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Comparing ground below-canopy and satellite spectral data for an improved and integrated forest phenology monitoring system

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ABSTRACT

Phenology monitoring allows a better understanding of forest functioning and climate impacts. Satellite indicators are used to upscale ground phenological observations, but often differential responses are observed, and data availability can be limited. In view of climate impacts, new tools capable to detect rapid phenological changes and to work at single species level are needed. This research compares indices derived by the TreeTalker© (TT +) below canopy upward-looking spectral data and Sentinel 2 satellite data, used to assess the phenological behavior and changepoints in several European beech forests. Overall, a mismatch between the information derived by the two sensor types is evidenced, with main differences in: start/end and length of season and phenology changepoints; larger variability captured by TT + with respect to Sentinel 2 especially in the leaf on period; mixed signal response from multiple vegetation layers in Sentinel 2 data. The complementarity of satellite and TT + indices allow exploring the phenological responses from different vegetation layers. TT + higher temporal resolution demonstrates precision in capturing the phenological changepoints in beech forests, especially if satellite image availability is limited by cloud cover and leads to miss critical phenological dates. The best settings for TT + data collection and the advantages to have two spectral data sources for improved forest phenology monitoring are also commented. The TT+, collecting additional tree parameters, can be a valuable tool for an integrated monitoring system based on spectral signals from above and below the canopy, at high temporal frequency and high spatial resolution.

1. Introduction

Plant species go through a sequence of developmental stages, called phenology, which is mainly influenced by temperature and has an important impact on the capabilities of ecosystems to provide their services, also providing feedback to the climate system (Piao et al., 2019). Alterations of the phenological stages in response to global warming have been largely documented in different ecosystems and species (Menzel et al., 2020). Phenological changes have impacts on the biogeochemical cycles (Richardson et al., 2010), and on the population dynamics of species connected at various trophic levels (Morellato et al., 2016).

Our understanding of the forest tree phenology response to the changing climate is still limited as multiple drivers concur to shape this response, such as weather, photoperiod duration, carbohydrates allocation, and soil moisture (Caparros-Santiago et al., 2021). Even more limited is our comprehension of the consequences and quantification of the impacts of climate change occurring at species and ecosystem levels. Different data sources generally agree on a trend of advanced tree leaf unfolding and delayed leaf coloring due to global warming (Piao et al.,

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2019). However, other factors such as the elevation that influences temperature or the freezing events during winter may have a role, leading to different results according to locations and species (Chamberlain and Wolkovich, 2021; Chen et al., 2018a). In a changing climate epoch, monitoring phenology provides opportunities to advance toward a better understanding of ecosystem functioning and climate impacts, and to produce information needed to select better adaptation and mitigation strategies (Cleland et al., 2007).

Multiple methods exist to monitor vegetation phenology. Gray and Ewers (2021) list visual assessment and collection traps in the field; remote and proximal spectral data analysis by satellite, airplanes or UAVs, or cameras installed over the canopy; accelerometers, dendrometers, and micro-coring that monitor phenology approximating tree mass or growth at given intervals; and eddy covariance flux towers that measure CO_2 fluxes to estimate gross primary productivity, which can indicate the phenological start and end of season dates. Several phenology observation networks exist, at global, country, and local levels: ICP Forest (https://icp-forests.net/), PEP725 (https://www.pep725.eu/), eLTER (https://elter-ri.eu/) are examples at European scale. Among the methods to monitor vegetation phenology, those based on satellite remote sensing have played a major role in land surface phenology studies, providing global evidence that phenological changes are a good indicator of ecosystem dynamics (Caparros-Santiago et al., 2021).

Different algorithms, software and packages were developed to detect changes and anomalies in phenology data. Examples include: the *npphen* R package (Chávez et al., 2022), designed to detect not only vegetation anomalies from remotely sensed vegetation indices, but also to quantify the position of the anomalous observations within the historical frequency distribution of the phenological annual records; or the *phenor* R package (Hufkens et al., 2018), that is a modeling framework that leverages measurements of vegetation phenology from four common phenology observation datasets: the PhenoCam network (https://phenocam.nau.edu/webcam/), the USA National Phenology Network (https://www.usanpn.org/usa-national-phenology-network), the PEP725 network, and MODIS satellite phenology data (MCD12Q2), combined with (global) retrospective and projected climate data; the phenopix R package (Filippa et al., 2016), which is collection of functions to process repeated digital images, analyze greenness index trajectories and extract relevant phenological stages; or the phenofit package (Kong et al., 2022) that adopts state-of-the-art phenology extraction methods, such as a weight updating function for reducing optical noise contamination, a growing season division function for separating the time series into different vegetation cycles, and rough and fine fitting functions for reconstructing time series.

However, different algorithms often provide conflicting interpretations of the same data, and phenological metrics are known to be very sensitive to the choice of algorithm (Misra et al., 2016). This lack of consensus can be mitigated via ensemble modeling, such as the Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) model (Zhao et al., 2019), which was used in the present study. As an ensemble algorithm, BEAST quantifies the relative usefulness of individual decomposition models, leveraging all the models via Bayesian model averaging, alleviating model misspecification, addressing algorithmic uncertainty, and reducing overfitting. BEAST detected changepoints, seasonality, and trends in the data reliably; it derives realistic nonlinear trends and credible uncertainty measures.

The phenology of European beech has been examined in multiple studies and locations, and even for different provenances of the species (Di Fiore et al., 2022; Proietti et al., 2020; Visnjic and Dohrenbusch, 2004). Large variability in beech phenology and growth patterns can be found according to site latitude, temperature, precipitation, soil, and other environmental variables (Bórnez et al., 2020; Di Fiore et al., 2022; Piovesan et al., 2005; Urban et al., 2015). Ground data are essential in phenology monitoring, but they need to be scaled up to derive information at the species, habitat, or ecosystem level: remote sensing is the optimal tool to perform this task (Masek et al., 2015). However, a mismatching between ground and satellite data has often been observed and related to the examined season, the satellite data type, or the indices used (Ferrara et al., 2023; Zhang et al., 2018).

Ground and satellite data complement each other, but do not observe the same traits. The first usually provides responses at individual tree level while most of the satellites, even at very high spatial resolution, give the response from multiple tree crowns or stands. Even if the quantity and quality (in terms of spatial, temporal, and radiometric resolution) of satellite data are strongly increasing, some challenges still hamper the use of remote sensing to monitor phenology, especially to detect rapid changes such as those induced by abrupt climate anomalies or to work at single species level. In fact, cloud cover can limit optical remote data acquisition for long periods; the spatial resolution can limit the analysis for single species, due to the presence of mixed species pixels; the LAI estimated from optical data is known to be affected by signal saturation in dense vegetation cover; and in deciduous forests satellite can first see the greening of the understory. Badeck et al. (2004) observed at a 1-km scale a mismatch between phenology from satellite vegetation indices and that from ground data due to heterogeneity of cover. Even when using very high spatial resolution Sentinel 2 or Landsat data the correlation between satellite-observed phenological stages and ground-based observations often resulted moderate for deciduous forests (Kowalski et al., 2020; Melaas et al., 2016; Misra et al., 2016; Rodriguez-Galiano et al., 2015; Tian et al., 2021). In drylands this correlation resulted moderate too, especially with respect to the detection of end of season phenological events (Kato et al., 2021). Nevertheless, coupling ground and satellite data is fundamental to upscale *in situ* collected information. Remote sensing phenological observations are also fundamental to understand the relationships between phenology and climate (Meier et al., 2015). Piao et al. (2019) suggest that new observation tools are needed, as well as research into the scaling of observed phenology from species to landscape level.

Fagus sylvatica L., or European beech, is one of the most important and widespread broadleaved trees in Europe, covering a range from southern Scandinavia to southern Italy (Sicily), and from Spain in the west to northwest Turkey in the east. At the southern part of its range (Spain, Italy) it is only normally present at altitudes > 1000 m, as high summer temperatures, drought and moisture availability are limiting factors for its distribution. It is expected that climate change will impact its future distribution, particularly at the extremes of its range (Innangi et al., 2015; Madsen et al., 2010; Saltré et al., 2015). Understanding the growth dynamics and the response of beech forests to climate change is crucial to identify advantageous management strategies and improve the species resilience (Antonucci et al., 2021). In this context, a more accurate detection of beech phenological stages and their changes in time and space is needed.

The aim of this research is to report on the preliminary results of comparing indices derived from the *in situ* TreeTalker© devices (TT +) and satellite remote sensing. The comparison provides important insights for innovative phenology monitoring, often based on the not easy task of scaling up the ground data with remote sensing information. In this study, data from a TT + network from six European beech forests located along a gradient in Italy are used to detect -in almost near time- beech phenological stages. TT + is an innovative below canopy sensor collecting several tree parameters including spectral information in multiple bands, from which vegetation indices can be derived and linked to indicators from satellite sensors (Valentini et al., 2019). The collected TT + data and derived phenological changepoints were compared to those obtained by remote sensing Sentinel 2 data, commenting on the advantage in a climate change scenario to complement the two sources of phenological information for improved forest monitoring, and also reviewing the best settings for TT + ground data collection based on the gained experience. The hypotheses are that: (a) the TT + below canopy upward-looking spectral sensors can efficiently monitor phenological changes in trees; (b) the ground and satellite data capture complementary indices and phenological information, being linked to tree functional traits spatialization; (c) the integration of below canopy upward-looking spectral and remote sensing monitoring systems can help to solve issues of satellite mixed pixels and data availability, allowing for a prompt detection of changes.

2. Methods and materials

2.1. The study sites

Data from five study sites were available in 2021 and for six in 2022 (Fig. 1 and Table 1). All the study sites represent European beech stands. At northern latitudes four sites are present, managed by the University of Bozen (U Bozen; Bolzano site) and the Edmund Mach Foundation (FEM; Cembra sites P3, P4 and P7). In central Italy two sites are managed by the University of Florence (U Florence; S. Antonio 1 and 2 sites). In southern Italy other two sites are present, managed by the University of Campania (UniCampania; Campo Braca and Falode sites).

The Bolzano site is located in the Trentino-Alto Adige region, in the Alto Adige northern autonomous province, Appiano municipality (46.454 N, 11.233 E), at an elevation of 774 m a.s.l., with mean annual precipitation equal to 902 mm and mean air temperature of 12.7 °C. The forest is a beech dominated stand, with sporadic presence of Chestnut and Scots pine. The mean diameter at breast height (DBH) is 17 cm and the dominant height is 15 m. The management is a coppice in conversion to high forest with productive and protective functions.

The Cembra site is also located in the Trentino-Alto Adige region, in the southern Autonomous Province of Trento (46.129 N; 11.1235E) at an elevation of 1270 m a.s.l. with mean annual precipitation of 1053 mm and mean annual air temperature of 11 °C. Cembra hosts a mixed forest with high stands and even aged structure, originating from coppice abandonment and with an estimated age of 85 year; most abundant species include European beech, Norway spruce (*Picea abies L.*) and European larch (*Larix decidua L.*). The sites P7, P3, P4, and P7 where the TT + sensors were installed host almost exclusively beech trees, since conifers were harvested in 2015 in order to obtain almost pure mono-specific stands. The average DBH of the stands is 18 cm and the dominant height is 21 m.

The two study sites in the Tuscany region are in the S. Antonio Forest (43.698 N, 11.583 E), located at 1200 m a.s.l., with annual mean precipitation equal to 1200 mm and mean air temperature of 10 °C. The forest represents a pure beech stand: the mean age of trees is 55 years, with an average DBH of 35 cm and a mean height of 22.8 m. The forest is only managed for conservation purposes, with thinning performed by controlled felling.

In the Campania region the two sites are unmanaged pure beech stands: the Falode site (41.41 N, 14.43 E) is located at 1085 m a.s.l. with mean annual precipitation of 1933 mm and mean air temperature of 10.85 °C; the Campo Braca site (41.41 N, 14.34 E) is located at 1141 m a.s.l. with mean annual precipitation of 1812 mm and mean annual temperature of 10.6 °C. The tree mean age is 54 ± 3 years at Falode and 66 ± 20 years at Campo Braca, with similar tree density (160 dominant individuals/ha) in the two sites. The mean height of Falode trees is 26.8 m with a DBH of 63 cm, while in Campo Braca is 24.5 m with a DBH of 47 cm.

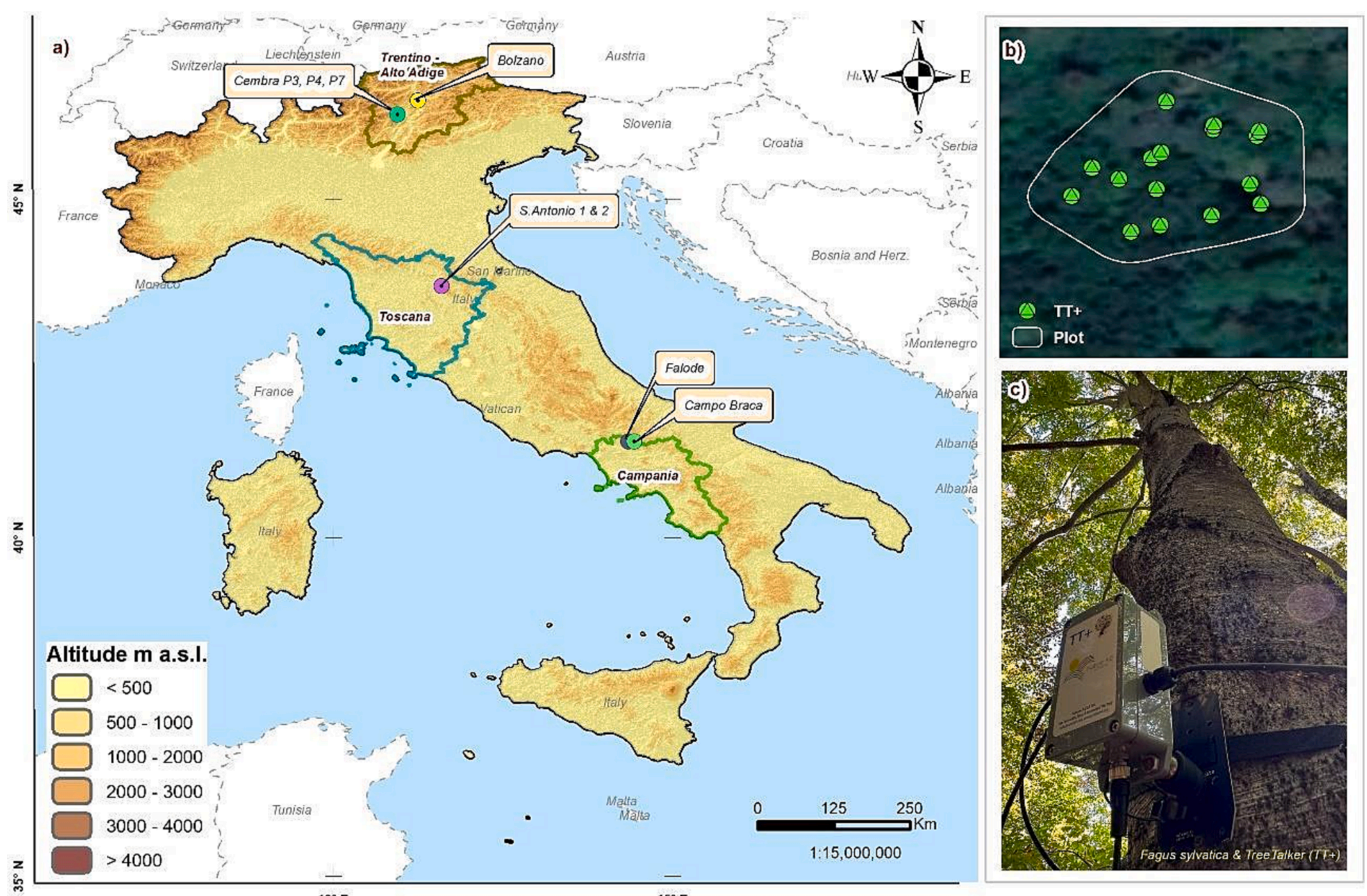

Fig. 1. The study sites in different Italian regions (a); example of a TT_plot, an area that includes a cluster of TT + sensors (b); a TT + device installed on a beech trunk (c).

Table 1
Summary of TT + and S2 data collected in the different study sites. # stands for 'number'.

Region	Site name	Start date	End date	# TT	TT_plot (m^2)	# days of TT data	# S2 images	# S2 pixels
2021								
Campania	Campo Braca	2021/04/21	2021/12/31	20	2924	255	39	29
Campania	Falode	2021/01/01	2021/12/31	10	982	365	51	11
Alto Adige	Bolzano	2021/03/12	2021/11/03	18	715	237	35	7
Trentino	Cembra P3	2021/01/12	2021/12/31	11	645	365	52	7
Trentino	Cembra P4	2021/01/12	2021/12/31	10	649	365	52	8
2022								
Region	**Site name**	**Start date**	**End date**	**# TT**	**TT_plot (m^2)**	**# days of TT data**	**# S2 images**	**# S2 pixels**
Toscana	S. Antonio 1	2022/01/01	2022/12/01	9	1383	335	73	14
Toscana	S. Antonio 2	2022/01/01	2022/12/02	6	1431	336	73	13
Alto Adige	Bolzano	2022/02/26	2022/11/28	18	715	276	56	7
Trentino	Cembra P3	2022/01/01	2022/12/31	10	645	365	76	7
Trentino	Cembra P4	2022/01/01	2022/12/31	11	649	365	76	8
Trentino	Cembra P7	2022/01/01	2022/12/31	11	922	365	76	10

2.2. The TT + ground sensors

The Tree Talker© (TT+; Fig. 1c) is a system for the monitoring of physical and functional parameters of trees exploiting the Internet of Things technology. The system is based on digital sensors, designed to be deployed on tree clusters, featuring continuous operability and automatic data transmission to provide semi-real time and cost-effective monitoring of variables. The TT + consists of a microcontroller with an ATMega 328 processor chip enclosed in a case (11.5 x 6.5 x 6 cm), that acquires information on: light transmitted through the canopy, water transport in the xylem of the trunk, wood temperature and humidity, tree trunk radial growth, tree movements, air temperature and relative humidity. A TT + is typically mounted on trees by means of a belt tightened around the tree trunk and is powered by a combination of Lithium-ion batteries (3.7 V) and a small solar panel attached to the battery case. A wireless chipset LoRa transmits data to a node managed by another microcontroller (the TT-Cloud) serving up to 48 devices in one. Data transmission is typically set at hourly frequency; the TT-Cloud is in turn connected to the internet via GPRS network and sends data to a computer server (Valentini et al., 2019).

Here details are provided only for the collection of below canopy incident light data used in this study. Multispectral measurements of transmitted sunlight are hourly performed by 2 spectral sensor chips in the visible to near infra-red electromagnetic region, mounted on top of the TT + case with a field of view of 40°, and each collecting data in 6 bands. The AMS AS7262 spectrometer covers the 450–650 nm range with bands (40 nm bandwidth) centered at 450, 500, 550, 570, 600, 610, and 650 nm. The AMS AS7263 covers the 610–860 nm range with bands (20 nm bandwidth) centered at 680, 730, 760, 810 and 860 nm (Tomelleri et al., 2022). The spectrometer has limited field of view of 40°, it is installed on the tree trunk portion facing north with an inclined axis of 20° with respect to nadir, in order to have the FOV covering the $50^{\circ} - 90^{\circ}$ zenithal angle range and excluding the tree trunk from the view in case of a perfect straight tree. TT + spectral data are however influenced by the absence of a light diffuse filter to limit the impact of incident light beams on signal quality and saturation. The TT + instrument is under further development; to limit the impacts in this TT + preliminary version only data from 9 am were used, also matching satellite passing time, and an accurate data screening was performed by visual evaluation of data plots.

In the different study sites the TT + are mounted into clusters (6 to 20 geolocated devices) over an area extent from around 645 to 2924 m^2. The area that includes a cluster was selected for representing the surrounding forest ecosystem conditions. The areas were mapped in a GIS environment applying a 5 m buffer to the perimeter obtained joining with a line the most external TT + devices; the areas were stored as 'TT_plot' vector file (Fig. 1b). Information on the TT + data available at each site are provided in Table 1. The size of the plot, the number of sensors inside it, and their position have an impact on the accuracy of the collected phenological information. Being this a preliminary attempt to shape a TT + network, different set ups were experimented, and suggestions from ground experience are also discussed for future development of such a network.

The preprocessing of TT + data include the following steps: (i) data download from the TT + server; (ii) exclusion of digital numbers (DN) > 65000 that exceed the 16-bit system capacity (ii) conversion of DNs into energy values according to experimentally retrieved calibration factors (Belelli Marchesini et al., 2023); (iii) selection of data from 9 am CEST to match the average hour of Sentinel 2 satellite pass in Italy; (iv) visual evaluation of TT + data plots to detect malfunctioning in any device, and in case excluding it; (v) grouping of TT + included in the same TT_plot and median computation to obtain the TT_plot area-based values; (vi) computation of the Normalized Difference Vegetation Index (NDVI; Huang et al., 2021) for each TT_plot area. All the TT + data preprocessing was carried out using the *ttprocessing* R package (Kabala et al., 2022).

Instrument and data failures can occur for many reasons, including changes in the original field of view (FOV) due to natural causes (branches breaking, animals' activity), failures of sensors or data transmission due to water intrusion in the instrument, low battery charge, and obstruction of the sensor's view due to dust, snow, or canopy litter, among the reported ones. Frequent revisits at the sites ensure the proper working of the instrument and the capability to fix issues such as those caused by environmental disturbances.

All the TT + data used in this case study are summarized per study site in Table 1.

2.3. The satellite imagery

The Copernicus Sentinel 2 (S2) mission comprises two satellites designed to monitor the variability in land surface conditions. The mission has a high revisit time (5 days with 2 satellites at the equator under cloud-free conditions) and satellites are equipped with a multispectral sensor, recording 13 bands distributed in a range from visible to short wave infrared region (0.443–2.190 nm), with variable spatial resolution (10 to 60 m). S2 Level 2A atmospherically corrected and cloud free (<30 % cloud cover) products were obtained through Google Earth Engine facilities (Gorelick et al., 2017); the NDVI index was then computed. The Sentinel 2 images used in this research are summarized per study site in Table 1.

2.4. Data analysis

The processing of TT + data includes download from TT + server and data cleaning using the '*ttprocessing*' R package R (Kabala et al., 2022), to exclude values with digital number (DN) > 65000 and to convert DNs into microwatt/cm^2 after the application of calibration factors. TT + data filtering included two steps. The first was the selection of hourly data, considering sun elevation (<30° to avoid TT + sensor saturation) and to match the hour of satellite pass in the region, resulting in Italy in the selection of data from 9 am. The second step was to retain only those TT + offering enough data continuity (>160 records) during the vegetative season (end of April – beginning of November) for capturing phenological variations. The remaining data were grouped into TT_plot, that were considered useful for the analysis only if their area covered at least three pixels in the remote sensing imagery. For each TT_plot the band median was computed using the TT + sensors included in the area and eventually NDVI values were calculated using bands centered at 810 and 650 nm. The processing of Sentinel 2 included the selection from Google Earth Engine of atmospherically corrected level 2A data for the study sites, selecting all dates matching those of TT + data occurrence, and applying a 30 % threshold for maximum cloud coverage. S2 bands median was computed at TT_plot level and NDVI was calculated using B8 and B4 bands, which resulted in the closer ones to TT + bands used. The flowchart illustrating the different processing steps is presented in Fig. 2.

To test the capability of TT + sensors to monitor phenological changes, NDVI trends from TT_plots were plotted for each site and year, comparing the results with those observed for Sentinel 2 NDVI, and evaluating the information with respect to the known phenological beech behavior for data quality evaluation. Using the BEAST algorithm, the phenological changepoint dates were obtained for ground and satellite data, allowing a comparison of the results for the detected phenology, to evaluate if TT + ground and satellite data capture comparable phenological information. Finally, a Spearman correlation analysis between TT + and S2 data was carried out for the leaf on period and for the whole year.

3. Results

The impact of the two-step filtering procedure on TT + data is shown in Table 2, that illustrates per each site and year the amount of data recorded at 9 am by the TT + installed in the TT_plot, and the final amount of data and sensors selected for having > 160 records in the leaf on period. The percentage of records remaining after filtering is also included; they were included in a very variable range (30.5 – 73.9 %).

The variability at TT_plot level of the NDVI values captured by TT + and S2 was explored computing the standard deviation of the NDVI values for all TT + sensors and S2 pixels included in the plot, per each site and year, as reported in the following Fig. 3. The variability captured by S2 is much lower than that of TT + in most cases.

All the available NDVI values computed at TT_plot level in the study sites for 2021 and 2022 years, from TT + sensors and Sentinel 2 imagery, are illustrated in Fig. 4. During the leaf-off periods the observed TT + NDVI values are usually very low (<0.3); S2 NDVI resulted moderately higher in the same period, especially in some of the sites. In the leaf on period satellite and ground data display similar high NDVI values, even if the inter-site variations captured by TT + NDVI result higher compared to those from S2. The change of values from the leaf off to the leaf on period and vice-versa, appear more abrupt in the TT + data with respect to that from S2 data.

The results obtained by the application of the BEAST algorithm to the TT + and S2 NDVI data are presented in Table 3 where the differences in the estimated length of the phenological season (N. days from leaf on to

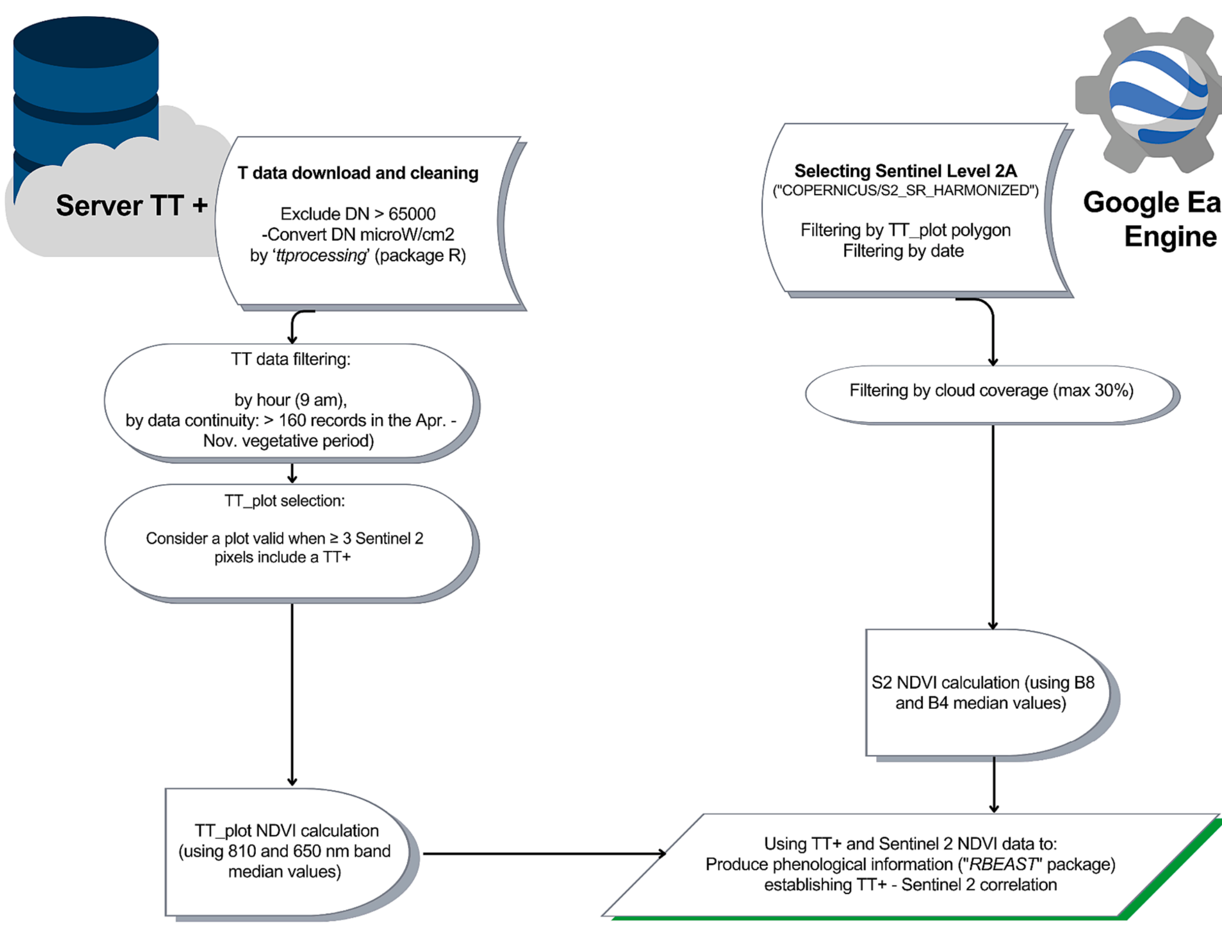

Fig. 2. Flowchart of TT + and Sentinel 2 data processing.

Table 2
Summary of TT + data availability before and after the filtering procedure. # stands for 'number'.

2021 Site name	# of 9 am records	initial # of TT+	# of records after filtering	final # of TT+	% of records after filtering
Campo Braca	3774	20	2757	19	73.1
Falode	2393	10	1397	9	58.4
Bolzano	3984	18	2944	18	73.9
Cembra P3	2873	11	1572	10	54.7
Cembra P4	2847	10	867	10	30.5
2022					
S. Antonio 1	1765	9	730	6	41.4
S. Antonio 2	1424	6	694	5	48.7
Bolzano	4119	18	2643	18	64.2
Cembra P3	3175	10	1204	10	37.9
Cembra P4	2681	10	942	10	35.1
Cembra P7	2693	13	1106	10	41.1

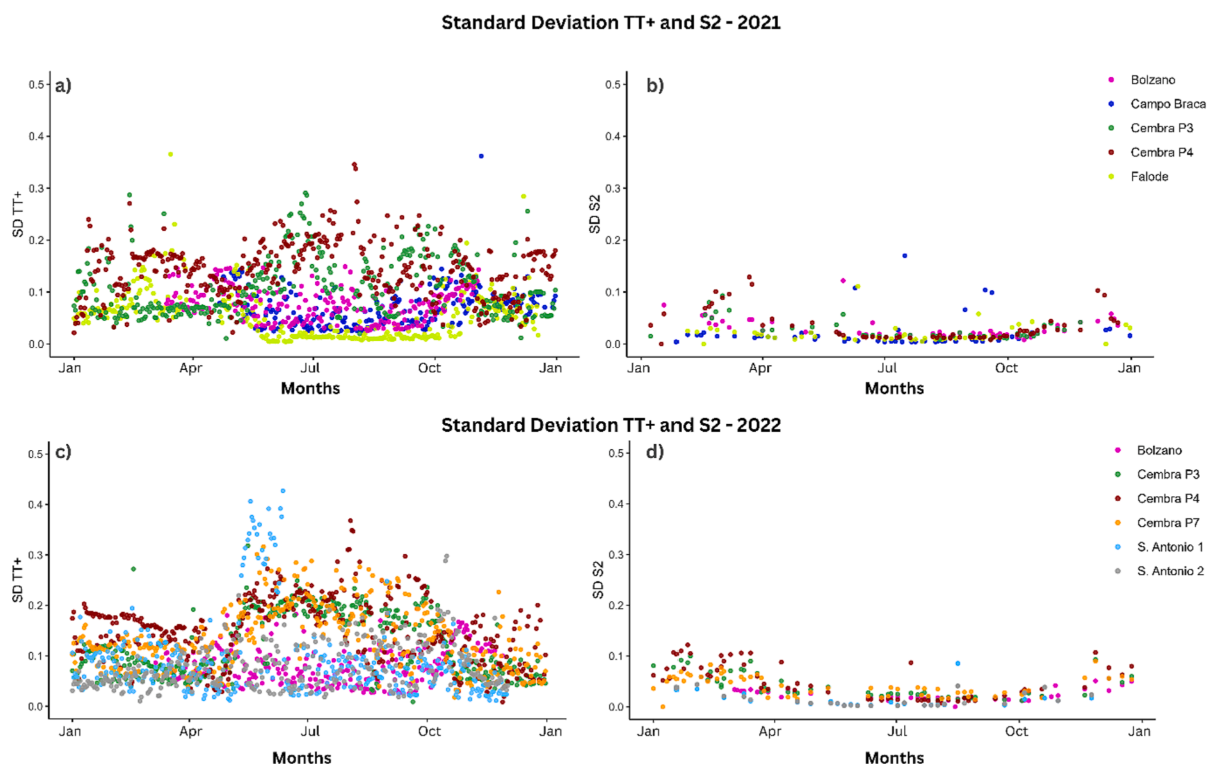

Fig. 3. Standard deviation of the NDVI median yearly values for TT + and S2 data.

leaf-off) between TT + and S2 appear evident. Years are considered separately to account for different sites in different years. In 2021, according to TT + the site-averaged length of the beech growing season results equal to 159 days, and to 151.8 days in the sites of 2022; instead, according to S2 this value is equal to 155.2 days in 2021 and 157 in 2022. The inter-site variation in season length, expressed as coefficient of variation, resulted from TT + data equal to 17.3 % and 8.0 % for 2021 and 2022, respectively; while from S2 data these coefficients resulted equal to 8.5 % and 3.8 %.

At the site level, the three Trentino experimental plots (Cembra P3, P4, and P5) show differences in the starting and ending dates and in the length of both seasons according to TT + or S2, with minor intersite difference for belonging to the same site at close distance from each other. The Bolzano site, located in the Alto Adige province, shows according to both data types and years a longer season length with respect to Cembra, as expected for being at lower altitude. Also, for Bolzano differences between dates estimated with TT + or S2 are present; e.g. the ending date in 2021 is postponed by 13 days in S2 data with respect to TT+, and the ending date in 2022 is anticipated by 5 days according to TT + data with respect to S2 ones. The data for Campania region refer only to 2021: the differences according to TT + between Falode and Campo Braca sites are negligible, but according to S2 are substantial with 29 days of difference in the season length. The data for Toscana region are available only for 2022: again, according to TT + data no difference occurred between the two S. Antonio sites, while according to S2 a relevant difference (15 days) occurs in the starting date and consequently in the length of the season in the two sites.

The changepoints from low to high NDVI values, that mark the start of the leaf on period, are found in the Bolzano site (having lower elevation) at the very beginning of May. Small differences are present among the dates computed with S2 and TT + data (max 3 days). Instead, for the changepoints from high to low NDVI values larger differences are found in the Bolzano site, as in 2021 the TT + data locates the point 13 days after the date found with S2, and in 2022 6 days after.

The two Campania sites, located at intermediate elevation, have data referring to 2021: the low to high NDVI changepoint is found for both sites about one week after the Bolzano date according to TT+, while S2 locates the point very early in Falode (3 days after Bolzano) and 20 days

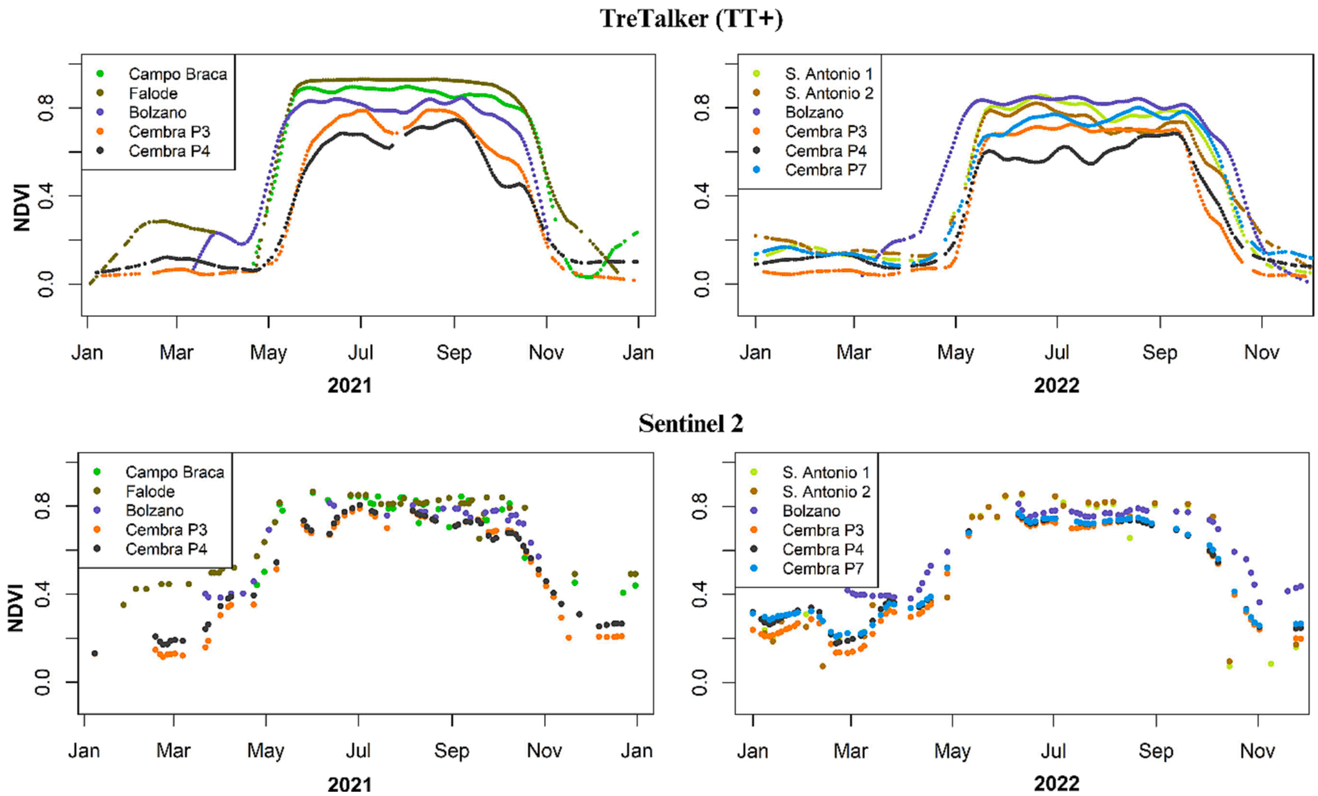

Fig. 4. NDVI values computed at TT_plot level in the study sites for 2021 and 2022 years, from either TT + data and Sentinel 2 imagery. Different study sites are indicated by different colors.

Table 3
Phenological changepoint dates resulted from the analysis carried out using the BEAST algorithm for each study site and year.

Region / Province	Site	Start date	End date	Julian start date	Julian end date	N. days	Elevation / mean °C
TT + 2021							
Campania	Falode	2021–05-09	2021–11-06	128	309	181	1085 / 10.85
Campania	Campo Braca	2021–05-10	2021–11-05	129	308	179	1141 / 10.6
Alto Adige	Bolzano	2021–05-03	2021–10-27	122	299	177	774 / 12.7
Trentino	Cembra P3	2021–05-29	2021–10-09	148	281	133	1270 / 11.0
Trentino	Cembra P4	2021–05-29	2021–10-01	148	273	125	1270 / 11.0
Sentinel 2 2021							
Campania	Falode	2021–05-05	2021–10-23	124	295	171	1085 / 10.85
Campania	Campo Braca	2021–05-25	2021–10-12	144	284	140	1141 / 10.6
Alto Adige	Bolzano	2021–05-02	2021–10-14	121	286	165	774 / 12.7
Trentino	Cembra P3	2021–05-25	2021–10-22	144	294	150	1270 / 11.0
Trentino	Cembra P4	2021–05-25	2021–10-22	144	294	150	1270 / 11.0
Region / Province	**Site**	**Start date**	**End date**	**Julian start date**	**Julian end date**	**N. days**	**Elevation / mean C°**
TT + 2022							
Toscana	S. Antonio 1	2022–05-14	2022–10-15	133	287	154	1200 / 10.00
Toscana	S. Antonio 2	2022–05-14	2022–10-15	133	287	154	1200 / 10.00
Alto Adige	Bolzano	2022–04-28	2022–10-18	117	290	173	774 / 12.7
Trentino	Cembra P3	2022–05-13	2022–10-03	132	275	143	1270 / 11.0
Trentino	Cembra P4	2022–05-13	2022–10-03	132	275	143	1270 / 11.0
Trentino	Cembra P7	2022–05-13	2022–10-04	132	276	144	1270 / 11.0
Sentinel 2 2022							
Toscana	S. Antonio 1	2022–05-15	2022–10-12	134	284	150	1200 / 10.00
Toscana	S. Antonio 2	2022–04-30	2022–10-12	119	284	165	1200 / 10.00
Alto Adige	Bolzano	2022–05-01	2022–10-13	120	285	165	774 / 12.7
Trentino	Cembra P3	2022–05-11	2022–10-12	130	284	154	1270 / 11.0
Trentino	Cembra P4	2022–05-11	2022–10-12	130	284	154	1270 / 11.0
Trentino	Cembra P7	2022–05-11	2022–10-12	130	284	154	1270 / 11.0

later in Campo Braca. For the other changepoints, from high to low NDVI, TT + indicates about the same day (5 and 6 of November) while according to S2 there are 11 days of difference between the sites, with the first one located 7 days after the date according to TT + data. Sentinel 2 found much more differences in the phenology of the two Campania sites with respect to TT+, with delayed starting of leaf on period in Campo Braca and delayed starting of leaf off period in both areas.

The two S. Antonio sites have data for 2022. According to TT + the sites have the same start and end dates for the changepoints of the vegetative period, while according to S2 the end date is the same but for the starting that there are 15 days of difference among the sites.

At Cembra the plots are two in 2021 and three in 2022. Cembra has higher elevation with respect to other sites and includes a very small number of species other than beech; here the length of the period with leaves presence is always shorter with respect to other sites according to TT+, but not according to S2. With TT+, in 2021 the leaf on changepoint is found at the end of May, and with S2 is located 4 days before; in 2022 the point is found in mid-May, 2 days earlier with S2 than with TT +. With respect to the high-to-low NDVI changepoint occurring in late fall, the TT + data indicate 8 days of difference between Cembra plots in 2021, and 1 day in 2022; according to S2, the date is the same for all the plots, but located 13 days later for one (P3) and 21 for the other (P4) with respect to TT + in 2021, and 2 days before in 2022.

The following Fig. 5 (for 2021) and 6 (for 2022) show the results obtained with the BEAST model for TT + and S2 sensors and support the visualization of Table 3 data, and of the NDVI trends, changepoints, and the associated uncertainties (Zhao et al., 2019).

The Figs. 5 and 6 show in Cembra sites a greater variance in TT + data with respect to data from the other sites.

Prior to the correlation analysis between TT + and S2 NDVI data, normality tests were carried out for each area and dataset: results indicate that in most cases the distributions are not normal, so the Spearman non-parametric coefficient was used. Correlations between NDVI from TT + and S2 in dates of both data acquisition were computed based on the mean of TT_plot values for the entire year and based on the median for the leaf on period, selected in this period of higher variability for being less sensitive to extremes. Table 4 reports the results and the amount of data to compute the coefficient.

The yearly correlation values resulted from high to very high and based on a larger number of records (collected in leaf on and leaf off periods) with respect to values found in the leaf on period only, which resulted in medium to low. Fig. 4 shows that the higher variability is found in TT + data in the leaf on period, which can impact, together with a reduced number of records, the degree of correlation with the more stable NDVI values from S2.

4. Discussion

The importance of phenology information to explore potential climate change impacts on beech has been shown by different studies. Dolschak et al. (2019) used leaf sprouting and senescence modeled data to show that the potential productivity increase due to warming is nullified by the summer soil water deficit. (Čufar et al., 2012) showed that changes in Slovenia climate affect mainly beech leaf unfolding, to a greater degree at higher altitudes than at lower ones; Wang et al. (2022) using 50 European beech provenances suggested that the adaptation to future climate change may decelerate the advance of the leaf-out date;

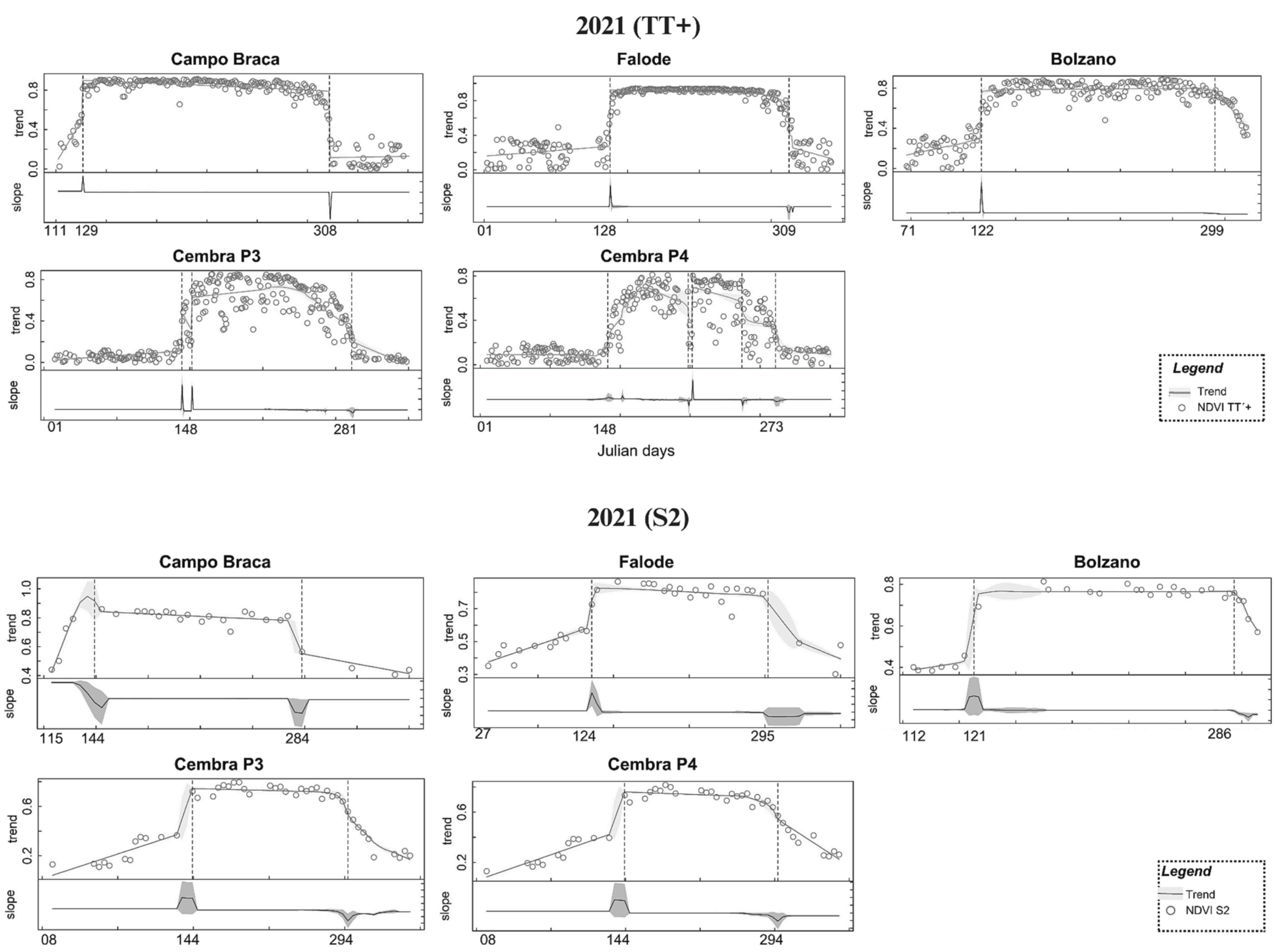

Fig. 5. 2021 phenology changepoint and trend detection resulting from the BEAST model with TT + and S2 NDVI data in input, with associated trend line (green line) and uncertainty (grey areas). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

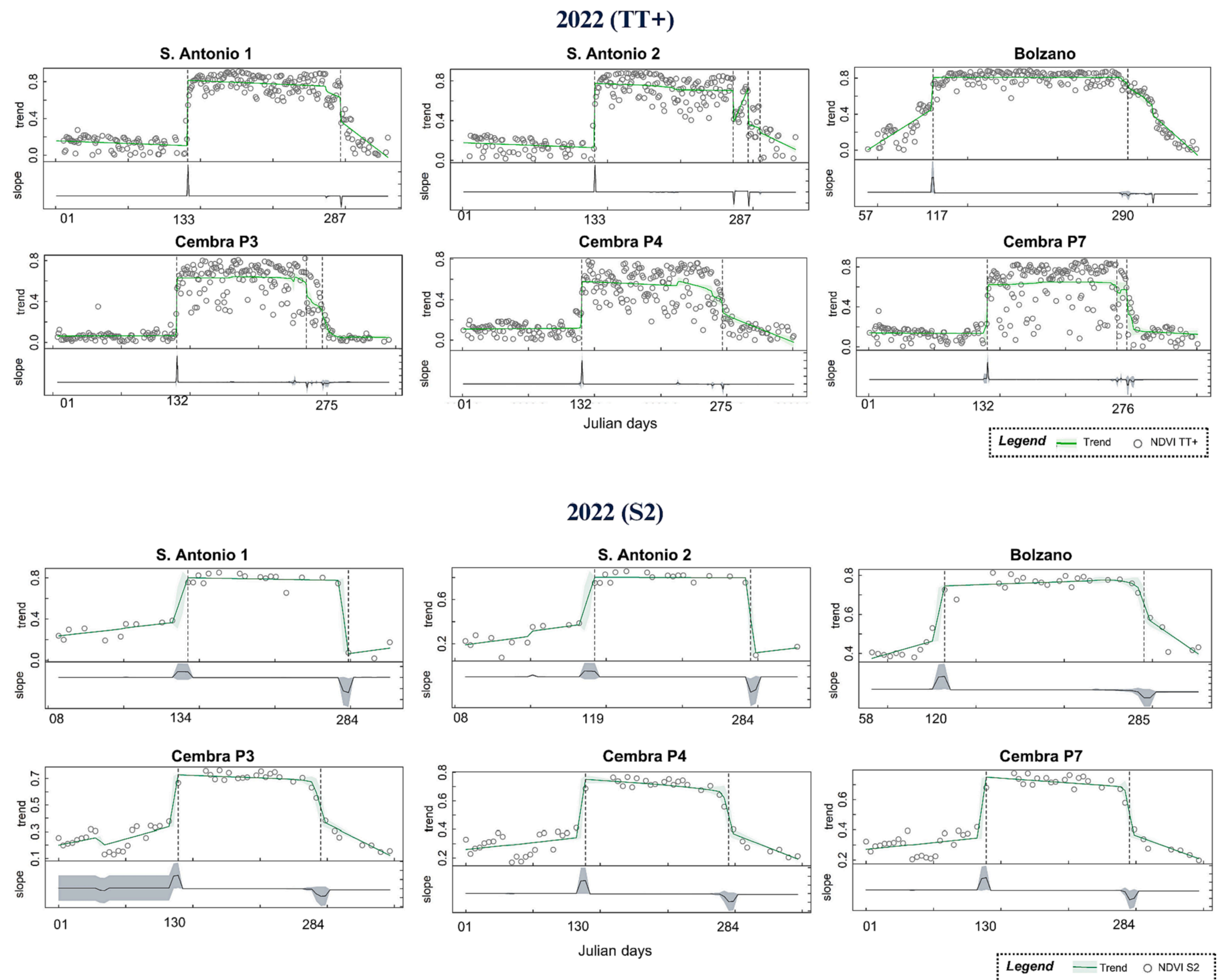

Fig. 6. 2022 phenology changepoint and trend detection resulting from BEAST model with TT + and S2 NDVI data in input, with associated trend line (green line) and uncertainty (grey areas). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Results of TT+ - S2 NDVI Spearman correlation analysis for each site and year.

Sites 2021	*Full year Spearman r (NDVI mean)*	*Full year # data*	*Leaf on Spearman r (NDVI median)*	*Leaf on # data*
Campo Braca	0.79	51	0.49	28
Falode	0.73	49	0.61	27
Bolzano	0.85	54	0.53	28
Cembra P3	0.85	50	0.24	23
Cembra P4	0.68	59	0.29	22
Sites 2022	*Full year Spearman r (NDVI mean)*	*Full year # data*	*Leaf on Spearman r (NDVI median)*	*Leaf on # data*
S. Antonio 1	0.83	48	0.74	13
S. Antonio 2	0.78	47	0.75	14
Bolzano	0.73	47	0.35	23
Cembra P3	0.81	56	0.12	20
Cembra P4	0.82	61	0.47	18
Cembra P7	0.83	60	0.62	19

(Proietti et al., 2020), using data from two Mediterranean beech populations located at different latitudes, found a statistically significant different length of the vegetative spring period between sites. Phenology can also help to differentiate traits among European beech populations, relevant for the selection of proper forest reproductive material in view of climate impacts (Gömöry et al., 2015).

In this study, the complementary nature of TT + below-canopy and S2 satellite data is investigated for monitoring phenological changes in European beech (*Fagus sylvatica*) forests, considering the need of improved monitoring in view of climate impacts. The presented results provide strong evidence in support of the working hypotheses, demonstrating that: (a) TT + sensors can efficiently monitor phenological changes in trees, (b) ground and satellite data capture complementary phenological information, and (c) that integrating these two data types can address the limitations inherent in satellite monitoring such as mixed pixels and data availability gaps, revealing significant insights into the complex dynamics of forest phenology and the potential for more effective monitoring systems.

The observed TT + NDVI trends clearly document the expected yearly and inter-site variations, confirming that this sensor can detect the general phenological behavior. The TT + NDVI variations result higher in the vegetative period with respect to S2 ones, while in the leaf-off period these variations are considerably lower (NDVI < 0.25) than those recorded by S2 (NDVI up to > 0.4). This variability is especially high in Cembra sites, possibly due to the lower canopy density with respect to other beech forests, caused by recent thinning and windthrows; consequently, a larger percentage of sky is included in the FOV and the variability may be partially linked with light conditions (cloudy/clear sky). In has to be noted that the number of TT + s in the TT_plot may also play a role: for instance, Bolzano and Campo Braga have in 2021 the higher number of TT + s (19 and 18) and a lower standard deviation of TT + NDVI values compared to other sites equipped with less TT + sensors. Furthermore, the study sites here considered belong to different Pavari's phytological belts (modified in Piovesan et al., 2005) and feature different composition in terms of tree species mixture, understory, tree density and canopy cover: thus the amount of inter-site variation observed in TT + data can be considered reasonable.

Instead, the high S2 NDVI values found in the inactive period are unusual and can be attributed to the mixed vertical signal from other vegetation layers captured by the satellite view over the TT_plot, a source of mismatching between ground and remote sensing data also evidenced by Fu et al. (2014) and Helman (2018).

These results highlight a critical nuance: TT + captures high temporal resolution data focused on the tree overstory, whereas S2 is focused on a stand-level spatial resolution, with a mixed overstory and understory view, especially during phenological transition phases or in low forest cover conditions.

This disparity demonstrates sensors' complementarity, and that integrating both data sources could offer valuable insights into the complex phenological behaviors across different forest layers, which have significant implications for resource allocation, habitat availability, and overall ecosystem functioning in the context of climate change (Pettorelli et al., 2014; Uphus et al., 2021).

Indeed, using different field, proximal, and remote phenological data, (Uphus et al., 2021) showed that the beech spring phenology overstory will advance more than understory, leading to an increased vertical phenological mismatch that can have major ecological effects. A possible anticipated leaf-out in the forest canopy, that could be measured by TT+, compared to the understory leaf-out potentially measured by S2, could lead to decreased light availability for the understory during its optimal photosynthetic window, thereby affecting carbon uptake, growth, and potentially impeding regeneration (Heberling et al., 2019; Landuyt et al., 2019). In ecosystems where *F. sylvatica* is a dominant species, wood production and animal habitats might be affected (Jolly et al., 2004). However, the understory's relatively slow phenological response to temperature changes may serve as a buffer against late-frost events, which could be an evolutionary advantage (De Frenne et al., 2019). Further exploring TT + and S2 data on a longer term and in other forest ecosystems could help to assess whether the findings presented here generalize across species or ecosystems.

The results also evidence differences in the estimated length of the growing season between TT + and S2 data, with TT + indicating 159 days and 151.8 days in 2021 and 2022 respectively, and S2 showing 155.2 days and 157 days for the same years (Table 3). Differences up to several days are also found in the timing of the changepoints, and in the length of the change phases during leaf on and leaf loss. For example, the length of the total period with leaves in Cembra is always shorter with respect to other sites according to TT + data, but not according to S2 data. Similarity between the two sensors data is observed only in the start of the leaf on period in Bolzano, which results earlier with respect to other sites according to TT + and S2. Often the growing season length is related to the elevation of the sites, with Bolzano being at the lowest and Cembra at the highest altitudes, a fact that explains what is observed by TT + data. Piovesan et al. (2005) also found that summer drought can impact beech growth with different intensities according to elevation; however no clear relationship was here found between site elevation and temperature, or sensor type, and the length of phenological events.

The observed differences show that TT + data can capture rapid changes in NDVI values, particularly in the leaf-out period (Figs. 5 and 6), thanks to its high temporal resolution in contrast to the more sporadic data capture from S2; the TT + continuous monitoring is particularly beneficial when satellite data are limited by cloud cover. Thus, the high-resolution TT + data can offer more accurate insights into subtle shifts in the length of growing seasons, enabling better assessment of the impacts of climate change. Providing information on the phenology of individuals, the TT + system can also be potentially useful for establishing the genetic basis of phenological change and response to climate.

The mismatch here observed between ground and satellite data was already observed in other research and related to multiple causes such as the examined season, the satellite data type, or the indices used (Ferrara et al., 2023; Zhang et al., 2018). For instance, satellite derived information was found to be more sensitive to canopy level changes, rather than to specific phenological events (Fisher and Mustard, 2007); satellite time series resulted not dense enough to capture fast-occurring changes (Vrieling et al., 2018), especially those occurring in the early stages of the growing season (Zhang et al., 2020); and mixed pixels problems affected those satellite data having higher frequency but lower spatial resolution (Chen et al., 2018b). Recently, Ferrara et al. (2023) studied the temporal discrepancy between ground and satellite data for the start of season metrics in European beech forests, using satellite data at low spatial resolution (250 m) and field direct observation (flowering, fruiting, leaf unfolding etc.), and also quantifying the influence of main biophysical factors on the mismatch. They found that all the metrics occurred earlier in satellite than in ground data, with latitude and temperature being the most important drivers for the differences. Given the increased satellite data availability and cloud-based processing facilities, higher spatial resolution data are often to be preferred, such as those here used at 20 m spatial resolution, because they minimize mixed pixel effects and allow to focus on certain species or forest types, including species targeted for their vulnerability, conservation, or economic importance (Anderegg and HilleRisLambers, 2016; Zang et al., 2014).

The correlation values between TT + and S2 data obtained at the year level are high but resulted lower when considering only the leaf on period. (Wang et al., 2004) in Finland found similar results when comparing NDVI from satellite and ground data, with good agreement for the main growth period but less in other months. Similarly, a multiscale comparison among near-surface and satellite spectral data revealed general good correlation (r > 0.5) but remarkable offset during green-up and senescence periods (Thapa et al., 2021). On the other hand, when metrics from ground multispectral and hyperspectral sensors were compared to those from S2, a strong correlation was show, especially for NDVI ($0.72 \leq R2 \leq 0.97$) (Lange et al., 2017); also land surface phenology from multi-sensor data showed strong correlations (r = 0.9) with PhenoCam data for green-up dates in deciduous broadleaf forests, whereas very weak correlations (r = 0.15) were found for evergreen needle leaf forests due to very small signal seasonal amplitude (Bolton et al., 2020). In the present research additional efforts are needed to understand the reasons for low correlation between TT + and S2 sensors in leaf on period. However, it is important to underline that the TT + offers the opportunity to easily acquire ground spectral data, differently from other types of phenological observations, and this opens the way for direct comparison or even to test the use of ground spectral value as a replacement of the satellite missing values for critical periods or dates.

Overall, the results of this study show that the observed differences in phenology data are to be attributed to two main factors: the different view of the two sensors and the temporal resolution. With respect to sensor view, the satellite top-down view implies that the reflectance captured by S2 over the TT_plot area is retrieved not only from the tree canopy but also from shrubs and herbs layers, visible through the foliage gaps. It is a mixed pixel effect that occurs through the vertical forest dimension, even if the S2 spatial resolution is good. The opposite TT +

view, bottom-up and pointing toward the canopy with a limited FOV, implies that the signal averaged from different TT + sensors in the plot is not affected by noise from other vegetation layers; the signal comes only from light transmitted through the leaves and branches in the canopy and this possibly allows to better capture canopy changes. With respect to temporal resolution, TT + acquires daily data in contrast to the variable revisit frequency of satellites, 5-day for S2 constellation, that can further be reduced due to cloud cover. If some image cannot be acquired during the short time frame in which phenological changes occur, the data derived from satellites can report wrong changepoints and length of periods.

The TT + sensor still has various limitations, such as the reduced field of view and the inclined axis with respect to nadir, which impacts must be better evaluated and that may affect the link to remote sensing data.

Improvements are on-going, such as the use of diffuse lenses and the definition of a better strategy for selecting the proper number of TT + in the TT_plot and to correctly positioning the sensors, to avoid data discard due to inclusion of portions of the trunk or branches in the FOV, or of portions of open sky.

For further developments of a TT + network, it is recommended that photographs of the FOV are taken at regular intervals to estimate the canopy cover, both of single TT + s and of the TT_plot. This helps to adjust unwanted FOV displacements, but also to position the sensors in order to better represent the canopy cover of the entire plot. The maintenance has also an important role: the percentage of TT + data retained after filtering in certain sites was linked to the resources available for monitoring; however in other sites it was more related to the structure of the forest affecting the sunlight transmission/reflection/scattering mechanisms, and thus to TT + sensor positioning.

5. Conclusions

Given the importance of phenological studies in forest ecology and climate change, and the differences emerged when comparing ground and satellite signals, it seems wise that the two data sources are integrated in view of a future regular monitoring that can also inform on climate impacts on forests. Satellite data collect valuable information over large extents and daily ground data are suited to capture sudden changes or climate induced shifts in phenological behavior. The TT + sensors, collecting below canopy spectral data, plus several additional tree parameters (Valentini et al., 2019), can be used for this purpose and be directly linked to satellite spectral reflectance. TT + can help to clarify the role of different forest layers in the phenological response, and light transmission data can be used for other purposes too, such as modeling solar radiation absorption in the forest (Olpenda et al., 2018). An integrated system requires that the network of sites is representative of the species or ecosystem type under study, to refine system installation settings, and that more research is conducted in mixed and evergreen forests, to evaluate how to disentangle mixed phenological signals from multiple species or how to capture very subtle phenological changes in evergreen species. The set-up of a TT + network was a remarkable first step toward the setup of an integrated monitoring system, able to collect spectral signals from above and below the forest canopy, at high temporal frequency and high spatial resolution. Such an integrated system will be of key importance for understanding phenological shifts and designing new climate smart forest management strategies.

CRediT authorship contribution statement

Gaia Vaglio Laurin: Conceptualization, Methodology, Formal analysis, Writing – original draft, Supervision. **Alexander Cotrina-Sanchez:** Data curation, Formal analysis, Methodology. **Luca Belelli-Marchesini:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – review & editing. **Enrico Tomelleri:** Data curation, Methodology, Writing – review & editing. **Giovanna Battipaglia:** Data curation, Methodology, Writing – review & editing. **Claudia Cocozza:** Data curation, Investigation, Writing – review & editing. **Francesco Niccoli:** Data curation, Formal analysis, Methodology. **Jerzy Piotr Kabala:** Data curation, Formal analysis, Methodology. **Damiano Gianelle:** Funding acquisition, Writing – review & editing. **Loris Vescovo:** Data curation. **Luca Da Ros:** Writing – review & editing. **Riccardo Valentini:** Conceptualization, Funding acquisition, Supervision. Gaia Vaglio Laurin and Alexander Cotrina-Sanchez contributed in a similar amount to this work. All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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