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# Exploring the discrepancies between ground- and satellite-based autumn phenology: a comparative analysis in European beech forests

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## ABSTRACT

Autumn phenology, related to leaf senescence processes, remains a neglected aspect in the study of climate change impacts in deciduous forests. Conventional field monitoring and remote sensing technologies have advanced our understanding of autumn phenological dynamics. However, integrating both approaches may lead to a spatial and temporal mismatch related to different observational scales, introducing uncertainties in the interpretation of satellite-derived phenology. To obtain a comprehensive view of the autumn phenology, this study explored the environmental significance of the mismatch between ground and satellite data, with the following objectives: (i) to quantify the temporal discrepancy between phenology from ground observations (Pan European Phenology database) and satellite-derived time series based on the Moderate Resolution Imaging Spectroradiometer (MODIS) Enhanced Vegetation Index (EVI) in European beech forests; (ii) to assess the influence of environmental factors (temperature, precipitation, latitude, elevation) on the mismatch. Ground observations were matched with autumn phenological metrics extracted from EVI temporal profiles in the period 2003–2015. Statistical comparisons and redundancy analysis were then used to assess their temporal discrepancies and explore environmental influences. The results identified two distinct leaf senescence phases, occurring in the mid-early and the mid-late portions of the autumn phenology. Environmental factors influenced mismatch with temperature and precipitation associated with the mid-late and mid-early portions, respectively. Overall, the observed discrepancies reflect different phenomena characterizing autumn phenology during senescence, each shaped by different environmental factors. Ground observations capture specific moments in leaf senescence, while satellite metrics reflect broader canopy-level dynamics. This study highlights the complexity of autumn phenology and the

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potential for proper integrating and interpretation of remote sensing and ground observations to improve monitoring of deciduous forests in the context of climate change.

## 1. Introduction

Vegetation phenology is regulated by a complex interaction between climatic and environmental factors (Dronova and Taddeo 2022) and its monitoring has become crucial to study actual changes and impacts on forest ecosystems (Ricotta and Bajocco 2023). In particular, autumn phenology (AP) has a significant impact on the extension of the growing season compared to spring phenology (Garonna et al. 2014), thus influencing primary production and consequent changes in net ecosystem productivity (Wu et al. 2013), and causing cascading implications on woody biomass growth rates and annual carbon uptake (Hufkens et al. 2016; Keenan et al. 2014). For temperate deciduous tree species, leaf fall occurs to minimize winter physiological activity, as well as to reduce the surface area for evapotranspiration, and avoid frost damage to leaves. Senescence processes in AP are mainly induced by the contraction of temperature and photoperiod (Körner and Basler 2010) and by their mutual interactions (Heide and Prestrud 2005), thus showing a general spatiotemporal variation along an altitudinal and latitudinal gradient (Gill et al. 2015). As a consequence, AP has remained mostly underexplored due to the large spatiotemporal variability of the senescence period (Gallinat, Primack, and Wagner 2015), i.e. leaf colouring and falling stages (Nagai, Saitoh, and Miura 2020; Tao et al. 2018).

Ground-based observation of phenological events are commonly used in time and there are several long-term phenological networks in Europe, such as the Pan European Phenology Network (Templ et al. 2018; van Vliet et al. 2003). They precisely capture temporal milestones of vegetation phenological shifts with a detail of plant scale, with relatively simplicity of execution (McDonough MacKenzie, Gallinat, and Zipf 2020). However, they have significant limitations related mainly to the localized site-level scale of observations, as well as the nature of the data susceptible to subjective biases and the cost of acquisition (Bajocco, Raparelli, et al. 2019; Ferrara, Chianucci, and Bajocco 2023). Remote sensing technologies allow to overcome these limitations and detect seasonal variation of forest canopy on a large spatiotemporal scale (Bajocco, Ferrara, et al. 2019; L. Zeng et al. 2020). Temporal profiles of satellite-derived vegetation indices (VIs), notably the Normalised Difference Vegetation Index (NDVI; Rouse et al. 1974) and the Enhanced Vegetation Index (EVI; Huete et al. 2002), are commonly used as proxies to highlight changes in the spectral response of the photosynthetically active biomass during the growing season (Huete et al. 2014). The EVI has well-documented advantages in forest phenological studies than the NDVI (Gong et al. 2024), since it was designed to optimize the vegetation signal and enhance sensitivity for vegetation monitoring by effectively decoupling the canopy background signal (L. Zeng et al. 2020; X. Zhang et al. 2003). The core process of autumn phenology is leaf fall, which progressively exposes the forest soil and litter. The NDVI is known to be sensitive to the brightness of the soil background. EVI was specifically designed with a soil-adjustment factor and the inclusion of the blue band to minimize these background effects, thus providing a clearer signal of the actual

vegetation state (Broich et al. 2015; Buras, Rammig, and Zang 2020; Zhao, Donnelly, and Schwartz 2020). Furthermore, deciduous forests, like the European beech, often feature dense canopies prior to senescence. NDVI is well-known to ‘saturate’ in high biomass conditions, meaning it reaches a maximum value and becomes insensitive to further changes in leaf area or chlorophyll content. EVI is less prone to saturation (Gao et al. 2000; C. Wang et al. 2017). This allows it to more sensitively track the subtle, gradual decline in photosynthetic activity that marks the beginning of the senescence period, which might be missed by a saturated NDVI signal.

As a result, the annual pattern of vegetated areas can be characterized by satellite time series of VIs and key phenological moments can be detected, i.e. satellite-based phenological metrics (De Beurs and Henebry 2010). Metrics extraction is based on changes in the shape of the curves, which reflects specific timing and amplitude of the VI during the annual phenological cycle (Dronova and Taddeo 2022). There are various methods to derive AP metrics from VI temporal profile, which can be broadly categorized into two main approaches for phenological monitoring of forest vegetation (Gong et al. 2024). Some works refers to threshold methods by assuming that a phenological stage begins when VI values in the temporal profile reach a specific index (Delbart et al. 2005; M. A. White, Thornton, and Running 1997). They are subjective, noise-sensitive, and influenced by outliers, making them unstable over time and dependent on minimum and maximum VI values (L. Zeng et al. 2020). Other works used the change detection methods, which depend on the assumption that phenological phases correspond to rapid changes in VI values in time series (Tateishi and Ebata 2004). They are widely used and effective, but work best with distinct VI profiles, i.e. they can fail when changes in spring greenup or autumn senescence are gradual rather than abrupt (Tian et al. 2021; K. White, Pontius, and Schaberg 2014).

However, spatial and temporal gaps (mismatch) usually emerge between satellite-derived and ground observations (Jorge et al. 2021). The problem is related to the coarse spatial resolution of the satellite sensors generally used for the detection of phenological events at large scale (Chianucci et al. 2020), which, in many cases, leads to situations of mixed species composition or multi-canopy layer (Fu et al. 2014) at pixel level (Helman 2018). The mismatch is intensified by the increasing diversity in species composition and their varying sensitivity to climatic variations that contribute to the overall signal emitted within the same pixel (X. Zhang et al. 2017). Furthermore, the complexity in the stand structure plays an important role in relation to the influence of the understory phenology on the overstory signal (Ahl et al. 2006). In addition, raw satellite data are usually affected by perturbations or lacunae related to sensor and platform characteristics, acquisition noise and atmospheric interference (Ahl et al. 2006; Gong et al. 2024). As consequence, the VI annual profiles need to be pre-processed to enhance data continuity and smoothness, potentially affecting and contaminating the phenological metrics extraction, and the mismatch (L. Zeng et al. 2020). Curve fitting methods, notably the Savitzky-Golay filter and double logistic functions, are widely common in the literature (Gong et al. 2024; L. Zeng et al. 2020). Generally, as reported by (Cai et al. 2017; J. Chen et al. 2004) Savitzky-Golay filter is considered more accurate and conservative in reconstructing VI profiles, while double logistic functions are more effective in suppressing blur noise (Atkinson et al. 2012; Cai et al. 2017). This is particularly important for broadleaf forest during the senescence process, where usually a gradual VI decline precedes a drop, making AP

profile reconstruction more complex than the rapid VI increase in spring (Elmore et al. 2012; Guyon et al. 2011).

In line with Ferrara, Chianucci, and Bajocco (2023), this research aims to deepen the understanding of the discrepancy between remotely sensed and *in situ* AP phases, as well as the influence of climate and geographical features on this discrepancy. In this perspective, the objectives of this study are: (i) to explore the temporal mismatch between ground-based and satellite observations derived from Moderate resolution Imaging Spectroradiometer (MODIS) in European beech forests (*Fagus sylvatica* L.), one of the most widespread forest type in Europe (Barbati et al. 2014); (ii) to assess the role of the main environmental (geographical and climatic) factors, i.e. latitude, elevation, precipitation, and temperature, on the observed mismatch.

## 2. Materials and methods

### 2.1. Phenological and environmental data

The ground-based phenological time series were obtained from the Pan-European Phenology database (PEP725), which provides phenological observations collected by a network of stations distributed across Europe from 1950 to the present (Templ et al. 2018). PEP725 phenophases are defined using the BBCH (Biologische Bundesanstalt, Bundessortenamt and Chemical industry) codes (Meier et al. 2009). PEP725 stations monitoring beech forests were selected over the years 2003–2015, considering both data availability and alignment with the satellite data timeframe. Therefore, to determine the timing of AP stages, BBCH 94 (autumnal colouring of leaves 50%) and BBCH 95 (50% autumnal leaves fall) were selected (Table 1).

The satellite-based phenological metrics were estimated using a combination of MODIS MOD13Q1 and MYD13Q1 EVI composite products from 2003 to 2015, with 250 m spatial resolution and 16-day temporal frequency for each. Combining these two products allowed to increase the temporal density of the final dataset, reaching an overall 8-day frequency (Didan and Munoz 2019; Roy et al. 2006). Furthermore, the procedures used to generate the composite products already include noise reduction, e.g. from cloud or aerosol contamination, making them ready-to-use (Broich et al. 2015; Huete et al. 2002). The EVI 8-day temporal profiles were extracted from the MODIS data according to the position of the filtered PEP725 stations. The procedure was performed by averaging pixels values within a 250 m × 250 m square, corresponding to the spatial resolution of the

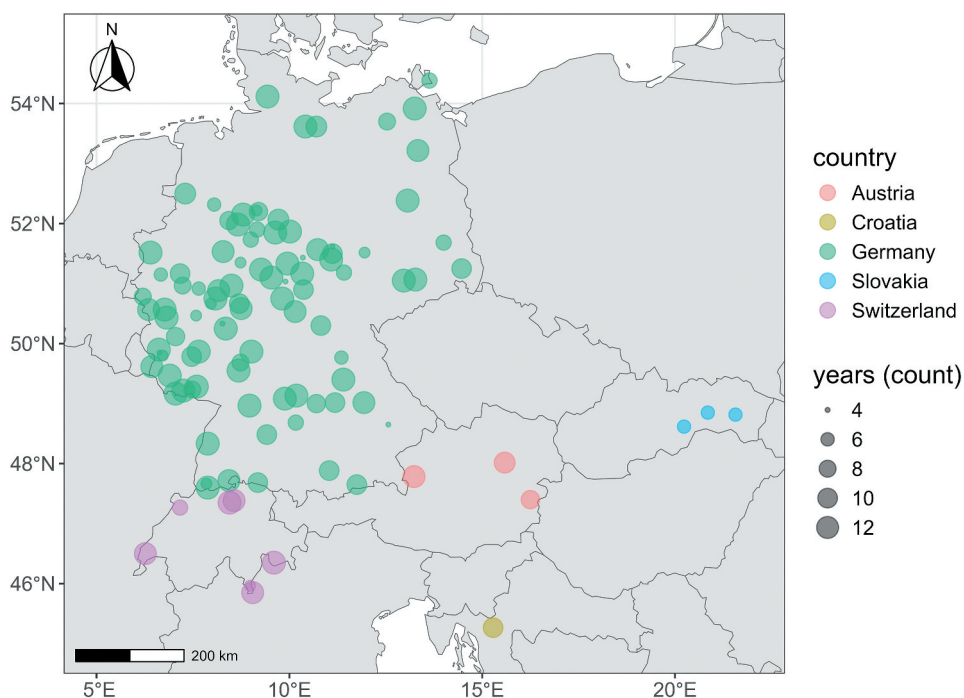
**Table 1.** Summary statistics for BBCH 94 and BBCH 95 stages according to PEP725 station data, by year.

		2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
BBCH 94	Count	82	84	90	94	87	90	83	84	79	80	76	69	58
	Median	286	283	286	290	277	279	282	281	285	283	286	283	285
	Mean	285	284	285	288	277	279	282	282	285	283	285	286	285
	Std Dev	12	12	12	13	11	11	13	11	12	11	10	12	9
BBCH 95	Count	72	75	74	83	75	80	77	79	76	76	71	6	5
	Median	305	301	303	306	302	297	305	303	306	301	300	301	302
	Mean	303	300	302	307	298	296	303	301	303	302	299	300	303
	Std Dev	15	11	10	12	13	12	11	9	12	11	10	7	10

satellite sensor, centred on each station. Depending on the station's position relative to the MODIS pixels, a maximum of 4 pixels were used to calculate the average EVI values around each PEP725 station (Gorelick et al. 2017). This step aimed to ensure the spatial representativeness of the signal respect to the variability of the canopy around each PEP725 station.

Furthermore, to minimize the mixed pixel-issue due to the spatial mismatch between MODIS pixel and ground observations, we selected only stations located in dense, homogeneous broadleaf forested areas. To this aim, two spatial filters were applied to the PEP725 stations. Initially, we selected only the PEP725 stations falling within the distribution range of European beech forests provided by EUFORGEN Programme (Caudullo, Welk, and San-Miguel-Ayanz 2017). This step was taken to exclude observations outside the species' natural climatic range, such as those from botanical gardens or other exceptional locations. Then, we employed the 2018 European Corine Land Cover (CLC) map to keep only those stations associated with the broad-leaved forests category (CLC 311), thus excluding small, heterogeneous, marginal or non-forested areas. The final dataset comprised 108 PEP725 stations, with a total of 1905 observations, spanning each year and both the BBCH stages (Figure 1).

The latitude (LAT) was obtained from the Universal Transverse Mercator geographical coordinates of the PEP725 stations. Elevation data (ELEV) was derived from the Copernicus Global Digital Elevation Model (GLO-30), featuring a spatial resolution of 30 metres. To consider the overall climatic conditions, rather than specific variations in local weather, we extracted bioclimatic variables from the TerraClimate dataset (Abatzoglou et al. 2018), which provides monthly aggregated climate data for temperature and precipitation

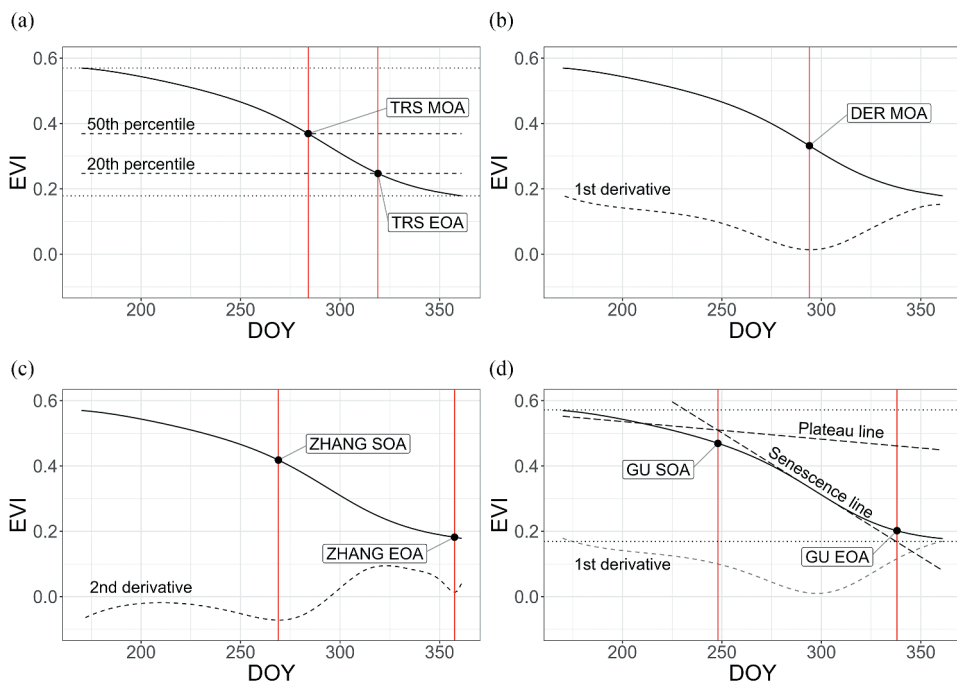


**Figure 1.** Distribution of filtered PEP725 stations across Europe. The dot size indicates the data availability during the years 2003–2015.

within the study period (2003–2015) at around 0.5 km spatial resolution. In particular, the selected bioclimatic variables were the mean temperature ( $T_{\text{mean}}$ , °C), and the precipitation accumulation ( $P_{\text{tot}}$ , mm) in autumn. All EVI time series, elevation data and bioclimatic variables were processed in Google Earth Engine environment (Gorelick et al. 2017).

## 2.2. Data analysis

The Savitsky-Golay filter (Press and Teukolsky 1990) was applied to smooth the EVI 8-day temporal profiles extracted from the satellite data for each filtered PEP725 stations. Then, daily EVI time-series were reconstructed using the Phenofit R package (Kong et al. 2022) using the double logistics function method as a curve-fitting approach (Elmore et al. 2012). Subsequently, we extracted AP metrics from the obtained daily time series using different techniques provided within the Phenofit R package (Figure 2). In particular, the Threshold method defines the day of the year (DOY) at which the EVI exceed a specific threshold, identifying the mid and end of AP by the 20th and 50th percentiles (TRS EOA and TRS MOA) of the annual EVI amplitude (L. Zeng et al. 2020). The Derivative method (DER MOA) also characterizes the mid of AP as the DOY corresponding to the minimum in the first derivative of the EVI time series, that is the day with the fastest senescence rate (Tateishi and Ebata 2004). The Zhang method determines the start and end of AP (ZHANG SOA and ZHANG EOA) by identifying two local minima of the change rate in curvature (the second derivative) within the EVI time series related to senescence and dormancy (X.



**Figure 2.** Illustration of the methods used for extracting AP metrics ((a): threshold, (b): derivative, (c): Zhang, (d): Gu).



Zhang et al. 2003). Finally, in the Gu method, the first derivative minimum is used to define the tangent line (senescence line) to the curve intersecting with the baseline and plateau line, defined by the minimum and the maximum EVI values (Gu et al. 2009). Also, in this case, the method also identifies two moments for the start and end of AP (GU SOA and GU EOA) (Gu et al. 2009).

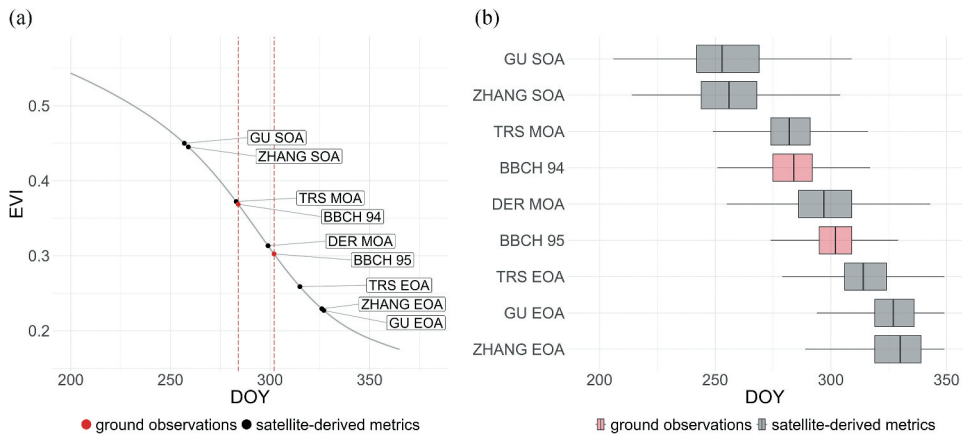
Prior to statistical analysis, a data cleaning procedure was applied to the satellite-derived AP metrics to reduce the influence of extreme values and artefacts. Specifically, metrics with DOY values below 150 or above 350 were excluded, as these values fall outside the expected range for AP in temperate deciduous forests according to the literature (Kloos et al. 2024; Mariën et al. 2022). In addition, for each phenological metric, the most extreme values were removed by applying a conservative filtering. The 5th and 95th percentiles of the DOY distributions were computed and the observations falling beyond one interquartile range from these thresholds were excluded. This approach allowed to maintain the internal variability of the distributions while discarding anomalous values which may reflect data and methodological artefacts (i.e. smoothing, curve fitting and phenological metrics extraction procedures) or uneven station distribution across latitudes and elevations.

At the end of the cleaning procedure, ground observations were matched with the satellite-derived metrics for each year and location. To explore the relationship between satellite-derived and ground-observed AP dates, after identifying a non-normal distribution using the Shapiro-Wilk's *W* test, a non-parametric paired-sample Wilcoxon test was used to investigate the significance of the differences between the AP dates obtained from the seven satellite-derived metrics (i.e. DER MOA, TRS MOA, TRS EOA, GU SOA, GU EOA, ZHANG SOA, ZHANG EOA) and the two ground-based BBCH phases (i.e. BBCH 94 and 95). We also analysed the linear slope of the EVI curves between the ground-based and the satellite-derived metrics to investigate their average rate of decrease over time. Finally, we performed a Redundancy Analysis (RDA) to explore the influence of selected environmental factors on the differences between satellite-derived and ground-observed AP metrics, both in terms of dates ( $\Delta$ DOY) and linear slope (m). RDA is a multivariate method that combines and analyses response variables while considering their linear relationships with predictor variables (Rao 1964; Ter Braak and Prentice 1988). In this context, environmental variables were used as predictors, while the date differences and the slopes between satellite-derived metrics and BBCH serving as response variables.

### 3. Results

The distribution of AP dates of all the different metrics revealed a clear temporal gradient in terms of average (Figure 3(a)) and distribution (Figure 3(b)). Between the first half of August and the first half of November, GU SOA, ZHANG SOA, TRS MOA and BBCH 94 sequentially occurred, exhibiting higher dispersion in GU SOA and ZHANG SOA of 137 and 128 days respectively. Those first four metrics were all related to the period between late summer and early autumn seasons interested by the leaf colouring process. Finally, the DER MOA (third highest dispersion of 94 days), BBCH 95, TRS EOA, ZHANG EOA and GU EOA defined the last part of the AP related to the falling process ranging from the end of September and the middle of December. Looking at the overall temporal distribution, BBCH 94 and 95 tended to occur in the mid-early and mid-late temporal portion of the AP,



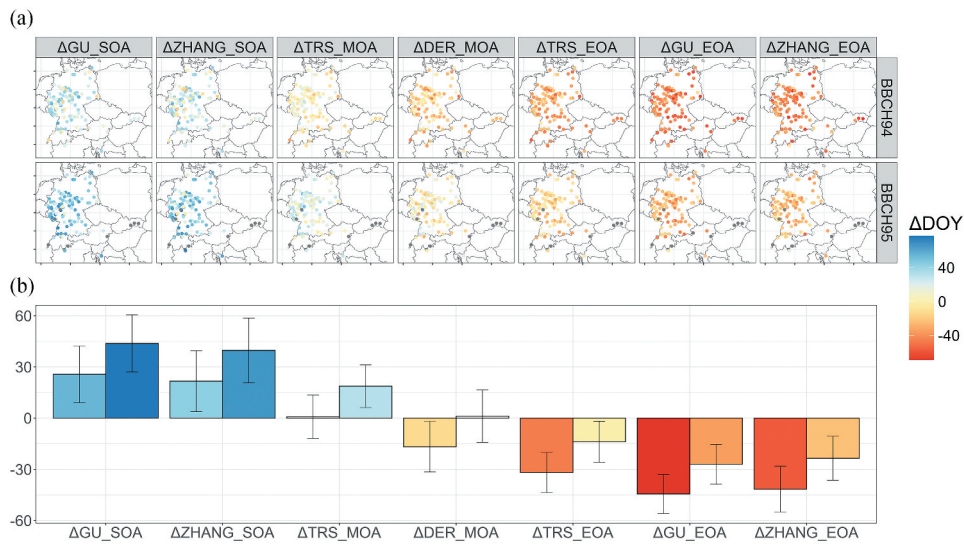


**Figure 3.** Summary results of the AP temporal gradient from all available sites (2003–2015). Panel (a): average values of the satellite-derived metrics (black dots) and the ground observations (red dots), with their position in the average MODIS EVI profile (lightblue). Panel (b): temporal distribution of the dates (DOY) for the two ground-based BBCHs and the seven satellite-derived phenological metrics.

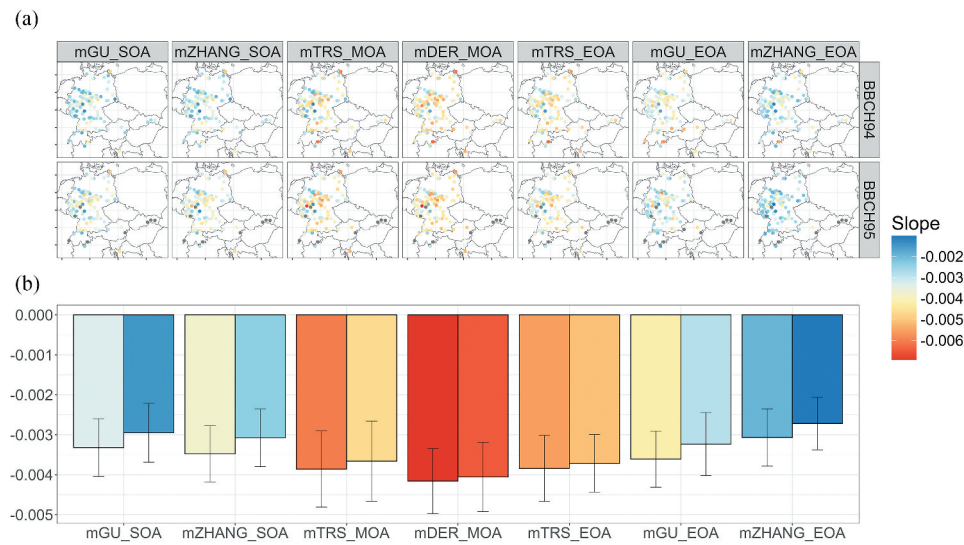
respectively, spanning from 247 to 334 DOY. DER MOA occur in between both BBCH ground metrics for almost 40% of observations and, on average, over 70% of PEP725 stations. For over 90% of observations, ZHANG SOA and GU SOA preceded BBCH 94, while ZHANG EOA and GU EOA followed BBCH 95. Finally, TRS MOA and TRS EOA occurred, respectively, just before BBCH 94 and after BBCH 95 in over 60% of the observations.

This evidence suggested a separation of satellite metrics into two groups: those describing the mid-early portion (ZHANG SOA, GU SOA, TRS MOA and BBCH 94) and those characterizing the mid-late portion (DER MOA, BBCH 95, TRS EOA, ZHANG EOA and GU EOA) of the AP. From the results of the paired-sample Wilcoxon test, almost all the satellite-derived metrics were significantly different from the ground-observation ( $p$ -values  $< 0.01$ ), apart for TRS MOA and BBCH 94 ( $p$ -value of  $2.71E-01$ ). The  $\Delta$ DOY discrepancies between each satellite-derived AP metric and both BBCH observations are reported in Figure 4. In detail, the satellite-derived AP metrics which tended to deviate from the ground observations were ZHANG SOA and GU SOA for the early portion and ZHANG EOA and GU EOA for the late portion. These metrics, characterized by a longer time lag, indicated different phenological phases in both the initial and final parts of the EVI curve, corresponding to the initial decline and the reaching of the descent plateau. In contrast, metrics aligned with ground observations were TRS MOA with BBCH 94, and to a lesser extent, both DER MOA and TRS EOA with BBCH 95, displaying more variability in terms of distribution. Furthermore, when considering the linear slopes between satellite and ground-based observations (Figure 5), the highest values occurred in the middle part of the gradient, with DER MOA exhibiting the maximum, followed by TRS MOA and TRS EOA. Conversely, ZHANG and GU displayed the lowest slopes at the margins of the gradient.

According to RDA (Figure 6), the temporal gradient of the mismatch between satellite-derived AP metrics and BBCH were confirmed. In detail, as for the temporal differences,  $\Delta$ ZHANG SOA,  $\Delta$ GU SOA and  $\Delta$ DER MOA were positively correlated with  $P_{\text{tot}}$  and ELEV and

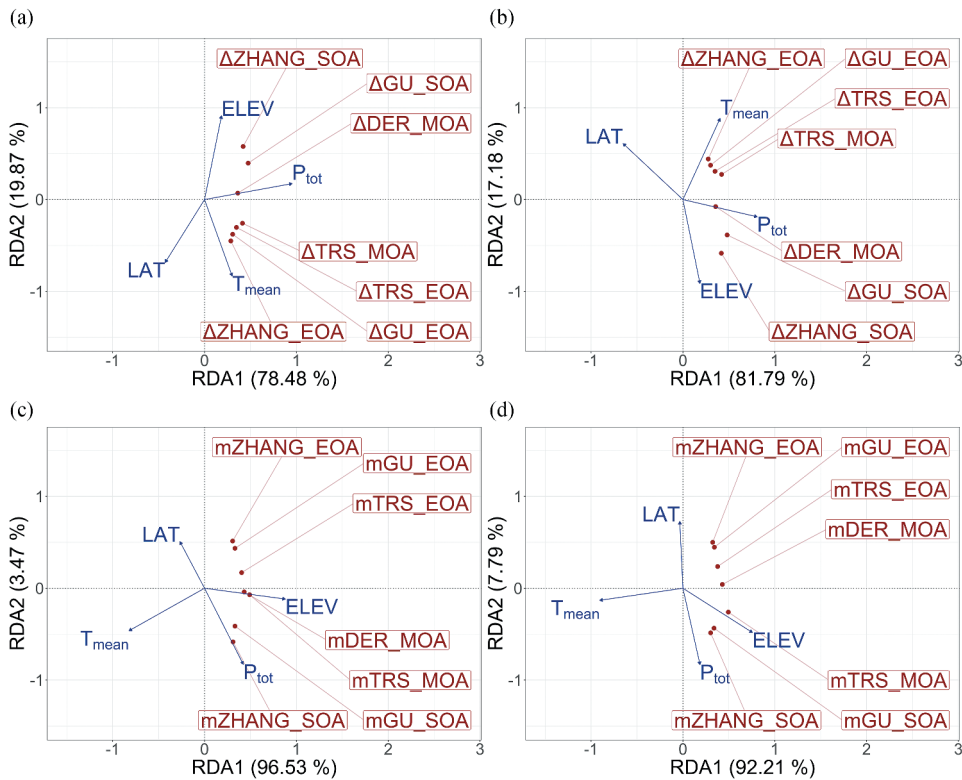


**Figure 4.** Panel (a): PEP725 stations reporting the mean differences between BBCHs and satellite-derived AP dates ( $\Delta DOY$ ). Panel (b): overall mean differences and standard deviation between BBCHs (left for 94 and right for 95) and satellite-derived AP dates ( $\Delta DOY$ ).



**Figure 5.** Panel (a): PEP725 stations reporting the mean slope between BBCHs and satellite-derived AP metrics. Panel (b): overall mean slope and standard deviation between BBCHs (left for 94 and right for 95) and satellite-derived EOS metrics.

negatively with LAT. Hence, under favourable precipitation conditions and higher elevation at lower latitudes, the discrepancies between the mid-early satellite-derived metrics and ground observations increase. On the other hand, temperature resulted as the main predictor associated with the discrepancies between the metrics of the mid-late portion of the AP (i.e.  $\Delta TRS$  MOA,  $\Delta TRS$  EOA,  $\Delta GU$  EOA,  $\Delta ZHANG$  EOA). This means that the late



**Figure 6.** RDA biplots showing the distribution of environmental variables (red arrows) in relation to the differences between satellite- and ground-observed phenological phases, in terms of  $\Delta$ DOY (panel (a) and (b)) and linear slopes (panel (c) and (d)), as response variables (black dots). Panel (a) and (c) refer to differences with BBCH 94, while panel (b) and (d) refer to differences with BBCH 95.

satellite-derived phenological metrics deviate further from the ground observations under higher temperatures. The EVI changes of linear slopes between ground and satellite metrics were positively correlated with ELEV and  $P_{tot}$  and negatively with LAT, with differences between BBCH 94 and 95. This influence was especially related to the mid-early metrics, i.e. mZHANG SOA, mGU SOA and mTRS MOA. Moreover,  $T_{mean}$  was confirmed to be the main predictor for the mid-late metrics (i.e. mDER MOA, mTRS EOA, mZHANG EOA and mGU EOA), showing a negative relationship for both BBCH ground metrics (i.e. the higher the temperatures, the lower the slopes). Also, based on the variance explained by each RDA component, RDA1 resulted to have the greatest weight in describing the influence of the environmental variables. This underlines the importance of  $T_{mean}$  rather than others environmental variables in influencing the differences in slope.

#### 4. Discussion

Satellite-derived phenology is defined as the seasonal pattern of variation in vegetated land surfaces observed through satellite remote sensing (X. Zhang, Friedl, and Schaaf 2006). Satellite-derived phenology improves ground observations by providing spatial

and temporal continuous data that extend the monitoring beyond isolated phenological moment, thus enabling to monitor the entire phenological dynamics of vegetation across an area (Donnelly et al. 2022). However, satellite data capture a composite signal generated by heterogeneous surface conditions, which often fails to represent the specific responses of individual plant species (Friedl et al. 2010). The recorded patterns integrate the reflectance responses of stands, with differences in species composition and canopy structural layers within the vertical and horizontal profiles, making challenging the biological interpretation of such responses (D'Odorico et al. 2015) and resulting in discrepancies between the phenological phases detected by remote sensing and field observations (C. Wang et al. 2017).

In this study, ground and satellite data were compared to explore AP dynamics, by assessing their discrepancies and the influence of environmental (geographical and climatic) factors on this mismatch. In line with previous study (Ahl et al. 2006; Bórnez et al. 2020; X. Chen et al. 2018), the primary cause of the observed discrepancies was the high phenological variability within the coarse-scale MODIS pixels. Such discrepancies revealed that satellite-derived metric occurred prior and after ground observation with a gradual delay in both directions. In particular, two main portions characterized the AP: the mid-early portion, capturing the beginning of the overall senescence process, and the mid-late portion, characterized by the transition from the canopy to the leaf-off. The mid-early AP corresponds to the leaf colouring phase as described by the initial phenological metrics, thus for the very initial moments by ZHANG SOA and GU SOA, and for the core of the colouring process by TRS MOA and BBCH 94 observations. This early metrics suggest the initial effects of changes in beech leaves colouration, starting from the sun-exposed leaves and gradually spreading throughout the canopy as the autumns season progresses (Koike 1990; Mariën et al. 2022). During this process, the reflectance experiences a slow decline, consequently detected by the remotely sensed phenology. However, the high variability of ZHANG SOA and GU SOA dates may indicate the contribute of ancillary species to the reflectance response detected by satellites (D'Odorico et al. 2015), which eventually reflects the variability of beech in terms of stands composition within the pixels (Helman 2018) and over the PEP725 stations (Král et al. 2014). Moreover, the timing of beech leaf senescence is forced by temperature and, especially, photoperiod (Koike 1990; Mariën et al. 2022), potentially increasing this variability along an altitudinal and latitudinal gradient across the study area. In the mid-early season portion, TRS MOA and BBCH 94 show a closer alignment and a lower dispersion. They probably indicate the core of the colouring process across most PEP725 stations, when the variability of senescence timing in terms of species composition and site-specific conditions, is overcome by the ongoing of the season. On the other hand, this also may represent the moment when the leaves begin to fall and the BBCH 94 and 95 observations overlap. Colouring and falling stages are deeply and progressively interconnected during the mid-season. In this sense, the high variability of DER MOA, which covers all the date ranges of both BBCHs, may be related to the wide spectrum of reflectance responses given by the different canopy cover conditions across the PEP725 stations after leaves start falling. However, since DER MOA is closer to BBCH 95 in terms of distribution statistics and average temporal difference than BBCH 94, it may be representative of the switch to mid-late AP. From DER MOA and the BBCH 95 observations, occurring approximately from September to October, the leaf shedding leads to a faster decline of the remotely sensed phenological curves. The

increase in average slope reaches its maximum between DER MOA and both BBCHs, potentially representing the peak of leaf fall activity. This trend progressively slow down again through TRS EOA and GU EOA, spanning from October to December, and finally ZHANG EOA, expressing the period when the transition to dormancy is nearly complete. As the falling phase progresses, these latter mid-late AP metrics may be gradually influenced by multiple factors contributing to the variability of the remotely sensed metrics (Testa et al. 2018). For example, the soil surface and dead leaves on the ground, that are relatively similar in terms of spectral properties (Smith et al. 2019), could lead a slow decline of the phenological curve (Hmimina et al. 2013; Nagler, Daughtry, and Goward 2000; van Leeuwen and Huete 1996). Furthermore, snow cover, particularly in stations at the highest latitudes and altitudes in the study area, may contribute to a faster decrease in vegetation indices based on red-edge reflectance, including EVI (Dronova and Taddeo 2022; Yang et al. 2022). Also, with a strong site-specific condition, the mechanical effect of wind plays a certain role in the transition from senescence to dormancy (Hmimina et al. 2013; Testa et al. 2018), influencing the speed of leaf falling phase and potentially the variability of the related metrics. Finally, the effect of drought and heat-waves on physiological activity has been reported to induce early leaf shedding in specific areas, further contributing to a more rapid decrease in satellite-detected reflectance (Descals et al. 2023).

However, it's important to notice that the extraction of phenology metrics are significantly influenced by the choice of remote-sensing data sources, indicators, and the variations introduced by different models and methods of parameter extraction (Peng et al. 2024; X. Zhang et al. 2017). This is because remote sensing data sources differ in their temporal, spatial, and spectral resolutions, which can substantially affect the results (e.g. low temporal resolution may not be sufficient to monitor the rapid changes in vegetation phenology) (Dronova and Taddeo 2022). Moreover, various greenness-based indicators capture distinct aspects of phenology and tend to be high affected by the optical effect of the sensor, further contributing to differences in the observed patterns (Yang et al. 2022). For instance, NDVI has good performance in mitigate topographic effects, lighting conditions, cloud cover (Huete et al. 2002), but tends to exhibit saturation tendencies, with consequently reduced sensitivity in areas of dense vegetation (Gong et al. 2024). On the other hand, EVI demonstrated to be effective in mitigating noise and interference from clouds and soil (Xiao et al. 2003) but suffers from a high sensitivity to variations in solar sensor geometry and a low sensitivity to variations in vegetation vigour in areas with low vegetation biomass (X. Wang et al. 2022).

Throughout the RDA, both the timing between the metrics and the rate of change of the remotely sensed phenological curve were explored in relation to environmental factors. In the mid-late portion of the AP, temperature emerges as a main determinant of the observed disparities between satellite-derived and ground metrics. Stations experiencing higher temperature are characterized by lower slopes between satellite and ground metrics and greater degree of temporal differences. Rising temperatures may lead to a longer growing season and, consequently, broader curves with slower descendant slopes and wider time gaps between metrics. These results are consistent with the literature regarding the main controlling influence of temperature on the EOS leaf senescence variability in midlatitude deciduous forests at macroscale level (Fu et al. 2018; Kloos et al. 2024). On the other hand, the difference between satellite and ground metrics in the mid-early portion indicates additional complexity from the influence of

precipitation, latitude, and elevation on the colouring process. The  $\Delta$ DOY results suggest that the varying precipitation patterns across the study area may have an impact on the timing discrepancies between satellite and ground data. Precipitation can either advance or delay the onset of senescence, depending on the interplay with favourable or adverse thermal conditions (Estiarte and Peñuelas 2015; Lukasová et al. 2020). Moreover, the temporal differences decrease at higher latitudes, which may be consistent with the contraction of the photoperiod. The shortened photoperiod limits the overall growing season, potentially resulting in a narrower remotely sensed phenological curve. As a result, the mismatch between what is seen from the satellite and the ground decreases at the beginning of AP. Additionally, when considering the elevation influence, the greater temporal differences at higher stations may indicate EVI limitation due to topographic effect on surface reflectance, particularly related to macroscale shadows and changes in local sun-surface-sensor geometry (Hao et al. 2018; Y. Zeng et al. 2022). Furthermore, despite the advantages of minimizing the impact of cloudiness by using an 8-day EVI composite, the high-altitude variations in aerosol concentrations, water vapour and cloud properties could give rise to significant variations in direct and diffuse irradiance (Wen et al. 2018). Also, considering the limited number of PEP725 stations at higher altitudes, further uncertainties in ground observations may be introduced. Overall, it is important to acknowledge that the environmental influences emerged from the RDA to the observed discrepancies do not consider recent years characterized by an intensification of extreme weather events (Perkins-Kirkpatrick and Lewis 2020). This limitation is primarily due to the availability of PEP725 ground observations. Extending the analysis to more recent years would improve the relevance of the results for current and future interactions between environmental factors and AP phenology. This issue highlights the central importance of maintaining and expanding long-term terrestrial phenological networks such as PEP725 (Templ et al. 2018). These networks provide irreplaceable reference data to be integrated with satellite observations, and their continuity is essential for monitoring ongoing ecological responses to climate change.

A potential limitation of this study is its exclusive reliance on the Enhanced Vegetation Index (EVI). While EVI proved valuable in mitigating soil background effects and signal saturation, issues particularly pertinent during the autumn senescence, different vegetation indices can exhibit varied responses to canopy structure and background influences (C. Wang et al. 2024). Consequently, the magnitude of the temporal mismatch observed between ground and satellite-derived phenometrics might be, to some extent, index-dependent (Atkinson et al. 2012). A valuable avenue for future research would be to build upon our findings by conducting a multi-index comparative analysis, incorporating other widely used indices such as NDVI, the two-band EVI (EVI2), and red-edge-based indices (H. Zhang et al. 2022). Such an investigation would be instrumental in disentangling the universal challenges of satellite-based phenology monitoring from the specific sensitivities of a given spectral index, thereby enhancing the generalizability of our results and aiding efforts to harmonize phenological data from diverse remote sensing platforms.

## 5. Conclusions

This study shifts the focus from simple comparisons between ground-based and satellite-derived AP to a more integrative framework that goes beyond purely quantifying



discrepancies. Examining the underlying meaning of the mismatch reveals that these two perspectives capture fundamentally different phenomena, each influenced by distinct environmental drivers. Ground observations capture specific biological moments in leaf senescence and fall, while satellite metrics reflect broader canopy-level dynamics influenced by factors like mixed species composition, understory phenology, soil reflectance, and acquisition noise. The mismatch between these approaches is not merely a technical issue but rather a reflection of the diverse phenomena that characterize autumn phenology, with different environmental influences in the various phases. Since both data sources complement each other, ground observations should not act as validation of satellite data. In this integrative perspective, linking multi-scale observations to adaptive management creates a decision support pathway that reinforces the importance of phenological networks for forest ecosystems. The adoption of hybrid protocols, combining multi-source phenological metrics with ground-based observations, could enable the calibration of standardized phenological thresholds and predictive models at regional and local scales. Such tools are essential in the context of climate-smart forestry purposes, with potential implications for silvicultural practices, functional diversity and forest regeneration. The integration of multi-scale phenological data provides an operational basis for adaptive decisions, reducing uncertainty and improving the capacity to respond to climate change.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

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## Data availability statement

Data derived from public domain resources:

- the elevation was extracted from the Copernicus Global Digital Elevation Model (30 m) product available at <https://dataspace.copernicus.eu/explore-data/data-collections/copernicus-contributing-missions/collections-description/COP-DEM>.
- the phenological ground observations was extracted from the Pan-European Phenology database at [www.pep725.eu](http://www.pep725.eu).
- the phenological satellite observations was extracted from the MODIS database at <https://modis.gsfc.nasa.gov/data/dataproduct/mod13.php>.



- the 2018 European Corine Land Cover map is available at <https://land.copernicus.eu/en/products/corine-land-cover>.
- the Euforgen beech distribution map is available at <https://www.euforgen.org>.
- the climate data was extracted from the TerraClimate database at <https://www.climatologylab.org/terraclimate.html>.

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