}	MODIS 500m	Phenocam	SOS EOS	-	$R^2 = 0.81$; RMSE =7 $R^2 = 0.77$; RMSE =11	$R^2 = 0.31-0.81$; RMSE =7-18 $R^2 = 0.11-0.77$; RMSE =11-27
Luo <i>et al.</i> (2013)	(M) North China ^{Mix}	AVHRR 8km	Visual obs.	SOS	-	-	MAE=6-11 $r=0.17-0.77$
Melaas <i>et al.</i> (2013)	(M) USA ^{HomD}	Landsat 30m	Visual obs.	SOS SOF	$R^2 = 0.79$; RMSE =3 $R^2 = 0.64$; RMSE =5	-	-
Hmimina <i>et al.</i> (2013)	(M) France ^{HetD}	MODIS 250m	Radiometer	SOS EOS	-	$R^2 = 0.8$; RMSE =3 $R^2 = 0$; RMSE =14	$R^2 = 0.2-0.8$; RMSE =3-11 $R^2 = 0$; RMSE =14-22
Hufkens <i>et al.</i> (2012)	(M) USA ^{HomD}	MODIS 500m	Phenocam	SOS EOS	-	MAE =4 MAE =4	MAE =4-18 MAE =4-25
Coops <i>et al.</i> (2012)	(M) Canada ^{Mix}	fused [MODIS-Landsat] 30m	Phenocam	SOS EOS	$R^2 = 0.65$; RMSE =4 $R^2 = 0.72$; RMSE =3	-	-
Gonsamo <i>et al.</i> (2012)	(M) North America ^{Mix}	MODIS 500m	Carbon flux	SOS EOS	-	-	$r = 0.24-0.88$; RMSE=6-29 $r=0-0.77$; RMSE=9-20

Pouliot <i>et al.</i> (2011)	(M) Canada ^{HetD}	AVHRR 1 km	Visual obs _{vol}	SOS	-	-	MAE =6-8
		MERIS 1 km			-	-	MAE =6-8
Garrity <i>et al.</i> (2011)	(M) USA ^{HetD}	MODIS 0.25 -1 km	Carbon flux	SOS EOS	-	R ² = 0.76; MAE=19 R ² = 0.60; MAE=39	R ² = 0-0.76; MAE=0-19 R ² = 0.5-0.6; MAE=39-42
Liang <i>et al.</i> (2011)	(M) USA ^{Mix}	MODIS 250m	Visual obs.	SOS	MAE =2	-	MAE = 0-16
Tan <i>et al.</i> (2011)	(M) USA ^{Mix}	MODIS 500 m	Visual obs.	SOS	-	-	R ² =0.21-0.66; RMSE=11-23
Li <i>et al.</i> (2010)	(M) USA ^{HetD}	MODIS 1 km	Visual obs.	SOS	-	-	MAE=10-18; r=(-0.32) to 0.51
Soudani <i>et al.</i> (2008)	(M) France ^{HetD}	MODIS 500 m	Visual obs.	SOS	-	-	bias =(-8) to 25; RMSE=8-27
Fisher and Mustard (2007)	(M) USA ^{HetD}	MODIS 500 m	Visual obs.	SOS	-	-	R ² =0.7-0.86; MAE =2-8
Beck <i>et al.</i> (2007)	(M) Fennoscandia ^{HetD}	MODIS 250 m	Visual obs _{vol}	SOS EOS	R ² =0.49; RMSE=12 R ² =0.27; RMSE=10	-	-
Zhang <i>et al.</i> (2006)	(M) USA ^{Mix}	MODIS 1km	Visual obs.	SOS	MAE =10	-	-
Fisher <i>et al.</i> (2006)	(M) USA ^{HomD}	Landsat 30 m	Visual obs.	SOS	R ² =0.91	-	-
Delbart <i>et al.</i> (2005)	(M) Siberia ^{HomD}	SPOT-Veg. 1 km	Visual obs.	SOS SOF	-	R ² =0.75; RMSE=9 R ² =0; RMSE=16	R ² =0.47-0.75; RMSE =9-22 R ² =0; RMSE =16-26

^{HomD}Homogeneous Deciduous forest (one (dominant) tree species); ^{HomE}Homogeneous evergreen forest (one (dominant) tree species); ^{HetD}Heterogeneous Deciduous forest (more than one tree species); ^{Mix}Mixed deciduous and evergreen forest; ¹Period = Indicate whether the data set used is composed of either a Multi-(M) or Single-(S) year time series; ²UAV = Unmanned Aerial Vehicle; ³HLS = Harmonized Landsat 8 and Sentinel-2 imagery; ⁴Visual obs_{vol}= The 'vol' stands for visual observations including volunteers; ⁵Phenocam = near-surface RGB cameras.

3 Satellite-derived phenology

The first efforts to observe the dynamic cycles of the vegetated land surface from satellites began with the Landsat era in the 1970s (Tucker, 1979), when many studies focused on the monitoring of crop phenology in agriculture (Kanemasu, 1974; Heilman *et al.*, 1977; Badhwar, 1984). Despite the relatively high spatial resolution of Landsat data (<60 m), a key limitation was the long return interval relative to vegetation dynamics (Henebry and de Beurs, 2013). The launch of the Advanced Very High Resolution Radiometer (AVHRR) sensor in the 1980's brought, in contrast, much finer temporal resolution (sub-daily) data at the cost of much coarser (1-4 km) spatial resolution (Yates *et al.*, 1986). This spatial-for-temporal trade-off made it possible to capture seasonal vegetation dynamics at the continental scale (Zhang, 2015).

Up to the launch of the Sentinel-2 satellites (2015 and 2017), and development of the harmonized Landsat and Sentinel-2 (HLS) product (Claverie *et al.*, 2018), the Landsat series was the highest spatial resolution data (30 m) at which phenology studies could be cost-effectively carried out (Isaacson *et al.*, 2012; Melaas *et al.*, 2013; Baumann *et al.*, 2017). However, as frequent observations are necessary (Zhao *et al.*, 2012; Miao *et al.*, 2013), the low frequency temporal acquisition of images (16-day), missing data due cloud cover/cloud shadow and sensor technical problems significantly reduce the number of suitable images per year (Isaacson *et al.*, 2012; Melaas *et al.*, 2013), consequently making it difficult to use the Landsat series for phenology purposes (Fisher *et al.*, 2006). Nevertheless, motivated by the high spatial resolution and long-term data offered by the Landsat series, approaches were developed to overcome the temporal resolution limitation (section 6.1). However, the precision of the phenometrics derived from the reconstructed Landsat series can be affected by land cover changes (natural and anthropogenic disturbances), land cover heterogeneity within the coarser spatial

resolution data (used as reference) (Fisher *et al.*, 2006) and uncertainties introduced by the algorithm applied (Baumann *et al.*, 2017; Moreno-Martínez *et al.*, 2020).

Therefore, at spaceborne level, phenology studies were most commonly made using sensors with higher temporal resolution, but with coarser spatial resolution (> 250 m) (see Table 2), such as the AVHRR, MODIS, Satellite Pour l' Observation de la Terre (SPOT, VEGETATION programme) (Miao *et al.*, 2013), Medium Resolution Imaging Spectrometer (MERIS) (Brown *et al.*, 2017) and, more recently, the Visible Infrared Imaging Radiometer Suite (VIIRS) (Zhang *et al.*, 2018b). A more comprehensive description of these satellite missions can be seen in Zeng *et al.* (2020). Although these satellites have a potential daily temporal resolution (the ideal scenario for vegetation phenology studies), in practice the original time series data are frequently composited (e.g. using the maximum-value composite -MVC- (Holben, 1986)) to reduce noise such as overcast conditions (Pouliot *et al.*, 2011). A compositing period is the time interval (e.g. 16 days (Cui *et al.*, 2020)) over which a sample (generally a VI) is selected from an underlying set of observations (Pouliot *et al.*, 2011); see Rodriguez-Galiano *et al.* (2015a) for a list of different composite periods commonly applied to high temporal resolution satellite data. The length of the time series (e.g. 6 months, 10 years) is another important aspect of a satellite data set, as it determines whether intra- and/or interannual phenology dynamics and trends can be assessed (Maignan *et al.*, 2008; Luo *et al.*, 2014; Rodriguez-Galiano *et al.*, 2016; Donnelly *et al.*, 2017; Liu *et al.*, 2017b).

The majority of studies investigating LSP have used time series of optical imagery (Table 2 and Zeng *et al.* (2020)), exploiting the exclusive and well-known spectral characteristics of green healthy leaves over the 400-2600 nm wavelengths, which have low spectral reflectance in the visible and middle-infrared wavelengths and high reflectance in the near-infrared (NIR) wavelengths (Gates, 1970). This behaviour results

in a spectral contrast which makes the basis for many vegetation indices (VI) (see examples in Table 3, but see Zeng *et al.* (2020) for a more comprehensive list). VIs are robust satellite products (Jackson and Huete, 1991) defined as optical measures of canopy "greenness", a composite property of leaf chlorophyll content, green leaf area, canopy cover and structure (Glenn *et al.*, 2008).

Table 3. Example of spectral and colour indices derived from remote sensors often used in vegetation phenology studies. The light-grey highlighted lines are those based on colour bands, whereas the remaining ones are based on spectral bands.

Index	Name	Formula	Author(s)
NDVI	Normalized Difference Vegetation Index	$\frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$	Tucker (1979)
EVI	Enhanced Vegetation Index	$G \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + L}$	Huete <i>et al.</i> (2002)
EVI2	Two-band EVI	$G \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + (6 - 7.5/c) \times \rho_{red} + 1}$	Jiang <i>et al.</i> (2008)
NDWI	Normalized Difference Water Index	$\frac{\rho_{NIR} - \rho_{MIR}}{\rho_{NIR} + \rho_{MIR}}$	Delbart <i>et al.</i> (2005)
ExG	Excess Green Index	$2 * \rho_{green} - (\rho_{blue} + \rho_{red})$	Hufkens <i>et al.</i> (2012)
GCC	Green Chromatic Coordinate	$\frac{G}{G + R + B}$	Sonnentag <i>et al.</i> (2012)
RCC	Red Chromatic Coordinate	$\frac{R}{G + R + B}$	Toomey <i>et al.</i> (2015)

Note: Spectral reflectance in the blue (ρ_{blue}), green (ρ_{green}), red (ρ_{red}), near-infrared (ρ_{NIR}) and middle-infrared (ρ_{MIR}) wavelengths; L = Factor to account for background effects; C_1 and C_2 = Factors to correct for aerosol influences; c = Factor relating the blue and red spectral reflectance; G = Gain factor; R, G and B are digital number (or brightness) values in the red, green and blue channels.

The seasonal life-cycle events of vegetated surfaces have been also investigated with the aid of microwave satellite data (e.g. Dostalova *et al.* (2016), Ruetschi *et al.* (2018)), although to significantly less of an extent than with optical data (at least for forest

phenology detection). Microwave data has the advantage of being less (or not) affected by factors commonly hampering the data acquisition of high quality optical data: darkness, atmospheric composition, clouds, and off-nadir viewing angles (but depending on surface roughness) (Ryan *et al.*, 2012; Lu *et al.*, 2013a). Nevertheless, the two data sources are sensitive to different characteristics of the land surface: microwave remote sensing data are likely to respond to vegetation structure and moisture content (including soil moisture) (Jones *et al.*, 2011; Ryan *et al.*, 2012). For this reason, microwave LSP metrics are usually considered a complement to the optical LSP metrics, potentially providing a more comprehensive assessment of LSP (Jones *et al.*, 2011; Ryan *et al.*, 2012; Ruetschi *et al.*, 2018). The fusion of optical and radar bands is considered a current challenge for remote sensing phenology studies (Bajocco *et al.*, 2019).

3.1 Time series of satellite data for phenology

Time series of satellite-derived VIs (or microwave derived products) can therefore be used to identify seasonal transitions in vegetation activity (see example in Figure 1), where significant changes in VI values over time can potentially be associated with the biophysical/physiological phenomena occurring on the ground (Zhang *et al.*, 2003; Henebry and de Beurs, 2013). Various methods have been developed to estimate timing of key phenological transitions from a time series of VIs (section 5). These methods are used to derive phenometrics, which are defined as occurring on a particular DOY (Zhang *et al.*, 2003). In an annual cycle, the primary phenometric of interest has been the SOS (White *et al.*, 2009; Liang *et al.*, 2011), due to its importance within the context of climate change (Menzel, 2002; Polgar and Primack, 2013) and relationship with key transition dates of carbon and energy seasonal cycles (Toomey *et al.*, 2015). SOS can be defined as a rapid sustained increase in greenness (green-up) after the annual period of photosynthetic senescence, as a result of increases in chlorophyll and leaf area (White *et*

al., 2009; Garrity *et al.*, 2011). The EOS, or end of fall season, is another phenometric with great value for phenology studies as it allows estimation of the growing season length (Garrity *et al.*, 2011; Liu *et al.*, 2015), which can be characterized by a decrease in greenness (relatively slower than SOS) after a period of constant chlorophyll content and leaf area (Garrity *et al.*, 2011; Liu *et al.*, 2015) (Figure 1). For further discussions on the definition of SOS and EOS please see Helman (2018), and for the many other phenometrics that can be derived from a complete annual time series of VI please see Reed *et al.* (1994) and Xie and Wilson (2020).

However, there remains a significant challenge to associate satellite-derived LSP metrics (e.g. Figure 1) with the phenological phases from plant phenology (e.g. Table 1), as these metrics may not necessarily correspond directly to phenological events as observed on ground, but provide indicators of ecosystem dynamics at a specific scale (Reed *et al.*, 1994; Henebry and de Beurs, 2013). This fact can be attributed to the limited capacity of satellite remote sensing data to monitor species-specific phenology, mainly due to the underlying spatial complexity/heterogeneity of the objects which might be present within the resolved scene (White *et al.*, 2009). This complexity is evident in Figure 2, where a 30 x 30 m grid representing the Landsat 8 pixels and a 10 m Sentinel 2 grid are overlain on a UAV-derived orthomosaic. Overall, the fine-grain spatial variability of vegetation phenology is expected to be lost at coarser scales (scale dependency), as clearly shown in Klosterman *et al.* (2018). This problem, however, can be minimized by applying consistent scaling-up approaches, such as the step-wise landscape scaling method proposed by Liang *et al.* (2011).

Figure 2: Example of a 5 cm spatial resolution orthomosaic made of RGB UAV imagery acquired on 27/04/2015 (DOY 117) over a mixed deciduous and evergreen woodland in northeast England. The satellite grids illustrate the spatial heterogeneity of the objects which might be present within a single satellite pixel. The arrow shows the first tree to leaf-out. This mosaic is part of the UAV time series data used by Berra *et al.* (2019).

Another major challenge is to define what degree of certainty is necessary from these LSP metrics in order to allow a consistent monitoring of possible shifts expected to occur due to climate change (Richardson *et al.*, 2012). This is critically important if these metrics are to be used as an indicator of climate change by the public and scientific community (IPCC, 2014). Recent figures for observed phenology shifts are presented in section 4 and the agreements of estimated phenological events from time series of remote sensing data with *in situ* observations are presented in section 6.

4 Observed and expected shifts on plant phenology

Many studies have reported shifts in plant phenology as a likely response to climate change; these are well summarised in the meta-analysis studies of Gill *et al.* (2015) and Fitchett *et al.* (2015). In England, records of tree-leaf out from temperate forests (1772 to 2006) have detected phenological advances of 3-8 days per 1°C increase in temperature (Thompson and Clark, 2008). In Europe, for the period 1971-2000, an

increase of 1°C was reported to cause an overall advancement of 2.5 days in spring phenology and a delay of autumn phenology of 1 day (Menzel *et al.*, 2006). Another recent study in Europe, reported that the start of growing season advanced on average by 0.22 (± 0.55) days year⁻¹ and the length of growing season extended on average by 0.42 (± 0.86) days year⁻¹, during 1999-2013 (Han *et al.*, 2018).

In USA, plant flowering advanced approximately 8 days in the period 1885-2002 (Primack *et al.*, 2004). In Japan, tree phenological observations from 1953 to 2005 revealed that plant phenological events in spring occurred 0-8 days earlier and in autumn 4-5 days later, for each degree Celsius increase in temperature (Ibáñez *et al.*, 2010). Ge *et al.* (2015) found that leaf senescence in trees and woody shrubs was delayed by 1.98 days per decade (1960-2011) across China. In a meta-analysis study in northern hemisphere deciduous trees, Gill *et al.* (2015) found that leaf senescence was delayed by 0.33 ± 3 days year⁻¹ and 1.20 ± 0.17 days °C⁻¹. These studies report therefore that, overall, warming temperatures are related to earlier spring and later autumn phenology. In temperate zones, if trends of rises in air temperature continue to occur over the next decades (Christensen *et al.*, 2007), earlier spring leaf-out (0.7 days per decade) (Lebourgeois *et al.*, 2010) and later senescence (1.4 to 2.3 days per decade) (Vitasse *et al.*, 2011) are predicted to occur, which will lead to consequent longer growing seasons. However, despite this broad pattern observed in mid and high latitudes, not all species are responding similarly (some species having shorter growing season (Piao *et al.*, 2019)), and there is significant variability even within species (Thompson and Clark, 2008; Vitasse *et al.*, 2009; Ibáñez *et al.*, 2010), a fact which can add uncertainties in models forecasting phenology under climate change scenarios. There are also uncertainties coming from the different climate changes scenarios available to feed the models

(Christensen *et al.*, 2007), and uncertainties due to different models (Migliavacca *et al.*, 2012; Richardson *et al.*, 2013a; Xin, 2016).

Therefore, it is important to stress that the expected plant phenology shifts are small, often less than 1 day/decade. Therefore, vegetation phenology monitoring needs to be very precise, or at least consistent and the errors well understood, if it is to usefully track such shifts.

5 Methodologies to derive phenometrics from satellite imagery

The effects of using different methodologies to derive LSP metrics was thoroughly investigated and quantified by White *et al.* (2009) and Atkinson *et al.* (2012), and most recently re-discussed and expanded by Misra *et al.* (2016) and Helman (2018). Here, we provide an overview of the most common methods to detect phenometrics from time-series of remote sensing data; a more comprehensive review can be seen in Zeng *et al.* (2020).

Many approaches have been developed to derive LSP metrics and they usually follow three key steps (Zeng *et al.*, 2020): 1) data cleaning and flagging; 2) data smoothing and time-series data reconstruction, and 3) phenometrics extraction based on the reconstructed time series data. In the first step, the original remote sensing derived products (e.g. VIs or backscatter) have noisy and spurious points filtered out; for example, by applying the MVC method to generate temporally composite data (e.g. MODIS 8-day (Xie and Wilson, 2020)). In the second step, the “cleaned” data set are smoothed and reconstructed to a daily series, most commonly using a curve fitting approach (Zeng *et al.*, 2020), such as Fourier filter (Roerink *et al.*, 2000; Studer *et al.*, 2007), Gaussian filter (Jonsson and Eklundh, 2002), Savitzky-Golay filter (Chen *et al.*, 2004), spline filter (White *et al.*, 2009), polynomial function (Piao *et al.*, 2006), piecewise logistic functions

(Zhang *et al.*, 2003), generalized additive mixed model (GAMM) (Alberton *et al.*, 2019) or machine learning-based algorithms (Belda *et al.*, 2020). Among them, Zhang *et al.* (2003)'s logistic function itself (Figure 1) or its modifications (e.g. Elmore *et al.* (2012)) seems to be the most used, as some studies indicated that logistic-based functions can successfully monitor vegetation phenology from local to regional scales (Zhang *et al.*, 2003; Fisher *et al.*, 2006; Garrity *et al.*, 2011; Zhu *et al.*, 2012; Polgar *et al.*, 2013).

In the third step, phenometrics are derived from the reconstructed daily time series in order to determine the timing of vegetation changes (e.g. SOS). Different methods have been developed for calculating phenological markers from time series of data (Soudani *et al.*, 2008), and the most common may be sorted into two general categories (Zeng *et al.*, 2020): i) threshold-based methods (White *et al.*, 1997; Schwartz *et al.*, 2002; Chen *et al.*, 2004; Delbart *et al.*, 2005; White and Nemani, 2006; Studer *et al.*, 2007; Delbart *et al.*, 2015), and ii) VI change detection methods (Jonsson and Eklundh, 2002; Zhang *et al.*, 2003; Jonsson and Eklundh, 2004; Fisher *et al.*, 2006; Garrity *et al.*, 2011; Klosterman *et al.*, 2018; Berra *et al.*, 2019).

Thresholding methods, despite having been able to detect the general expected seasonal cycles of deciduous vegetated surfaces (Delbart *et al.*, 2005; Studer *et al.*, 2007), need an arbitrary threshold to be defined which in turn may not be applicable to all vegetated surfaces (Zhang *et al.*, 2006). This fact means that they might be not flexible enough to track complex spatio-temporal changes in phenology resulting from wider areas, due to variations in forest types, micro and regional climate regimes, topography, soils and land management (Zhang *et al.*, 2003; Fisher and Mustard, 2007; Bradley and Mustard, 2008). On the other hand, methods based on change detection are more flexible since each pixel will have its own characteristics to track changing phenology (Zhang *et al.*, 2006). This flexibility may justify the preference of the scientific community for

deriving phenological markers using change detection methods in the last 15 years (Fisher *et al.*, 2006; Fisher and Mustard, 2007; Soudani *et al.*, 2008; Richardson *et al.*, 2009; Liang *et al.*, 2011; Hufkens *et al.*, 2012; Polgar *et al.*, 2013; White *et al.*, 2014; Liu *et al.*, 2015; Baumann *et al.*, 2017; Zhang *et al.*, 2018b; Berra *et al.*, 2019).

It has been shown that phenological markers derived from different methods can result in very different dates (Reed *et al.*, 2009; White *et al.*, 2009; Wang *et al.*, 2014; Liu *et al.*, 2016; Misra *et al.*, 2016). In a comprehensive study, White *et al.* (2009) conducted an intercomparison of ten methods to derive SOS from AVHRR NDVI time series across North America and it was found that the relative differences between the individual methods were up to ± 60 days and none of the SOS methods performed uniformly well across the different regions. Similar conclusions were reached by Bradley and Mustard (2008) and Wang *et al.* (2014). New modelling techniques for vegetation phenology, such as GAMM (Alberton *et al.*, 2019), Generalized Additive Model (Kowalski *et al.*, 2020), or machine learning-based (Belda *et al.*, 2020), are promising alternatives to reduce relative errors due to different ecosystems and/or due to model choice.

It has also been shown that LSP monitoring can be also sensitive to the choice of VIs (Reed *et al.*, 2009; White *et al.*, 2009; Garrity *et al.*, 2011; Hufkens *et al.*, 2012; Nagai *et al.*, 2014; Kowalski *et al.*, 2020). While the effectiveness of VIs can vary with environmental conditions, plant functional types and aim of the research, phenological studies have most commonly employed NDVI and EVI (Zhang *et al.*, 2003; Liang *et al.*, 2011; Liu *et al.*, 2015; Bajocco *et al.*, 2019). Generally, EVI (or EVI2) has been shown to be more appropriate than NDVI to track forest phenology (Liang *et al.*, 2011; Klosterman *et al.*, 2014; White *et al.*, 2014; D'Odorico *et al.*, 2015; Baumann *et al.*, 2017; Peng *et al.*, 2017a; Kowalski *et al.*, 2020), which can be due to the EVI ability to remain sensitive to canopy changes at higher Leaf Area Index (LAI) values (Huete *et al.*, 2002;

Reed *et al.*, 2009). However, in some studies, EVI performed worse than NDVI (Hufkens *et al.*, 2012; Balzarolo *et al.*, 2016). Furthermore, mid-infrared based VIs (e.g. NDWI) have shown to be effective in detecting seasonal patterns of vegetation in regions of high snowfall or with seasonal snow cover (Delbart *et al.*, 2005; Delbart *et al.*, 2015; Cao *et al.*, 2020); also, VIs sensitive to water (e.g., land surface water index - LSWI) or less influenced by soil (e.g. optimized SAVI) showed better potential in tracking growing season phenology of evergreen forest ecosystems (Wu *et al.*, 2014). Also, some VIs were developed specifically to improve vegetation phenology, such as the Phenology Index and the Plant Phenology Index (Wang *et al.*, 2018).

Finally, it has also been shown that the best combination of “method + VI” for detecting phenometrics might be sensitive to the season being monitored (Zhao *et al.*, 2012; Klosterman *et al.*, 2014). Therefore, when different study areas are analysed or when different sensors and data sets are employed, different combinations of methods and VIs might need to be tested (sensitivity analysis) in order to assess the most suitable (less uncertain) combination for phenology monitoring (Klosterman *et al.*, 2014; Filippa *et al.*, 2016; Bornez *et al.*, 2020). This can be determined by comparing the derived phenometrics against reference observations, i.e., assessing the phenometrics.

6 Assessing phenological metrics derived from satellite imagery

It has been discussed that the multiple methodologies available to derive LSP phenometrics can give very different results (section 5). Assessing of LSP phenometrics therefore requires a comparison with independent data, typically ground observations of species- or community-specific phenology (Liang *et al.*, 2011; Delbart *et al.*, 2015). Plant phenology observations have been traditionally used for this purpose (Table 2); the method consists of visually assessing the plant canopy development phases, which can

be made on the ground (traditional method) (Liang *et al.*, 2011) and, more recently, manually interpreting phenophases from RGB cameras positioned either over (most common) (Hufkens *et al.*, 2012) or under the canopy (Fisher *et al.*, 2006). However, this approach is not free of uncertainties and some studies have reported differences of up to 7 days among different observers (Schaber, 2002; Klosterman *et al.*, 2014), which is due to the degree of subjectivity involved when visually assessing a canopy (Table 1), but it also depends on the observer experience, chosen protocol and characteristics of the study area. Besides this, it is often difficult to check the quality of those plant phenology observations coming from volunteer citizens interested in nature (Delbart *et al.*, 2015; Mehdipoor *et al.*, 2015; Jorde, 2016), and these may be subject to biases, for example, primarily making observations on weekends (Courter *et al.*, 2013).

Nevertheless, these data are considered very useful given their explicit information on the plant phenological stages (Schwartz *et al.*, 2002; Liu *et al.*, 2015), but might lack landscape representativeness (point observations). On the other hand, satellite imagery has the potential to track phenology patterns over continental scales but might have large uncertainties in detecting phenological events at species and community levels (Fisher and Mustard, 2007; White *et al.*, 2009). In this context, many studies have been devoted efforts to developing approaches to consistently evaluate LSP metrics based on ground observations (Table 2).

LSP metrics have been derived at various scales, ranging from (infrequently) a few dozens of metres (e.g. using Landsat, Fisher *et al.* (2006)), a few hundreds of metres (using MODIS, Liang *et al.* (2011) and the VIRSS, Zhang *et al.* (2018b)), to kilometres (using MODIS, Zhang *et al.* (2003), AVHRR, White *et al.* (2009) and the SPOT's VEGETATION S10, Delbart *et al.* (2015)). At any of these scales, one of the biggest challenges for evaluating LSP metrics is to have ground phenology data which are

representative of the variability in phenology events occurring within the whole pixel area (Delbart *et al.*, 2005; Liang *et al.*, 2011). Over forests, this variability mainly arises from heterogeneity in tree species composition and heterogeneity in timing of phenological events, since phenology events can vary among species (interspecific variations) and within species (intraspecific variations) (Delbart *et al.*, 2005; Fisher *et al.*, 2006; Polgar and Primack, 2011; Peng *et al.*, 2018). Intercomparison studies conducted over more homogeneous deciduous forests, such as taiga in Siberia (Delbart *et al.*, 2005), tundra in low-arctic ecosystem (Delbart and Picard, 2007) and taiga in boreal Eurasia (Delbart *et al.*, 2008), have shown that even a low density of ground plots (in relation to the pixel area) might achieve good agreements. Overall, lower uncertainties in LSP estimates can be achieved when a combination of factors occurs (Delbart *et al.*, 2005): 1) low tree species diversity (but all dominant species have to be representatively sampled (Beck *et al.*, 2007)); 2) high deciduous forest fractional cover (e.g. Klosterman *et al.* (2014)), and 3) observed canopy phenology dates being highly uniform for the different species assessed (e.g. Klosterman *et al.* (2018)).

Ideally, comparing ground phenology observations of trees to LSP-derived phenometrics entails the observed trees being representative of the trees species within the pixel area and observations made at an appropriate frequency (Liang *et al.*, 2011; Delbart *et al.*, 2015). This might be challenging when the following factors are present alone or combined: different land cover types, accentuated slope terrains, high plant species diversity and pronounced heterogeneity in timing of phenological events (Fisher *et al.*, 2006; Polgar and Primack, 2011; Delbart *et al.*, 2015; Streher *et al.*, 2017). Some methods have been suggested to tackle such challenges, which include using medium resolution imagery (Fisher *et al.*, 2006; Melaas *et al.*, 2013; White *et al.*, 2014), cross-comparing results obtained at different spatial resolution (Fisher and Mustard, 2007) and

using ground, near-surface and UAV sensors (Hufkens *et al.*, 2012; Hmimina *et al.*, 2013; Klosterman and Richardson, 2017; Berra *et al.*, 2019). These methods are presented in the following sub-sections, focusing in the degree of agreements of the LSP estimates (presented in Table 2), where advantages and limitations are discussed.

6.1 Using medium spatial resolution imagery: Landsat and Sentinel-2

This section focuses on Landsat studies as: 1) it was, until recently, the satellite data with the finest spatial resolution used in phenology studies, and 2) it is expected to provide long-term continuity in LSP measurements at a 30 m scale (Wulder *et al.*, 2019). The potential of Sentinel-2 is analysed lastly.

The Landsat series has contributed, and continues to contribute, to the understanding of regional scale LSP in many ways. It has been shown that the phenometrics estimated from LSP is highly likely to be different from plant phenology (Garrity *et al.*, 2011; Polgar and Primack, 2011; Henebry and de Beurs, 2013). This satellite series has helped to spatially quantify the dependency of vegetation phenology to elevation and latitude (Fisher *et al.*, 2006; Vitasse *et al.*, 2009; Klosterman *et al.*, 2014; White *et al.*, 2014). The Landsat series has also contributed to understanding of variability in phenology within coarser spatial resolution sensors, such as MODIS (Fisher and Mustard, 2007; Liu *et al.*, 2017c) and VIRSS (Liu *et al.*, 2017c; Zhang *et al.*, 2017; Zhang *et al.*, 2018b). Furthermore, the unique value of Landsat historical data keeps motivating the development of new approaches to enhance its temporal resolution (e.g. Moreno-Martínez *et al.* (2020)).

Despite the challenge of having cloud-free Landsat data in temperate and boreal regions (Fisher *et al.*, 2006; White *et al.*, 2014; Berra *et al.*, 2019), some studies were able to acquire relatively consistent time series of Landsat data and reported the agreements in phenometrics estimates. *In-situ* spring leaf-onset dates were compared to Landsat-

derived spring metrics, yielding a strong relationship ($R^2 = 0.91$) across homogenous stands of deciduous forests (Fisher *et al.*, 2006). White *et al.* (2014) achieved a MAE of 11 and 7 days when comparing Landsat EVI-derived SOS to full leaf out date of heterogeneous and homogeneous stands, respectively. Melaas *et al.* (2016a) compared multi-year SOS and EOS dates from Landsat with corresponding dates estimated from phenocam imagery and found a strong correlation with SOS ($R^2 = 0.86$; RMSE = 5 days) but a weak correlation with EOS ($R^2 = 0.25$; RMSE = 10 days). More recently, Berra *et al.* (2019) achieved an RMSE = 12 days when comparing UAV-derived SOS against Landsat-derived SOS across a deciduous woodland. Overall, the above studies suggest that even at Landsat 30 m spatial resolution, mixed composition is still an issue (as illustrated in Figure 2) and that the Landsat's 16-day repeat period impose limitations in acquiring dense time series. There is an opportunity here to investigate whether the improved spatial (10–60 m) and temporal (~5 day) resolution of the Sentinel-2 mission would diminish these problems.

In fact, time series data from the two Sentinel-2 satellites (A and B) have shown potential in some initial phenology studies (Lange *et al.*, 2017; Jonsson *et al.*, 2018; Vrieling *et al.*, 2018). Lange *et al.* (2017) tested the Sentinel-2 10 m data to monitor LSP across a deciduous forest; Vrieling *et al.* (2018) observed that the variability in Sentinel-2 (10 m) derived SOS was well-explained by field camera GCC-based SOS ($R^2=0.74$, MAE=8.0 days) across salt marches. Overall, it is evident that the finer spatial resolution scale of Sentinel-2 can reduce the effect of uncertainty coming from different tree (or other plant) species within a grid cell, as compared to coarser satellite series like MODIS and even Landsat 30 m (see a comparison example of Landsat 8 and Sentinel-2 grids in Figure 2). However, large data gaps in the Sentinel-2 series can still occur due to frequent cloud-cover (Lange *et al.*, 2017; Kowalski *et al.*, 2020), hampering a precise phenometric

estimation. Combining or harmonizing Sentinel-2 with Landsat 8 may largely resolve this constraint (Li and Roy, 2017; Pastick *et al.*, 2018).

Harmonized time series of Landsat and Sentinel-2 (HLS) observations itself (Claverie *et al.*, 2018; Zhou *et al.*, 2019), or the fusion of HLS with coarser resolution satellite sensors (e.g. with VIRSS (Zhang *et al.*, 2020)), has been opening the way for operational monitoring of LSP at 30-meter spatial resolution (Bolton *et al.*, 2020; Pastick *et al.*, 2020). Bolton *et al.* (2020) found that the relationship between SOS dates derived from HLS and those derived from phenocams was strongest for deciduous broadleaf ($R^2 = 0.90$, RMSE = 6.3 days) and weakest for evergreen needleleaf ($R^2 = 0.15$, RMSE = 21.9 days) sites. Kowalski *et al.* (2020) evaluated the HLS-based SOS estimates against *in-situ* plant phenology dates of broadleaf tree species in Germany and found RMSE < 8 days; they also noted that phenometric estimates from either Landsat 8 or Sentinel-2 alone generally increase uncertainties. Overall, these two studies show that a consistent estimation of LSP at a 30 m scale is now feasible with combined Landsat and Sentinel-2 time series.

6.2 Ground and near-surface remote sensing of phenology

Ground and near-surface sensors have been increasingly used, over the past decade, to collect data for satellite-derived LSP assessment purposes in place of or in complement to traditional plant phenology observation (as it is evident in Table 2). Imaging and radiometric sensors are used to automatically collect very high temporal resolution of phenological time series (daily or sub-daily), providing species-specific and/or ground LSP observations (Hmimina *et al.*, 2013; Klosterman *et al.*, 2014; Brown *et al.*, 2016).

Consumer-grade cameras are usually employed as imaging sensors and the aim is to monitor changes in canopy colour associated with the different plant development

stages (Moore *et al.*, 2016) and/or photosynthetic activity (Toomey *et al.*, 2015). A variety of colour indices can potentially be formulated from the RGB DN values (please see Mizunuma *et al.* (2014)), including the commonly used GCC (Table 3).

Because a quantitative time series of data is generated, the series can be processed similarly to satellite time series (e.g., as in Figure 1), i.e., phenometrics can be automatically calculated (Filippa *et al.*, 2016), allowing a more direct comparison (in relation to visual assessments) with orbital-derived phenology (Hufkens *et al.*, 2012). In this section, some examples of ground and near-surface remote sensing data are presented in more detail, with comparisons with visual assessments presented first, followed by comparisons with satellite measurements.

Some studies quantified the uncertainties of phenodates derived from ground and near-surface remote sensing data against visual observations of tree canopy phenology. Ryu *et al.* (2012) found a mean bias of 5 days and RMSE of 5.4 days for SOS and a mean bias of 2 days and RMSE of 4.8 days EOS, using time series data from upward viewing cameras. Zhao *et al.* (2012) fitted daily colour indices from phenocams to estimate SOS, SOF and EOS dates; they found differences between observed and estimated phenological dates ranging from -4 to 1 days. A similar MAE for SOS (4 days) was found by Bater *et al.* (2011), who also derived phenometrics from phenocams. Klosterman *et al.* (2014) found higher uncertainties between near-surface remote sensing-derived phenometrics and visual assessments (RMSE = 7 days for SOS and RMSE = 22 days for SOF). Overall, because the visual assessments contain uncertainties due to both inter-observer and intra-observer error (Schaber, 2002; Klosterman *et al.*, 2014; Morrison, 2016), ground and near-surface estimates are expected to have higher precision (or at least higher consistency) than the comparisons with visually assessed dates. This is mainly because ground and near-surface remote sensing observations are usually

acquired at a much higher frequency than the human visual assessments (Klosterman *et al.*, 2014).

Several studies took advantage of the species-specific monitoring capacity and the daily/sub-daily temporal resolution of ground and near-surface remote sensing observations for evaluating satellite LSP, results which are summarized in Table 2. Hufkens *et al.* (2012) cross-compared various spring and autumn phenological metrics derived from phenocam and MODIS observations and found MAEs ranging from 3 to 67 days, depending upon the MODIS data, metric and site analysed. Similarly, Klosterman *et al.* (2014) compared MODIS- and phenocam-derived metrics and found various degrees of correspondence (dependent on “method + VI”), ranging from 7 to 18 days (RMSE) for SOS and ranging from 14 to 28 days (RMSE) for SOF. In a multi-year analysis, Baumann *et al.* (2017) observed the phenodates of growing season being estimated consistently later by the orbital sensors, in comparison to phenocam (Landsat up to 12 days and MODIS up to 18 days later). Comparing phenocam- and MODIS-derived phenological transition dates, Richardson *et al.* (2018) found bias values of 8-23 days for spring and 8-29 days for autumn metrics, across all vegetation types; for deciduous broadleaf, RMSE=17 days for spring and RMSE=22 days for autumn. Therefore, these studies suggest that near-surface sensors have great potential to be used as reference data for satellite estimates; however, such approaches have a number of common limitations.

Firstly, dependent upon the sensor location, only a small area and reduced number of trees can be observed per sensor (Ryu *et al.*, 2012; Zhao *et al.*, 2012), which is a constraint in obtaining a conclusive estimate of the phenology of some species. Moreover, this constrains the ability to compare the results with satellite data as satellite sensors' pixel area is generally much larger than the area viewed by these *in situ* sensors (Hufkens

et al., 2012; Richardson *et al.*, 2013b; Klosterman *et al.*, 2014); Secondly, issues of calibration and long-term stability of the imaging sensors are not yet fully addressed (Henebry and de Beurs, 2013; Keenan *et al.*, 2014), raising questions about how to use such data for intercomparison purposes and how to compare data between different cameras and different sites; Thirdly, cameras above the canopy are usually inclined at a fixed position (e.g. 45°), meaning that phenocams and satellite may have very different zenith angles when acquiring images; additionally, this oblique angle can impact on data quality as more distant targets will have weaker signals and stronger atmospheric influence (Richardson *et al.*, 2009) and the effective LAI incorporated within a phenocam's field of view can be greater than for the same sensor mounted at a nadir position (Brown *et al.*, 2017). Finally, at sites characterised by medium to high satellite VIs, phenocam-derived VIs can saturate asymptotically when compared with satellite-derived VIs, as phenocams usually do not incorporate near-infrared wavelengths, resulting in a lower sensitivity to LAI increments than satellite VIs (Brown *et al.*, 2017).

Some of these challenges have been addressed or are subject of on-going research. Calibration issues are minimized by using a same camera model in as many sites as possible, and by adopting standard protocols for data acquisition (Brown *et al.*, 2016) and processing (Hufkens *et al.*, 2018). An expansion phenocam networks worldwide allows broad geographic areas and different biomes to be represented (Toomey *et al.*, 2015; Filippa *et al.*, 2016), with efforts being made towards a global phenocam network (Brown *et al.*, 2016). As an example, the Phenocam network (Richardson *et al.*, 2007) monitors hundreds of sites (mainly in North America); but there are a few more networks fully operational in Europe, Asia and Australia (Moore *et al.*, 2016) and Brazil (Alberton *et al.*, 2017; Alberton *et al.*, 2019). Besides this, studies have being investigating the potential of using traffic and security cameras as phenocams (Morris *et al.*, 2013;

Bothmann *et al.*, 2017), which could increase dramatically the number of sampling locations and diminish installation costs. Furthermore, additional instrumentation is usually available (e.g., meteorological stations), which can supply with extra ground-truth data (Moore *et al.*, 2016), which in turn could: 1) feed models such as the Quadratic, which requires the calculation of the accumulated growing degree-days (White *et al.*, 2009); and 2) enable comparisons with meteorological data (Bradley *et al.*, 2010). Overall, the association of long-term phenocam data with such instrumentation (including flux towers – section 6.3) allows a wide range of studies, especially linking phenological patterns to climatic drivers and the impact of climate changes on plant responses (Alberton *et al.*, 2017).

6.2.1 Spectral radiometers

Although less common, near-surface remote sensing of phenology has also used methods based on spectral radiometers (Jenkins *et al.*, 2007; Eklundh *et al.*, 2011; Hmimina *et al.*, 2013; Nagai *et al.*, 2015; Liu *et al.*, 2019). Sensors are usually installed on towers, at a height well above the canopy and inclined towards the target of interest (Eklundh *et al.*, 2011) (but see Roy *et al.* (2020) for an example of below the canopy radiometer). The reflected radiance of the viewed surface is measured at a high temporal frequency, allowing dense time series of spectral reflectance and VIs to be calculated and used to track vegetation phenology (Hilker *et al.*, 2011; Nagai *et al.*, 2015). Hmimina *et al.* (2013), for example, intercompared MODIS/NDVI phenometrics against *in situ* NDVI-derived phenometrics; the agreements ranged from $3 \leq \text{RMSE} \leq 10.5$ days for spring metrics and $6 \leq \text{RMSE} \leq 22$ days for autumn metrics. EOS derived from near-surface radiometer and MODIS time series VIs presented various degrees of correspondence, dependent on “method + VI” ($0.38 \leq R^2 \leq 0.67$; $3 \leq \text{MAE} \leq 7$ days), across a Chinese temperate deciduous forest (Liu *et al.*, 2019).

The drawback of using non-imaging sensors or not using traditional visual assessment as reference data (Garrity *et al.*, 2011; Soudani *et al.*, 2012; Hmimina *et al.*, 2013) is that it might be difficult to be conclusive about which phenological phase the data actually represent. It can also be problematic because the footprint of the spectroradiometer is often much smaller than that of orbital sensors (Nagai *et al.*, 2014; Nagai *et al.*, 2015), although Hmimina *et al.* (2013) achieved a representativeness of around 90% of the forest within a MODIS pixel; this problem could be significantly diminished with the improved spatial resolution of the Sentinel-2 data (another research opportunity). On the other hand, high temporal resolution data (sub-daily) can be acquired (Nagai *et al.*, 2014) and the resulting measurements are analogous to quantities measured by satellites (Richardson *et al.*, 2013b), allowing tracking of the seasonal dynamics of the ecosystem in a manner similar to satellite sensors (Hmimina *et al.*, 2013), if the *in situ* sensor is representative of the area within the pixel. Another advantage is that *in situ* radiometers can detect the relatively weak seasonal signal of evergreen forests (Hmimina *et al.*, 2013) and, a combination of one radiometer above and another on the ground surface below the canopy could disentangle the contributions of overstory canopy (Roy *et al.*, 2020).

6.3 Carbon dynamics of vegetated surfaces

Carbon fluxes of vegetated surfaces can be estimated by eddy covariance instrumentation (Wu *et al.*, 2017; Donnelly *et al.*, 2019). Once the carbon balance of an ecosystem is calculated, it is possible to characterize whether this system is acting as a sink or source of carbon over time (Wilkinson *et al.*, 2012; Mizunuma *et al.*, 2013). Because phenocam are usually co-located at these instrumentation sites, the seasonal cycles of canopy photosynthesis (carbon fluxes) can be investigated in terms of camera-

derived canopy developments (Toomey *et al.*, 2015). Ultimately, carbon seasonality can be used to understand satellite LSP metrics in terms of physiological processes (Wu *et al.*, 2017), which remains a challenge (Fitchett *et al.*, 2015; Donnelly *et al.*, 2019). In fact, Bajocco *et al.* (2019)'s bibliometric survey found that terms related to carbon dynamics (ecosystem respiration, net ecosystem exchange, carbon uptake and eddy covariance) were among the 10 most relevant search terms in 2009–2018 in the remote sensing of phenology field.

Moderate to strong correlations between phenocam colour indices and canopy photosynthesis were found across a variety of plant functional types (Richardson *et al.*, 2007; Richardson *et al.*, 2009; Mizunuma *et al.*, 2013; Toomey *et al.*, 2015). For example, canopy greenness was effective in estimating the beginning and middle of the photosynthetically active period in deciduous forests ($0.62 \leq R^2 \leq 0.82$), whilst canopy redness was a better indicator of the end of the photosynthetically active period ($R^2=0.69$) (Toomey *et al.*, 2015). However, relationships generally weakened when ecosystem productivity was compared to satellite-derived LSP (Table 2).

Garritty *et al.* (2011) found that no single source of MODIS derived product was able to adequately characterize the annual seasonality of canopy photosynthesis, but one or more data set was significantly correlated with a specific carbon transition date; for SOS, MODIS LAI 5 km returned $R^2=0.76$ (MAE = 19 days) and for EOS, MODIS EVI achieved $R^2=0.76$ (MAE=39 days). Mizunuma *et al.* (2013) investigated the seasonal relationships between GPP and MODIS NDVI values in a deciduous forest in south England and found only moderate correlations ($0.36 \leq R^2 \leq 0.48$). Wu *et al.* (2017) related SOS and EOS from GPP and from orbital NDVI (MODIS and SPOT VEGETATION) totalling 376 site-years across the north hemisphere and found even lower correlations ($R^2 < 0.30$), with RMSE > 30 days. Overall, it seems that orbital VIs, alone, have difficulty

in explaining the seasonal variability of GPP at regional to global scales (Wu *et al.*, 2017; Wang *et al.*, 2018; Donnelly *et al.*, 2019). Donnelly *et al.* (2019) highlight the need for *in-situ* studies of different forest layers to explain satellite flux phenology discrepancies. Also, satellite-derived sun-induced fluorescence (SIF) has shown great potential of providing retrievals that are more related to photosynthesis processes (Walther *et al.*, 2016; Lu *et al.*, 2018), particularly in evergreen forest ecosystem where optical satellite observations might be limited to monitor changes (Wang *et al.*, 2018).

6.4 UAV for forest phenology

The use of UAVs represents a novel way to monitor plant phenology and/or LSP, at an intermediate level of observation between ground/near-surface and orbital scales (e.g. Figure 2), in a synoptic and georeferenced fashion (Berra *et al.*, 2019; D'Odorico *et al.*, 2020). Contrary to field surveys which have to sample a population due to time and costs constraints, UAVs offer the chance to individually measure all the dominant trees within a small area (Nogueira *et al.*, 2019; Berra, 2020). This can provide a comprehensive insight into how the ecosystem is functioning, at multiple scales (Klosterman *et al.*, 2018).

A series of potential advantages was brought by this technology, including user-defined temporal and spatial resolution, high-intensity data collection and flexibility regarding the kind of sensor on-board. UAVs can also be particularly helpful for surveying optical time-series data in regions that experience frequent cloud cover, such as Great Britain (Armitage *et al.*, 2013). Additionally, the more frequent data acquisition that is possible with UAVs favours a better modelling of canopy development (Berra *et al.*, 2016). Summed, these characteristics make UAV time series data very attractive for assessing satellite LSP metrics.

After investigating the quality and potential of UAV sensors to acquire consistent time series data across forests (Dandois and Ellis, 2013; Berra *et al.*, 2017), a few studies have derived phenometrics from UAV data. Klosterman and Richardson (2017) achieved an RMSD=4.7 days in the individual tree-level monitoring of UAV SOS, when intercomparing against ground visual observations of deciduous plots. In a subsequent study, Klosterman *et al.* (2018) used times series of UAV colour indices to track the seasonality of a mixed forest at a community level (10 x 10 m grid), and found UAV SOS differing by up to 10 days from both visual observations and phenocam observations of dominant deciduous species; however, the averaged UAV- and MODIS-derived SOS were in close agreement (MAE<3 days), likely because all communities reached SOS around the same time (SD = 4 days). More recently, Berra *et al.* (2019) found an RMSE=8 days between UAV SOS and visual observations of spring phenology, at an individual tree-level across mixed deciduous plots.

Although UAVs can allow a detailed, species-specific analysis of spatial and temporal patterns across the landscape, this is only feasible at a local scale. This can make it challenging to survey a forested area covering more than one pixel from moderate/low spatial resolution satellite data (>250 m), resulting in representativeness issues. Additionally, having several and continuous UAV acquisitions is still a major challenge due to the need of trained personnel in the field, non-optimal weather conditions and restricted air zones. These factors constrain analysis to either a single growing season (e.g. Berra *et al.* (2019)) or a single year (e.g. Klosterman *et al.* (2018)). Nevertheless, with the continuous technological advances expected in the UAV sector (e.g. robotic autonomous UAV systems (Lygouras *et al.*, 2018)), acquiring longer and good quality time series UAV data might be feasible in the near future.

7 LSP with microwave satellite data

Some studies have used low spatial resolution microwave satellite data to monitor vegetation seasonality at continental scales. Time series of backscatter measurements (~25 km) and MODIS LAI were compared by Froking *et al.* (2006) resulting in good agreements (generally $R^2 > 0.5$) but the SeaWinds series detected SOS earlier than MODIS LAI, mirroring results of Ryan *et al.* (2012) and Lu *et al.* (2013b) (using the same sensor but across China). Jones *et al.* (2011) found significant lags between phenometrics derived from satellite passive microwave remote sensing data (~25 km) and MODIS VIs, reflecting the large phase shift in the phenology curves detected from the different sensors.

A few studies have tested the potential of multi-temporal synthetic aperture radar (SAR) data for forest phenology monitoring. Distinctive seasonal backscatter patterns were observed across temperate deciduous forests with time series of Sentinel-1 SAR data (Dostalova *et al.*, 2016; Frison *et al.*, 2018; Ruetschi *et al.*, 2018). Radar backscattering and Landsat-8 time series were well correlated ($r = 0.77$) over stands of deciduous trees in France (Frison *et al.*, 2018). Ruetschi *et al.* (2018) observed differences between the Sentinel-1 SAR phenometrics and ground observations of <12 days, but no consistent bias was observed in between the two years analysed across mixed temperate forests in Switzerland. Overall, there seems to have a weak dependency of the backscatter on foliage (Proisy *et al.*, 2000; Ruetschi *et al.*, 2018), a fact which might represent a major challenge to conciliate SAR and optical VIs phenology (agreeing with Stendardi *et al.* (2019), but over a meadow ecosystem).

8 Future of quantifying forest phenology

An integrated framework comprising multi-scale, multi-discipline, multi-sensor and multi-site seems to be the likely future approach for quantifying and better

understanding the phenology of the land surface at different spatiotemporal scales (Piao *et al.*, 2019). This will be necessary in order to take advantage of the ever-increasing number of new data sets (“big data”) and techniques available to observe phenology. Linking different datasets and developing innovative technologies are key to broadening our understanding of vegetation dynamics (Bater *et al.*, 2011; Brown *et al.*, 2016; Wu *et al.*, 2017), particularly in process-based phenology modelling (Tang *et al.*, 2016).

The use of new sensors at a ground, near-surface and UAV level will bring new opportunities to assess and understand satellite LSP but also new challenges in the next decade. Multichannel, hyperspectral, gigapixel and LiDAR sensors are likely to be popularized as long as technological advances permit miniaturization and lower costs of these sensors. Multispectral and hyperspectral sensors with a broader range of wavelengths (visible to middle-infrared) (Yamamoto *et al.*, 2016) would allow analysis to move beyond solely visible and NIR wavelengths, incorporating a wider range of vegetation indices (optimal wavelengths could be selected). Hyperspectral sensors could provide insights into seasonal dynamics of specific biochemical attributes of vegetation (e.g., leaf water and pigment content) (Gholizadeh *et al.*, 2016) and seasonal variations of photosynthesis (Garzonio *et al.*, 2017). Time series of LiDAR data (Sankey *et al.*, 2017; Davidson *et al.*, 2019) could better characterize the seasonal development of canopy structure (e.g. LAI or plant area index (PAI)) and provide new insights into microwave satellite phenology products. Therefore, such leaf properties-related data (biochemistry and structure) can track the seasonality of plant physiology and offer an opportunity to better understand (Keenan *et al.*, 2014; Yang *et al.*, 2014): 1) the physiological meaning of VI-derived phenological metrics; and, 2) the relationships between seasonal patterns of canopy colour/spectral properties and changes in biophysical/biochemical properties. Future phenological research should seek a better

understanding of the physiological mechanisms behind the biological expression of plant phenology (Fitchett *et al.*, 2015; Tang *et al.*, 2016).

At spaceborne level, a synergy of a multi-sensor (optical and/or microwave) approaches are likely to be more routinely used in order to take advantage of the strengths of distinct image data for improvement of forest phenology monitoring. For example, combining Sentinel-1 and the RADARSAT Constellation Mission may offer an unprecedented temporal resolution of SAR observations (Canisius *et al.*, 2017; Steele-Dunne *et al.*, 2017), data sets which can open new opportunities for a better understanding of SAR-observed phenology over forested areas (Frison *et al.*, 2018). The fusion (Wang *et al.*, 2017b) and harmonization (Claverie *et al.*, 2018; Nguyen *et al.*, 2020) of Landsat 8 with Sentinel-2 imagery, or the fusion of Landsat with coarser resolution imagery (e.g. MODIS (Moreno-Martínez *et al.*, 2020)), is expected to improve LSP characterization at medium spatial resolution scales (10-30 m), as the likelihood of obtaining a dense time series at these scales will increase. Also, small satellite constellation (e.g. PlanetScope's CubeSats) acquiring daily global imaging at ~3 m spatial resolution (Houborg and McCabe, 2018) could provide an opportunity for better understanding vegetation phenology at species-specific level and/or support scaling approaches (e.g. Liang *et al.* (2011)). The greatest advancement in terms of synergetic use of multiple orbital sensors may be the fusion of radar and optical images (Kulkarni and Rege, 2020), potentially providing consistent time series data at a wider range of wavelengths.

Recently, researchers started exploring the potential of social media (crowdsourced) data to observe vegetation phenology. Silva *et al.* (2018) derived time series of greenness indices from images posted to Twitter across eight national parks and observed that such indices were able to track the broad seasonal cycles in most of the sites; the twitter greenness had a moderate correlation with MODIS NDVI ($r=0.62$).

Wilson *et al.* (2017) found that flower phenology estimated from images posted to Flickr was largely consistent with observations from professional scientists in a national park. These are encouraging results, which should motivate continued research with such datasets.

The continuous acquisition of ground, near-surface and/or UAV measurements will be essential for evaluation and calibration of satellite-derived LSP. This will be critical as the number of innovative instruments, new technological resources and novel methodologies increase, allowing for more complex and new questions to be formulated.

9 Conclusion

Evaluation of satellite-derived LSP is still one of the most critical and challenging tasks (Zhang *et al.*, 2018b; Liu *et al.*, 2019), partly due to challenges related to scalability, consistency and representativeness of *in situ* observations (Kowalski *et al.*, 2020). For this reason, many studies have devoted efforts in intercomparing/linking satellite LSP metrics with *in situ* observations of vegetation phenology to improving understanding of vegetation phenology at various spatial and ecological scales.

Table 2 summarizes intercomparison results from 56 studies across temperate and boreal forests, in the period 2005-2020. This survey reveals that the timing of satellite-derived LSP events can be detected, in the best-case scenarios, with a certainty of around half-week for spring metrics and around one week for autumn metrics (e.g. Xie and Wilson (2020)). MODIS was by far the most used satellite data (43 studies), followed by Landsat (8). Despite the increasing use of phenocams (15 studies), traditional visual observations of plant phenology were the most used *in-situ* data (33) for LSP assessment purposes. Also, 12 out these 33 studies included data collected by citizens.

Although volunteered observations of plant phenology can provide a large volume of observations across diverse ecosystems (high representativeness), there still exists an enormous challenge in quantifying its uncertainties. On the other hand, ground and near-surface phenological networks are providing more consistent time series of data, allowing more objective and similar comparisons with spaceborne measures (e.g. Bolton *et al.* (2020)). Furthermore, new methodological approaches have been continuously developed to both decrease uncertainties of the processed data and advance understanding of plant phenology (e.g. machine learning fitting algorithms (Belda *et al.*, 2020)).

While the observed and expected shifts in plant phenology average less than one day per decade (section 4), the uncertainty observed from satellite LSP is usually much higher than these figures, as summarized in Table 2. This indicates that satellite LSP monitoring still has limitations regarding the accurate monitoring of phenology shifts, at least in terms of specific plant species (Helman, 2018), and it is even more challenging in heterogeneous forests (Zhang *et al.*, 2017).

A current trend is integrating multiple (big) data to monitor LSP with enhanced spatio-temporal resolutions. Combining or harmonizing large data volume from different satellite sensors (specially from medium spatial resolution) has becoming feasible with cloud computing structures, such as Google Earth Engine (e.g. Moreno-Martínez *et al.* (2020), Nguyen *et al.* (2020)), or specialized data cubes software (e.g. Frantz (2019)). Additionally, machine learning fitting algorithms are improving performance of gap-filling of time series and vegetation phenology trends detection (e.g. Belda *et al.* (2020)). Nevertheless, while combining such approaches has the potential to improve the precision of phenometric estimations, the complexity of the used algorithms tends to increase. Critically, a rigorous assessment of LSP products against *in situ* data is necessary before applying these algorithms operationally. Continued efforts are necessary to maintain and

acquire new *in situ* observations which are, preferably, representative of the landscape sampled in a single satellite pixel.

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