



SwissPhenoCam: A country-scale dataset of tree-level phenocam greenness captures species-specific phenological variation along elevation gradients in Switzerland

Vivien Sainte Fare Garnot^{*1}, J. Jelle Lever^{*2}, Maaïke de Boer^{2,3}, Lynsay Spafford^{2,4}, Yann Vitasse², Christian Sigg⁵, Barbara Pietragalla⁵, Roman Zweifel², Arthur Gessler², and Jan Dirk Wegner¹

¹EcoVision Lab, DM³L, University of Zurich, Zurich, Switzerland

²Swiss Federal Institute for Forest, Snow and Landscape Research (WSL), Birmensdorf, Switzerland

³ETH Zurich, Zurich, Switzerland

⁴Faculty of Forestry and Environmental Management, University of New Brunswick, Fredericton, Canada

⁵Swiss Federal Office of Meteorology and Climatology (MeteoSwiss), Zurich, Switzerland

Correspondence: Vivien Sainte Fare Garnot^{*} (vivien.saintefaregarnot@uzh.ch) and J. Jelle Lever^{*} (jelle.lever@wsl.ch)

^{*} These authors contributed equally to this work.

Abstract. Vegetation phenology, the seasonal timing of recurring plant life-cycle events, is a key regulator of ecosystem functioning, carbon and water cycling, and species interactions, while also serving as a sensitive indicator of climate variability and climate change. However, existing phenological observations often face trade-offs between species-level detail, temporal frequency, and spatial coverage.

5 Networks of near-surface digital repeat cameras (phenocams) deliver robust, high-frequency phenological signals, but their spatial coverage remains a limitation. In addition to expanding such phenocam networks, this limitation can be tackled by repurposing the outdoor cameras already deployed for other purposes. Here, we present SwissPhenoCam, a country-scale dataset of tree-level phenological greenness observations derived from a network of outdoor digital cameras distributed across Switzerland. By repurposing cameras originally installed for meteorological monitoring, tourism, and other non-ecological applications, SwissPhenoCam demonstrates the potential of existing imaging
10 infrastructure for large-scale phenological observation.

The dataset comprises imagery from 34 sites spanning broad elevational, climatic, and biogeographic gradients, with archives extending up to 15 years. Individual trees were delineated and identified to species level where possible, enabling the extraction of species-specific greenness time series and phenological transition dates. The curated dataset contains 5,855 tree-years of observations representing more than 20 tree species and captures substantial environmental variability across Switzerland.

15 Validation against independent observations from the Swiss Phenology Network demonstrates strong agreement between camera-derived and ground-based phenological transition dates, confirming that non-specialized webcams can provide reliable phenological information. Analyses of the dataset reveal pronounced species-specific responses to environmental gradients. Spring green-up is consistently delayed with increasing elevation across deciduous species, whereas autumn senescence shows comparatively weak elevational trends. As a result, growing-season length decreases primarily because of later spring onset rather than earlier autumn decline.

20 The SwissPhenoCam dataset is openly available through Zenodo (<https://doi.org/10.5281/zenodo.20451225>) (Garnot et al., 2026) and is intended as a living resource that will expand as observations accumulate. By providing species-resolved, individual-tree phenological observations across a topographically complex landscape, the dataset offers a valuable benchmark for evaluating remote-sensing products, improving phenological models, and assessing climate-change impacts on forest ecosystems. Future work can use this resource to investigate long-term phenological trends, species-specific climate sensitivities, and ecosystem responses to ongoing environmental change.



25 1 Introduction

Vegetation phenology — the timing of recurring plant life-cycle events such as spring leaf emergence, flowering, fruit maturation, and leaf senescence — plays a central role in regulating ecosystem structure and function, carbon and water cycling, species interactions, and biosphere–atmosphere feedbacks (Peñuelas and Filella, 2001; Schwartz et al., 2003; Cleland et al., 2007; Richardson et al., 2013). At the same time, plant phenological processes are highly sensitive to climate variability and long-term climate change (Wilson and Baldocchi, 2000; Parmesan and Yohe, 2003; Menzel et al., 2006; Richardson et al., 2010; Jeong et al., 2011). As a consequence, shifts towards earlier spring leaf emergence and, to a lesser extent, a changed timing of autumn senescence have been observed in temperate and boreal regions (Fu et al., 2014), with important implications for forest productivity, species interactions, and carbon cycling (Richardson et al., 2010; Keenan et al., 2014; Kharouba et al., 2018). Despite this importance, substantial uncertainty remains in phenological modelling and in projections of ecosystem responses to future climate conditions. This uncertainty arises in part from incomplete understanding of how environmental cues — such as photoperiod, chilling, forcing requirements, and other abiotic factors — interact to control phenological timing across species. Even in the absence of long-term climate change, substantial natural inter-annual climate variability can obscure these relationships and hinder the disentangling of underlying mechanisms. Anthropogenic climate change is expected to further increase climatic variability and produce novel combinations of environmental conditions that fall outside the range under which current phenological relationships have been established. Together, these factors complicate both mechanistic understanding and the robust prediction of future phenological responses, highlighting the need for high-quality long-term observations across multiple years and diverse biogeographic regions.

Traditionally, phenology has been assessed through direct human observations, including long-standing phenological records and, more recently, citizen-science initiatives, e.g., the Pan European Phenology Database, Swiss Phenology Network, and USA National Phenology Network (Schwartz et al., 2013; Spafford et al., 2025; Templ et al., 2018). These observations provide species-level information and can capture fine-grained phenophase transitions, such as those defined by standardized classification schemes (Brügger and Vassella, 2003; Denny et al., 2014). However, human observations are inherently labor-intensive, lack automation, and are often irregular in time, spatially sparse, and inconsistent across regions. In addition, because these observations are primarily qualitative rather than quantitative, they may be susceptible to observer bias (Liu et al., 2021). These limitations complicate their integration across sites and scales and restrict their utility for large-scale monitoring and modeling applications.

Satellite remote sensing offers a complementary approach by enabling automated and repeatable monitoring of vegetation phenology at regional to global scales (Zhang et al., 2006; Caparros-Santiago et al., 2021). Satellite-based phenology products typically determine the timing of the start and end of the growing season using vegetation indices derived from multispectral imagery. While these products provide broad spatial coverage and consistent temporal records, they do not resolve phenology at the species level due to coarse spatial resolution and mixed land-cover signals. Moreover, satellite observations can be affected by cloud and snow cover and may suffer from limited temporal sampling, for example, due to revisit intervals of several days, which can obscure short-lived or rapidly progressing phenological transitions.



High-frequency digital camera imagery and vegetation indices derived from that imagery have emerged over the last decade as a powerful intermediate approach for monitoring vegetation phenology (Xie et al., 2018; Richardson et al., 2018a; Seyeds-
 rollah et al., 2019; Richardson, 2019; Young et al., 2025). This approach commonly relies on networks of fixed, ground-based
 digital cameras — often referred to as phenological cameras, or phenocams — that acquire visible-wavelength images of vege-
 tation at regular intervals throughout the day. By delivering continuous, high-frequency observations at the organism-to-canopy
 level, phenocams occupy a unique observational niche between ground-based human observations and satellite remote sens-
 ing. From these image time series, e.g., indices of canopy greenness derived from red, green, and blue (RGB) channels, can
 be extracted to provide robust indicators of seasonal phenological dynamics, capturing both gradual seasonal trajectories and
 distinct phenophase transitions such as spring green-up and autumn senescence. By bridging spatial and temporal gaps between
 field observations and satellite data, phenocams provide a critical link for scaling phenological processes across observation
 platforms, and coordinated phenocam networks, most notably in North America and increasingly in Europe, have demonstrated
 the value of standardized imagery and derived products for phenological research, satellite product evaluation, and ecosystem
 model development (Richardson et al., 2018b; Kumar et al., 2025). Since the first deployments in the late 2000s, phenocam
 networks have grown substantially: the PhenoCam dataset now encompasses 738 sites across 30 countries (Young et al., 2025).
 However, over 85% of these sites are located in North America, and global coverage remains uneven despite complementary
 regional efforts such as the Phenological Eyes Network in Japan (Nasahara and Nagai, 2015), EuroPhen in Europe (Wingate
 et al., 2015), and similar initiatives in Finland (Peltoniemi et al., 2018) and Australia (Cleverly et al., 2019). The ongoing ex-
 pansion of these dedicated networks remains essential for building long-term, standardized phenological records. In addition,
 we believe that a complementary approach lies in leveraging the vast number of outdoor digital cameras already deployed
 worldwide for meteorological monitoring, tourism, and other purposes. Many of these outdoor webcams are likely to regularly
 capture vegetation in their field of view. We argue that these cameras represent a largely untapped resource for phenological
 observation, but whether non-specialized imagery can yield phenological metrics of sufficient quality for scientific use remains
 an open question.

Here, we introduce the SwissPhenoCam dataset, which explores this potential and establishes the foundation for a country-
 scale phenocam observation network to support phenological research across Switzerland. Switzerland encompasses pro-
 nounced climatic gradients over short spatial distances due to its complex topography, elevation differences, and land-use
 history. These characteristics make the region a natural laboratory for studying phenological variability and climate sensitivity,
 while simultaneously posing challenges for coarse-resolution satellite products and spatially sparse ground-based observations.

In this context, the present work addresses two questions. First, can reliable phenological time series be extracted from
 outdoor webcams not originally deployed for ecological monitoring? The SwissPhenoCam network builds primarily on an
 existing infrastructure of digital cameras operated by MeteoSwiss for meteorological monitoring, complemented by additional
 third-party camera systems such as those operated by ski resorts and tourist offices. By leveraging this readily available cam-
 era network, SwissPhenoCam adopts a pragmatic and scalable approach to phenological observation that emphasizes spatial
 coverage and long-term continuity. We quantitatively assess the quality of the phenological metrics derived from these non-
 specialized cameras and compare them against independent phenological observations.



Second, how do phenological patterns vary across species along Switzerland's elevation gradient? A distinguishing feature of the SwissPhenoCam dataset is its explicit representation of phenology at the tree level. Rather than canopy-scale regions of interest (i.e. image segments) that combine multiple trees and sometimes species, the dataset provides segments and annotations for single trees, enabling species-level greenness time series extraction. This facilitates investigations of intra-site variability, species-specific phenological responses to climate drivers, and diverging phenological trajectories among co-occurring species within mixed forest stands — processes that are often unresolved in broader - scale phenological datasets.

From the archived imagery, we derive standardized time series of RGB-based color indices aggregated over user-defined regions of interest. These time series are subjected to quality control procedures and are provided at daily and multi-day temporal resolutions. For series exhibiting clear seasonal cycles, we further estimate key phenophase transition dates, including the onset of spring greenness increase and the end of autumn greenness decline, together with associated uncertainty estimates.

The SwissPhenoCam dataset demonstrates that outdoor webcams not originally deployed for ecological monitoring can also deliver phenological transition dates in strong agreement with independent ground observations, and it builds on this to resolve how co-occurring species differ in their seasonal timing, greenness trajectories, and growing-season length along Switzerland's steep elevation gradients. It thereby couples the spatial reach of a country-scale, multi-purpose camera network with the species-level, individual-tree resolution rarely available at this scale. The resulting record, boasting high temporal frequency, broad species and elevation coverage, and accompanied by quantified uncertainties, offers a benchmark for evaluating satellite phenology products in topographically complex terrain, for developing and testing phenological models, and for assessing climate change impacts on forests across spatial scales. Designed as a living resource that will grow as imagery accumulates and the network expands, SwissPhenoCam complements existing phenocam initiatives and helps extend high-resolution phenological monitoring into regions and species that remain under-represented in today's networks.

2 Materials and methods

In the following, we describe the webcam imagery and study sites our dataset is based on in Section 2.1, the methods we implemented to extract chromatic coordinate time series and phenological transition dates in Section 2.2, and lastly we give a description of the distributed data product in Section 2.3.

2.1 SwissPhenoCam imagery

2.1.1 Roundshot Livecams

One of the design principles of the SwissPhenoCam Network is to repurpose already existing cameras for phenology monitoring, enabling cost-effective spatial coverage. Our primary data source is a network of weather cameras operated by MeteoSwiss, the national weather and climate service of Switzerland. This camera network is set up along flight routes to support aviation safety and for other purposes such as the interpretation of extreme weather events. The cameras of this 'MeteoSwiss network' are Roundshot Livecams, i.e. high-resolution panoramic webcams designed and manufactured by Seitz Phototechnik

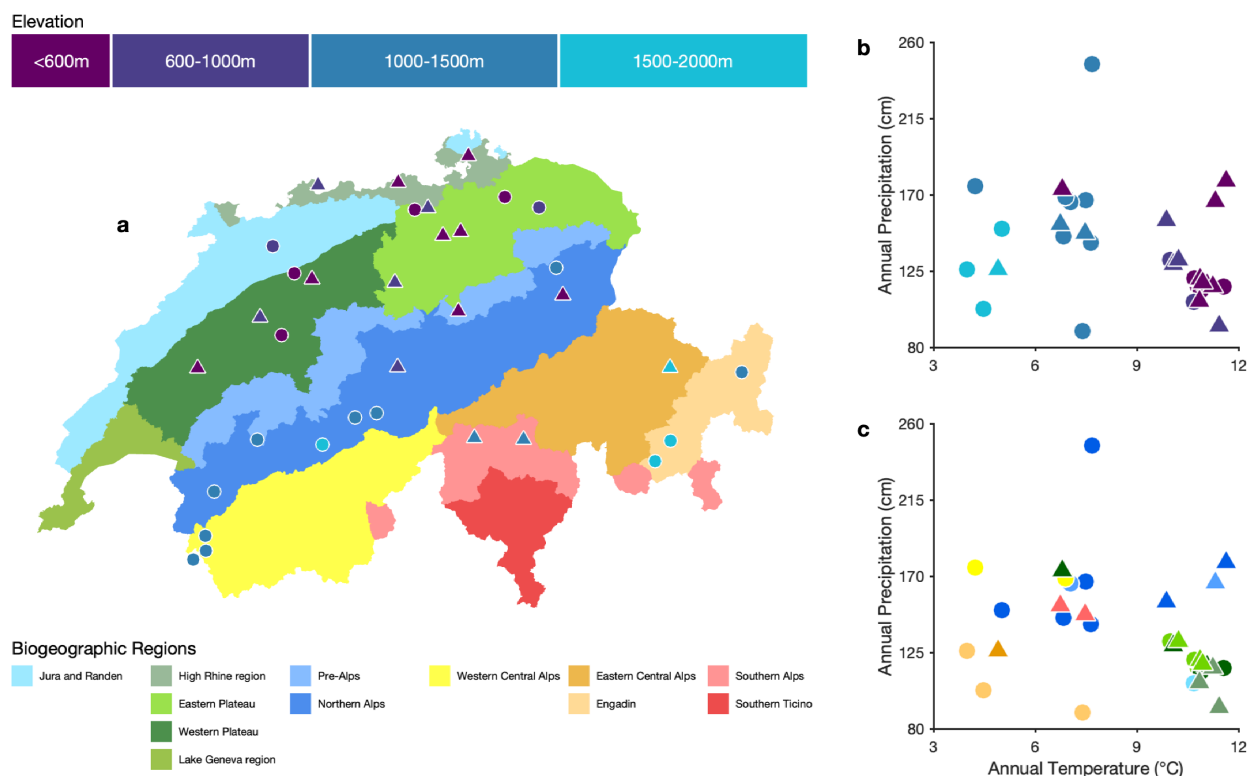


Figure 1. Map of the sites included in the SwissPhenoCam dataset. **a**) Site distribution across Switzerland: triangles indicate cameras at MeteoSwiss sites and at supersites, while circles indicate third-party cameras. Regions correspond to biogeographic zones as defined by the Bundesamt für Umwelt (2020). Icon colours (i.e. the purple–blue gradient) indicate elevation across low (<600 m), mid (600–1000 m), high (1000–1500 m), and very high (>1500 m) elevation bands. **b**) Mean annual temperature (°C) and annual precipitation (cm) for all sites (as recorded in 2023); icon colours indicate elevation. **c**) The same as **b**, but icon colours correspond to biogeographic zones.

125 AG, which in turn are part of a larger network of Roundshot Livecams owned by third parties of which Seitz Phototechnik AG
 manages the data streams and provides hosting services. These third-party cameras are used for a variety of purposes, often
 related to tourism, e.g. when the camera is owned by a hotel or restaurant. A key characteristic of the Roundshot Livecams is
 that they are mounted on motorized platforms that rotate along two axes, enabling full 360° horizontal rotation and vertical tilt
 allowing for image acquisition in many directions. The MeteoSwiss weathercam network consists of 35 cameras which are in
 130 operation since 2021, while there are more than 300 third-party Livecams installed across Switzerland and up to 100 additional
 cameras internationally (primarily in North America), of which some have been running for more than a decade. Beyond this
 pool of already existing cameras we installed four additional Roundshot Livecams at ‘super sites’ to enable further integration
 with other data types that are of relevance for phenology, tree and forest monitoring in the future. These cameras are, e.g.
 placed on top of flux towers or overseeing a phenological garden and are in operation since 2023.



135 2.1.2 Study sites

The SwissPhenoCam dataset currently comprises 34 sites distributed across a wide range of Switzerland's biogeographic zones (see Fig. 1.a). Images captured by all 300+ Roundshot Livecams were visually inspected and ranked according to their suitability for phenological observation, with particular emphasis on the visibility, abundance, and diversity of tree species within each camera's field of view. Approximately a third of the 300+ sites were deemed either suitable or very suitable. Site
 140 selection further accounted for the need to ensure broad coverage across Switzerland's elevational gradient and biogeographic regions, while also considering logistical constraints related to field visits for tree species identification. In some cases, these practical considerations favoured geographically proximate locations. The final selection thus represents a balance between the practical constraints of field visits and maintaining a broad spatial coverage.

While the dataset was designed to capture variability across Switzerland, we believe that the dataset holds relevance for
 145 understanding phenological responses to climate variability at a global scale. The steep elevational gradient in our dataset captures a substantial portion of global climate variability within a compact spatial extent with mean annual temperatures varying between ~3–12 °C and annual precipitation rates between ~80–200 cm (see Fig. 1.b–c and Fig. 2). This makes it a promising foundation for advancing process-based understanding of phenological mechanisms and improving forecasts of climate change impacts by enabling analyses that would be difficult to achieve in regions with more limited environmental
 150 gradients.

Out of the 34 sites, 18 Roundshot Livecams are owned by third parties, 12 are weather cameras owned by MeteoSwiss, while 4 were located at 'super sites' (see above). A substantially larger number of both MeteoSwiss- and third-party-owned, Roundshot Livecams were deemed suitable for phenological observations. These were simply not included due to the above-mentioned logistical constraints, and thus represent a great potential for further expansion of the dataset's spatial coverage.

155 2.1.3 Acquisition types

The cameras at super sites and the MeteoSwiss weather cameras are configured to support phenology monitoring through the acquisition of analysis images (Fig. 3.a-d). These images consist of a single camera shot with a 1.5 aspect ratio and are carefully oriented to minimize backscattering effects, in particular by avoiding the inclusion of the sky as much as possible. Moreover, these images preserve the raw sensor colour space and do not undergo post-processing, ensuring consistency in
 160 colour measurements crucial for quantifying relative greenness. Because the cameras are mounted on motorized platforms capable of rotation, a single camera can obtain multiple analysis images with different viewing angles.

In contrast, third-party cameras only provide *panorama* images (Fig. 3.e), which are intended to showcase a complete and scenic landscape. These panoramas are generated through the capture of a sequence of partially overlapping images in different directions, which are then automatically stitched together and projected onto a rectangular grid. Additional steps
 165 such as automatic white balance or colour enhancement may be applied to improve visual aesthetics. These transformations can alter the original colour information crucial for quantifying relative greenness and introduce geometric distortions due to the stitching process resulting in less standardised data. Despite these technical limitations, we still investigate whether

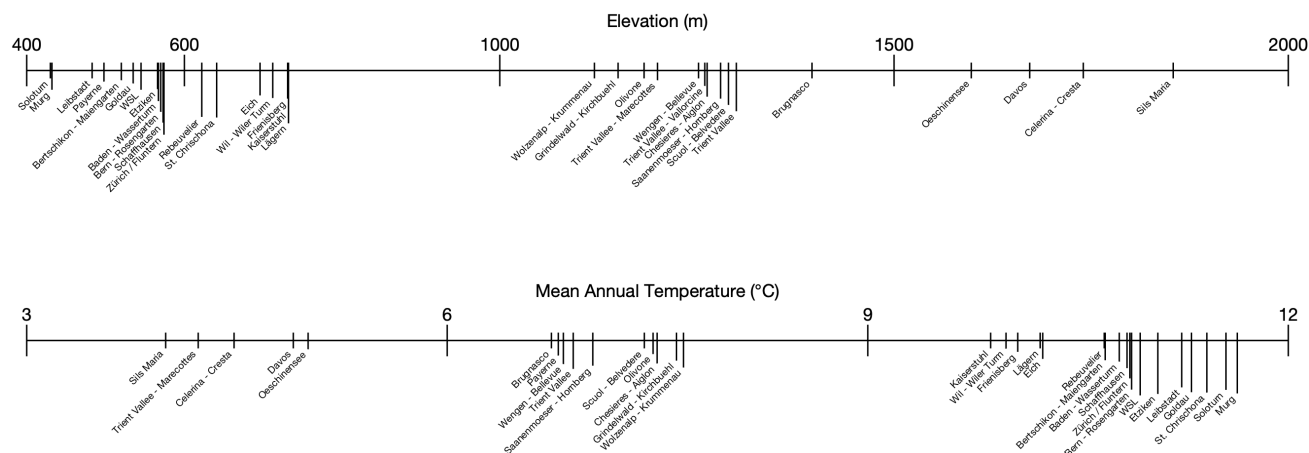


Figure 2. Distribution of sites across elevation and mean annual temperature. Ticks on the elevation axis indicate the start and end of low (<600 m), mid (600–1000 m), high (1000–1500 m), and very high (>1500 m) elevation bands.

170 compare these metrics between analysis and panorama image data (see Sec. 3.3.2).

The cameras deployed at super sites and by MeteoSwiss are Roundshot Livecam Generation 4 models, while we used a mix of Generation 3 and Generation 4 cameras at third-party sites. Both generations offer high-resolution panoramic imaging, with vertical resolutions of approximately 2k and 3.5k pixels and corresponding image sizes of about 66 and 144 million pixels for Generations 3 and 4, respectively.

175 2.1.4 Temporal sampling

The compiled archive spans up to 15 years of observations, depending on the site, amounting to a total of 187 site-years. The temporal resolution varies among site-years but has converged in recent years to one image every 30 minutes across all sites. The density and regularity of the temporal sampling depend on the site and year of acquisition. For all 16 sites for which analysis images are taken, we could record one image every 30 minutes during daytime, reaching a temporal resolution that is equivalent to that of existing phenocam networks (Richardson et al., 2018a). In our archival pipeline, we only kept images taken more than two hours after sunrise and two hours before sunset at any given date to exclude low sun-angle images and poor lighting conditions. On the 18 sites where panorama images are captured, the temporal sampling has evolved over the years. Many of these sites have been archiving images for varying periods going up to 2010, however in this archive only one image per day was kept. We chose to still include those site-years as they enable a glimpse into earlier years. In the past year, the temporal resolution of the archived images for these sites has also been progressively increasing towards one image every 30 minutes, and we reached a homogeneous temporal resolution across all sites since 2024 (see Fig 4). We study in detail the



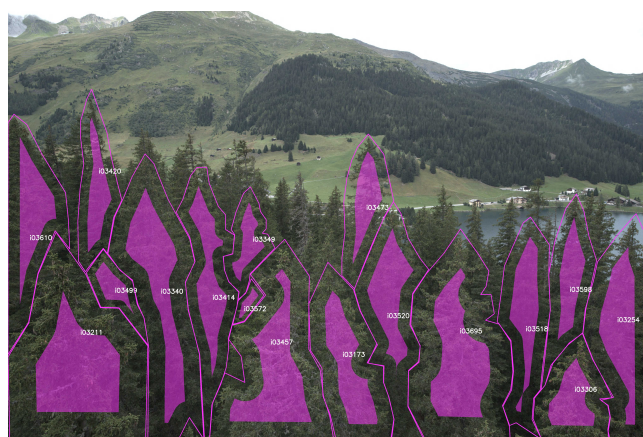
(a) Analysis image 1



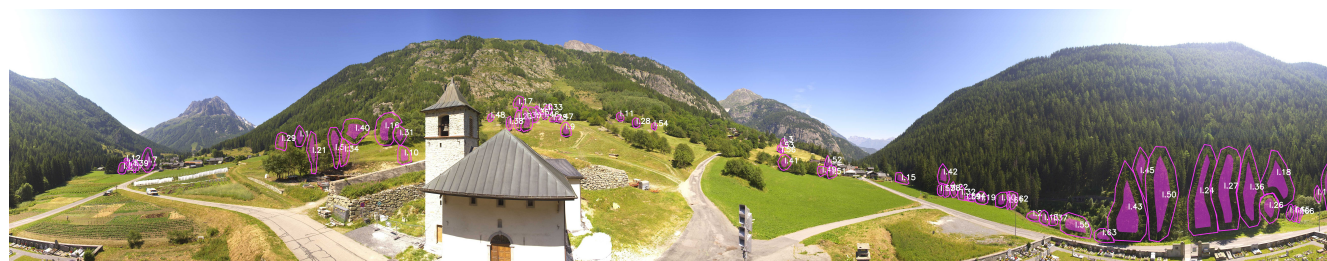
(b) Analysis image 2



(c) Analysis image 3



(d) Analysis image 4



(e) Panorama image

Figure 3. Image samples. Examples of four analysis images (a-d) with a resolution of 6198x4140 pixels and a panorama image (e) with a resolution of 10752x2048 pixels. On these images we also show the region of interest (ROI) defined for individual trees in pink. For each polygon, the exterior line shows the polygon that was manually annotated, and the shaded interior area shows the effective polygon that was used for chromatic coordinate extraction, the area of which corresponds to one third of that of the original polygon.

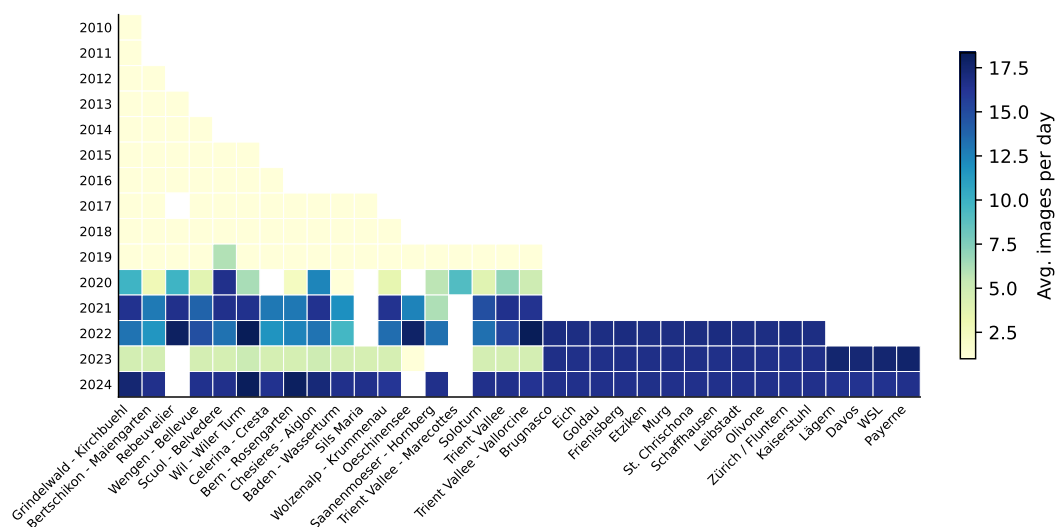


Figure 4. Overview of the available history and temporal resolution for each of the 34 sites of the SwissPhenoCam dataset. Third party sites capturing panorama images enable constituting an archive that traces back to 2010, albeit at a lower temporal resolution. We count the average number of image available during daytime only.

impact that the temporal resolution has on the quality of the greenness signal and the uncertainty of the estimated transition dates (see Sec. 3.3.3).

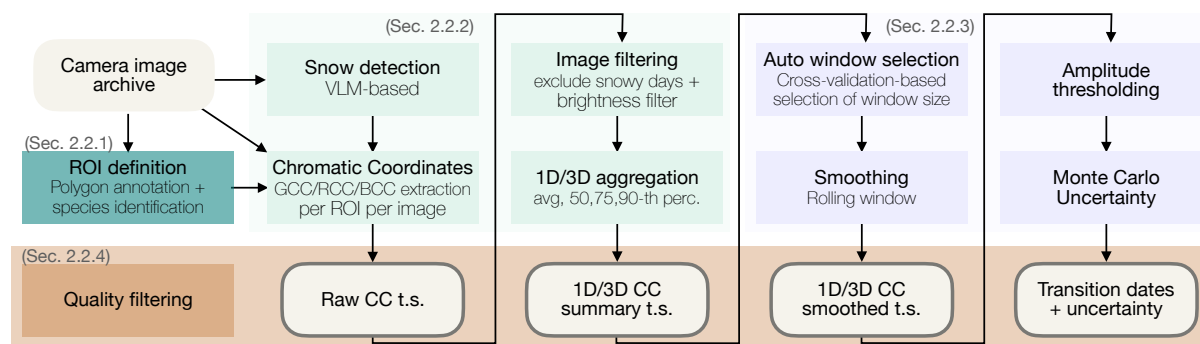


Figure 5. Overview of our processing pipeline. Regions of interest are manually annotated around individual trees, of which the species name is determined during site visits. The archive of raw camera images is then transformed into a dataset of individual tree-level time series of green, red, and blue chromatic coordinates at a one day (1D) and three day (3D) temporal resolution. Next, we extract phenological transition dates from the greenness and redness time series along with uncertainty values derived from Monte-Carlo sampling. Lastly, we apply a set of filters both on the time series and transition dates products to obtain the final dataset of tree-level phenology.

2.2 Processing pipeline

190 In this section, we describe the different steps we implemented to transform the available archive of outdoor webcam imagery into a dataset of individual tree-level chromatic coordinate time series and phenological transition dates (see Fig. 5). We first describe the annotation of individual tree-level regions of interest (i.e., image segments) in Sec. 2.2.1. We then describe the extraction of greenness and redness time series products per individual tree in Sec. 2.2.2, and how we extracted phenological transition dates from these time series in Sec. 2.2.3. Lastly, we outline the quality filtering measures we implemented in Sec. 2.2.5 to discard noisy or corrupt samples. The complete code implementation of the methods presented hereafter is available at github.com/VSainteuf/SwissPhenoCam-greenness-processing.

2.2.1 Region of interest definition and identification

Polygon annotation. Each camera view was manually annotated to identify regions of interests (ROI) as represented in Fig. 3. For cameras with a long archive, the same view was re-annotated every three to four years and re-used for multiple consecutive years after a visual check to remove irrelevant ROIs, e.g. trees that were cut down or became obstructed from one year to the next. The goal of the annotation task was to delineate all individual trees and groups of trees that are clearly visible on the image. The polygons obtained from this annotation effort provided an approximate delineation of the external boundary of each tree or tree group, as seen in Fig. 3.

Species and type identification. To enable species-level phenological monitoring, we conducted site visits to identify the species of each tree visible on the camera fields of view. The visits were done during the spring and summer period when trees had fully developed leaves and could therefore be correctly identified by in-situ close observation of leaves.



2.2.2 Raw chromatic coordinate time series product

Chromatic coordinate extraction For each camera view and each year of archive, we had a sequence of T images $\mathbf{X} = [X_1, \dots, X_T]$ with T the number of camera images. Each image X_t has the same resolution $h \times w$ such that it can be denoted
 210 as per Eq. 1, with $r_{i,j}$, $g_{i,j}$, and $b_{i,j}$ the red, green, and blue 8-bit Digital Numbers (DN) for pixel (i,j) . We visually inspected image-level daily time-lapses of all site-years to detect potential shifts in zoom level or camera angle and manually corrected them. For each camera view and year we also had a set of P ROIs each in the form of a binary pixel mask M_p , taking positive values in the extent of the tree or group of trees of interest. With these notations, the Green Chromatic Coordinate (G_{CC}) for a given ROI on a given image is computed as shown in Eq. 3. Similarly, we extracted the Red and Blue Chromatic Coordinates
 215 (R_{CC} and B_{CC}).

$$X_t = \{(r_{i,j}, g_{i,j}, b_{i,j}) \in [0, 255]^3\}_{i \in [1, h], j \in [1, w]} \quad (1)$$

$$M_p = \{(m_{i,j}) \in \{0, 1\}\}_{i \in [1, h], j \in [1, w]} \quad (2)$$

$$G_{CC}(X_t, M_p) = \frac{\sum_{(i,j)/m_{i,j}=1} g_{i,j}}{\sum_{(i,j)/m_{i,j}=1} r_{i,j} + g_{i,j} + b_{i,j}} \quad (3)$$

Temporal aggregation Applying the chromatic coordinate extraction to all images of a given site-year yielded a raw
 220 time-series of chromatic coordinates. Depending on the site-year and time of year, this time series had between 1 and 24 data points per day. We followed the established data processing pipeline (Richardson et al., 2018a; Seyednasrollah et al., 2019; Young et al., 2025) and aggregated these sub-daily G_{CC} values into a one day (1D) and a three day (3D) summary product. The 1D product was obtained by taking the 90-th percentile value of all raw values obtained for a given DOY. For the 3D product, we computed that percentile over non-overlapping 3-day bins, aligned to the PhenoCam convention. Note that we also
 225 included in our dataset summary products obtained using the average, 50-th, and 75-th percentile, but used the 90-th percentile time series as our main product for transition date extraction. Prior to this aggregation, we excluded data points for which the average brightness in the ROI, defined as the sum of the red, green, and blue channel values (range 0–765), was inferior to 50 or higher than 650. We also excluded observations that corresponded to days flagged as snowy by our snow flag (see below). We show an example of the resulting one-day product in Fig. 6 for an individual *Tilia cordata* tree.

2.2.3 Estimation of phenological transition dates

The temporally aggregated greenness products were then used to extract phenological transition dates. These dates were obtained by smoothing the greenness product followed by amplitude-based thresholding, and a Monte Carlo procedure was then carried out to obtain uncertainty values for each transition date.

Smoothing. The greenness threshold-based transition date extraction we used results in more stable transition dates when
 235 the amount of noise in the greenness time series has been reduced preliminarily. To that end, we chose to use a simple centered rolling window average, to avoid making strong assumptions on the shape of the time series, shown in dark grey on Fig. 6.



i03126_2022 — Tilia cordata — site 1179_2

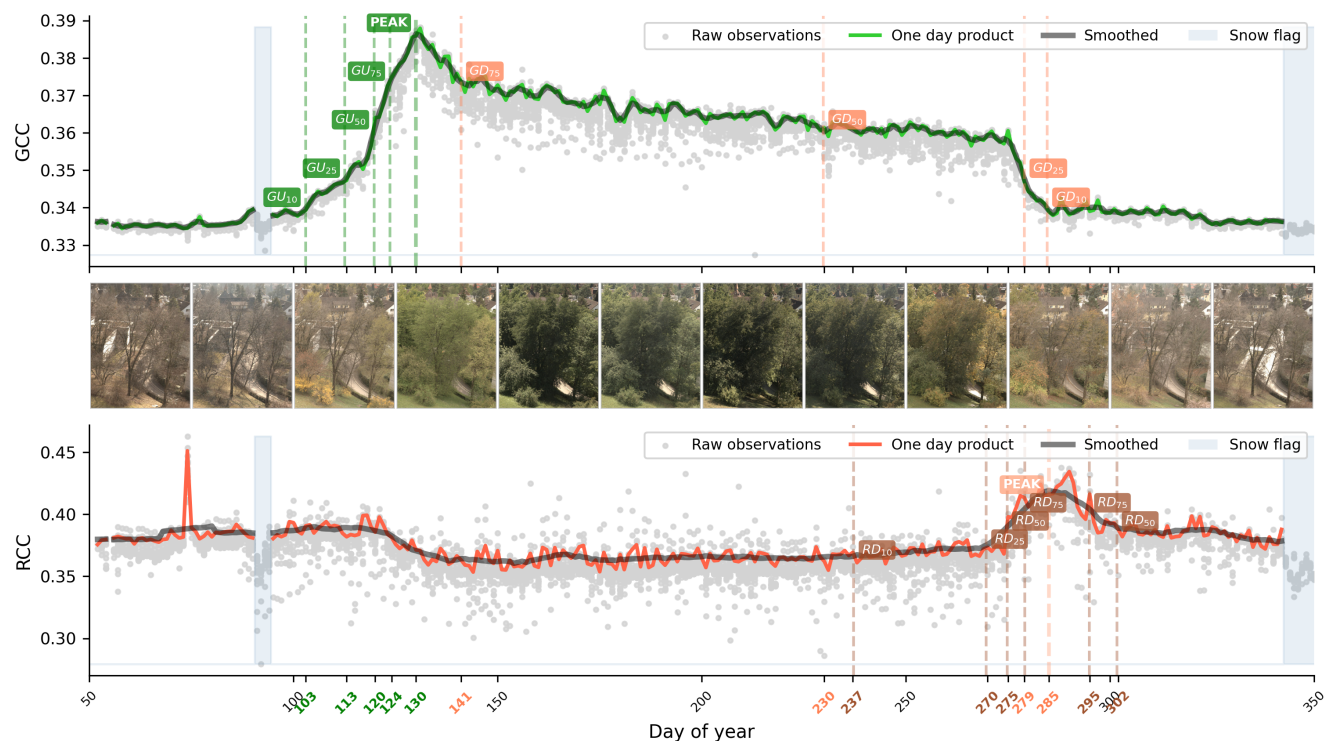


Figure 6. Sample of our dataset showing the different levels of processing for green (top) and red (bottom) chromatic coordinate time series. From raw observations (grey points), we aggregate a daily product by taking the daily 90-th percentile (green and red lines). We then smooth this product through a moving window average with automatic window size selection (dark grey lines). We then use this smoothed time series to extract transition dates based on different thresholds of the total green-up amplitude, as depicted by the vertical dashed lines.

Given the diversity of sensing conditions of our image database, with different levels of temporal resolutions and image quality, we opted for a dynamic selection of the window size for each tree-year based on a simple cross-validation algorithm (Hastie, 2009) as described in Algo. 1. The candidate rolling window sizes were all odd numbers between 3 and 21 days. We used a 5-fold cross validation, meaning that for each fold, 20% of the data points were randomly held out as test data. For a given candidate window size w , the smoothed series was computed on the remaining 80% training data, and the Mean Squared Error (MSE) was computed between the smoothed time series and the test data points. The selected window size w^* was the one achieving the lowest MSE averaged across the 5 folds. Lastly, we computed the smoothed product by taking the rolling window with size w^* on the complete time series.



Algorithm 1 Selection of the moving-average window by Cross-Validation (CV)

Require: Greenness signal y , candidate window sizes $\mathcal{W}$, number of folds K

- 1: **for** each $w \in \mathcal{W}$ **do**
 - 2: **for** each (training data, test data) in K -fold CV **do**
 - 3: Smooth training data using a centered moving average of width w
 - 4: Compute prediction error on the test data
 - 5: **end for**
 - 6: Compute mean CV error for window w
 - 7: **end for**
 - 8: **return** window size w^* with minimum CV error
-

245

Phenological transition dates. We determined the phenological transition dates using the amplitude-thresholding method described in Algo. 2. We first restricted the smoothed greenness time series to dates between day of year 60 and 320 (a window determined empirically to span the growing season while excluding winter-dormant and typically snow-covered periods), then extracted the peak greenness date t_{peak} and value g_{peak} as well as the baseline greenness g_{min} . Transition dates were then determined as the dates at which a certain percentage of the greenness amplitude $A = g_{max} - g_{min}$ was first or last crossed. We obtained sub-daily transition dates by linearly interpolating the greenness signal between the two consecutive dates where the crossing happened and finding the precise day fraction at which the threshold was reached. Following this process, we computed the dates of 10, 25, 50, 75, and 90% green-up and green-down for each greenness time series, depicted with vertical bars on Fig. 6.

250

Algorithm 2 Extraction of phenological transition dates from a greenness signal

Require: Dates t (Day of Year), smoothed greenness signal g , threshold percentages $\mathcal{P}$, season bounds $[t_s, t_e]$

- 1: Interpolate missing values in g
 - 2: Restrict t, g to season bounds $[t_s, t_e]$
 - 3: Identify peak greenness: $g_{max} = \max(g)$, $t_{peak} = \arg \max(g)$
 - 4: Identify baseline greenness: $g_{min} = \min(g)$
 - 5: Compute amplitude: $A = g_{max} - g_{min}$
 - 6: **for** each percentage $p \in \mathcal{P}$ **do**
 - 7: Compute threshold value: $g_p = g_{min} + p \cdot A$
 - 8: Extract Green-Up date t_u as last upward crossing of g_p with $t_u < t_{peak}$
 - 9: Extract Green-Down date t_d as first downward crossing of g_p with $t_d > t_{peak}$
 - 10: **end for**
 - 11: **return** peak date, baseline, amplitude, and transition dates
-

255

Uncertainty values. Following established phenocam practice (Seyednasrollah et al., 2019; Young et al., 2025), uncertainty on the transition dates was quantified through repeated perturbation of the greenness signal, *i.e.* a Monte Carlo approach. We generated multiple realizations by repeatedly adding Gaussian noise to the greenness time series. Each realization included the re-optimisation of the smoothing window with cross-validation, thereby incorporating uncertainty associated with both measurement noise and smoothing-window selection. Phenological transition dates were then re-estimated from the smoothed noisy signal using the same threshold-based method as for the original data. Uncertainty was defined as the standard deviation of transition dates across all Monte Carlo realizations. We estimated the noise level by computing the Root Mean Squared Error

260



between the smoothed greenness product and the summary product, and used 1000 realisations for each time series. The added noise was assumed to be independently and identically Gaussian-distributed, consistent with established phenocam practice (Seyednasrollah et al., 2019; Young et al., 2025).

Algorithm 3 Monte Carlo estimation of uncertainty in phenological transition dates

Require: Dates t , smoothed greenness signal $\mathbf{g}$, noise standard deviation σ , number of simulations N ,
 1: **for** simulated sample $i = 1, \dots, N$ **do**
 2: Create simulated sample by adding gaussian noise to smoothed signal: $\mathbf{g}^{(i)} = \mathbf{g} + \mathcal{N}(0, \sigma)$
 3: Select optimal smoothing window w^* using cross-validation on $\mathbf{g}^{(i)}$
 4: Smooth noisy signal using selected window $\bar{\mathbf{g}}^{(i)} = \text{rolling}(\mathbf{g}^{(i)}, \text{window} = w^*)$
 5: Compute phenological transition dates from the smoothed signal $\bar{\mathbf{g}}^{(i)}$
 6: Store estimated transition dates
 7: **end for**
 8: Compute standard deviation of transition dates across simulations
 9: Attach uncertainties to the reference estimates
 10: **return** transition dates and associated uncertainties

2.2.4 Quality control and iterative refinements

To ensure the reliability of the time series and their associated phenological metrics, we developed a quality-control procedure through an iterative process combining visual checks and fixes to the most commonly identified issues, e.g. through changes in polygon definition and statistical screening (see section 2.2.5).

Visual checks. For the visual inspection we generated ‘tree-year reports’ (see Appendix A) that displayed the G_{CC} , R_{CC} time series, the associated metrics of phenology, and imagery at key transition dates. Issues that were common in the initial, unfiltered, dataset were related to the definition of the region of interest (i.e. ‘polygon issues’), weather issues, background-colour issues, time-series issues, and canopy issues. Across multiple iterations, several hundreds (during the first iterations) to thousands (during the later iterations) of randomly selected tree-years were manually assessed and flagged according to the presence or absence of these issues, together with an invalidity score ranging from 0 to 5 (i.e. in which 0 corresponds to no issues identified). Based on these evaluations, successive fixes were implemented. During the first iterations, issues related with the definition of the polygon definition and weather issues were among the most common which were largely fixed by shrinking the size of the polygon and including a snow filter (see below). At later iterations, background-color issues and time-series issues became the dominant issues and were largely addressed by applying the automated filtering criteria (see section 2.2.5).

Polygon shrinking. To avoid contamination by boundary pixels in the greenness signal, e.g., because other objects/vegetation may be included near the edges, we used a shrunk version of these polygons for G_{CC} extraction. The shrunk polygons used for the extraction of greenness were obtained by buffering the original polygons inwards until the resulting polygon area was equal to one third of the original polygon area (a threshold determined empirically). We show examples of the original polygons and their shrunk version in Fig. 3.



Daily snow flag. To identify and remove images affected by snow, which can distort the color signals used in our analyses, we developed an automated snow-detection procedure based on a vision-language model (Wang et al., 2024). Because webcam images were often too large to analyze at once, each image was divided into smaller sections, and the model assessed whether snow was visible in each section. These section-level predictions were combined into a single snow score for the image, and images with at least half of the sections classified as snowy were flagged as containing snow. Evaluation on 1,000 manually labelled images showed high performance, with 98% overall accuracy and an F1-score of 95% for snow detection. We then aggregated one to three images per day to produce a daily binary snow flag for each site, with a simple temporal smoothing step to correct isolated misclassifications. See section B1 of the appendix for additional details on our snow detection pipeline.

2.2.5 Automated filtering criteria

We defined five criteria to characterise the time series of each tree-year in the dataset. These flags are stored in the per-tree-year `metadata.json` file and can be used to select subsets of the data appropriate for a given analysis. The thresholds described below reflect the values used to define the curated subset of tree-years included in the distributed dataset and in the phenological analyses presented in this paper.

Signal-to-Noise Ratio (SNR). The SNR characterises the clarity of the seasonal greenness signal, computed on the three-day p90 G_{CC} product. It is defined in decibels as $SNR = 10 \log_{10} \frac{\sigma_{\text{model}}^2}{\sigma_{\text{residuals}}^2}$, where σ_{model}^2 is the variance of the smoothed model curve and $\sigma_{\text{residuals}}^2$ is the variance of the residuals between the three-day product and the smoothed model curve. Tree-years are retained when the SNR is at least 6 dB.

Number of green-up cycles (n_{peak}). The number of green-up cycles is defined as the number of trough-to-peak transitions in the smoothed annual G_{CC} time series whose amplitude exceeds half the amplitude of the primary seasonal green-up. A value of $n_{\text{peak}} = 1$ indicates a single, well-defined seasonal cycle. Tree-years with $n_{\text{peak}} \geq 2$ are excluded, as multiple prominent upward cycles suggest a signal artifact that would prevent reliable identification of the primary phenological transition, such as the presence of grassland with strong seasonal variations in the background.

Season length. The season length is defined as the number of days between GU_{50} and GD_{25} . Tree-years are retained when the season length is at least 145 days. Values below this threshold indicate either a processing artifact or an implausible combination of transition date estimates.

Transition date uncertainty. The Monte Carlo standard deviation of the GU_{50} and GD_{25} transition dates, estimated from the 1000 realisations described earlier, are used as flags for the quality of spring and autumn estimates respectively. Tree-years are retained when both uncertainties fall below 7 days.

Consecutive missing days. This flag helps characterising the temporal availability of images during the different seasons. We simply count the maximum number of consecutive days without a single camera image. We compute those values separately for spring (day-of-year 60 to 160), and autumn (231 to 320). We *partially* filter tree-years with more than 14 days of consecutive missing data in spring or autumn, *i.e.*, only the green-up dates are discarded if the spring condition is not met, and vice versa for green-down and autumn.



320 We distribute the dataset at two quality-control levels, obtained by applying these criteria with different thresholds (Tab. 1):
 a *full* set, retained under lenient thresholds for users who wish to apply their own screening, and a *curated* set, retained under
 stricter thresholds (together with the visual checks of Sect. 2.2.4) as an analysis-ready default. The curated set is a strict subset
 of the full set.

Table 1. Summary of the two SwissPhenoCam releases: dataset size, the automated filtering thresholds applied to define each set, and the
 resulting number of retained tree-years (out of 14436 candidate tree-years). The curated set is a strict subset of the full set. Thresholds are
 applied to the three-day p90 G_{CC} product.

	Full	Curated
<i>Dataset summary</i>		
Tree-years	8 067	5 944
Individual tree ROIs	2 567	2 204
Camera sites	34	34
Site-years	187	185
Observation years	2010–2024	
<i>Filtering thresholds</i>		
SNR	≥ 0 dB	≥ 6 dB
Season length	≥ 100 d	≥ 145 d
Green-up cycles (n_{peak})	≤ 1	≤ 1
Spring max. consecutive missing days	≤ 21 d	≤ 14 d
Autumn max. consecutive missing days	≤ 21 d	≤ 14 d
GU ₅₀ uncertainty (SD)	≤ 14 d	≤ 7 d
GD ₂₅ uncertainty (SD)	≤ 14 d	≤ 7 d
Visual invalidity score	≤ 1	$= 0$
<i>Outcome</i>		
Tree-years retained	8 067 (55.9%)	5 944 (41.2%)

2.3 Structure of the data product

325 The dataset is distributed at two levels of quality control, each indexed by a master table at the dataset root. The *full* set
 (phenology_records_full.csv; 8 067 tree-years) applies a lenient set of filtering criteria and retains the broadest
 usable collection of tree-years; it is intended for users who prefer to perform their own quality control tailored to a specific
 application. The *curated* set (phenology_records_curated.csv; 5 944 tree-years) is a strict subset of the full set: it ad-
 330 ditionally satisfies the stricter automated thresholds described in Sect. 2.2.5 and the visual checks of Sect. 2.2.4, and is provided
 as the analysis-ready default used in the analyses presented in this paper. Users seeking ready-to-use phenological estimates
 should start from the curated set, whereas the full set offers maximal coverage at the cost of requiring additional screening.
 The two tables share an identical schema; the per-tree-year directories under greenness-phenology/ hold all tree-years
 of the full set, and membership in the curated subset is indicated by the rows of phenology_records_curated.csv.



```
SwissPhenoCam/
  readme.txt
  phenology_records_full.csv
  phenology_records_curated.csv
  greenness-phenology/
    {site_id}_{sublocation}/
      {uid}/
        {year}/
          {uid}_{year}_metadata.json
          {uid}_{year}-sampling-flags.json
          {uid}_{year}_raw-cc-data.csv
          {uid}_{year}-GCC-1D-product.csv
          {uid}_{year}-GCC-1D-smoothed.csv
          {uid}_{year}-GCC-3D-product.csv
          {uid}_{year}-GCC-3D-smoothed.csv
          {uid}_{year}-RCC-1D-product.csv (+ BCC equiv.)
          {uid}_{year}-RCC-1D-smoothed.csv (+ BCC equiv.)
          {uid}_{year}-RCC-3D-product.csv (+ BCC equiv.)
          {uid}_{year}-RCC-3D-smoothed.csv (+ BCC equiv.)
          {uid}_{year}-GCC-1D-p90-transitions.json
          {uid}_{year}-GCC-3D-p90-transitions.json
          {uid}_{year}-RCC-1D-p90-transitions.json
          {uid}_{year}-RCC-3D-p90-transitions.json
  auxiliary-data/
    phenology_records_full-filtering-report.txt
    phenology_records_curated-filtering-report.txt
    weather-data/
    validation-data/
    snow-index/
```

335 The dataset is organised in two top-level directories. The top level contains greenness-phenology/, auxiliary-data/,
 the two master tables phenology_records_full.csv and phenology_records_curated.csv, and readme.txt.
 The two master tables consolidate, for convenient analysis, the information otherwise distributed across the per-tree-year
 files. Each row gathers the identification and provenance fields, polygon geometry, seasonal coverage diagnostics, process-
 ing flags, and the full set of G_{CC} and R_{CC} transition dates, uncertainties, and signal-quality metrics (1D and 3D). The
 340 greenness-phenology/ directory holds a site-sublocation hierarchy (e.g. 1526_1, oebe_1). The sublocation index
 distinguishes multiple viewing angles at the same physical site. Each site-sublocation directory contains one subdirectory per
 individual tree, identified by a unique uid of the form iXXXX (e.g. i00240), and within each uid directory one subdirectory
 per processed year. Each year directory holds 19 files.

Raw data file (_raw-cc-data.csv). Each row corresponds to one camera image. The file contains nine columns:
 345 datetime, G_{CC} , R_{CC} , BCC, and brightness extracted from the full annotated polygon, plus G_{CC_s33} , R_{CC_s33} ,
 BCC_s33, and brightness_s33 computed on the inner 33%-shrunk polygon used as the canonical signal for phenophase
 extraction (see Sect. 2.2.2).

Daily and three-day summary product files (-GCC-1D-product.csv, -GCC-3D-product.csv and R_{CC} /BCC
 equivalents). These files contain the temporally aggregated chromatic coordinate time series at 1D and 3D temporal resolution.
 350 Within each product, four aggregation statistics are provided: mean (avg) and the 50th, 75th, and 90th percentiles (p50, p75,
 p90).



Smoothed time series files (`-GCC-1D-smoothed.csv` and equivalents). Each smoothed file contains the model curve produced by the cross-validated rolling-window average described in Sect. 2.2.3. Column structure is identical to the corresponding summary product file.

355 **Sampling flags file** (`-sampling-flags.json`). Records per-season coverage ratios, gap statistics, and resolution-change flags used by the quality filter to determine whether a tree-year passes downstream processing steps.

Transition date files (`-GCC-1D-p90-transitions.json` and equivalents for 3D, R_{CC}). Available for G_{CC} and R_{CC} products (not BCC). Each file contains a JSON object with two main dictionaries. The `dates` dictionary reports the estimated day-of-year (DOY, fractional) for the annual chromatic coordinate peak (PEAK) and for each of ten amplitude-based transition
 360 dates (GU_10, GU_25, GU_50, GU_75, GU_90 for spring and GD_90, GD_75, GD_50, GD_25, GD_10 for autumn); a value of `null` indicates that a given threshold could not be reliably estimated. The `uncertainties` dictionary gives the standard deviation of each estimate across 1000 Monte Carlo realisations. The file also records amplitude, baseline, peak_value, window_selected, noise_std, snr, and n_peak for the tree-year. The filename encodes the product resolution (1D or 3D) and the intra-day aggregation percentile used for smoothing (p90).

365 **Metadata file** (`_metadata.json`). Collects all per-tree-year provenance and quality information. Key fields include: species and genus (taxonomic identification), category (individual tree or group), unique_id and full_name (ROI identifiers), polygon vertices in both the original (`coords`) and shrunk (`coords_s33`) version, polygon area in pixels², avg_obs_per_day, and data gap statistics.

Auxiliary data. The `auxiliary-data/` directory provides supporting information and data. It contains a site meta-
 370 data table (`site-info.csv`) listing coordinates, elevation, network affiliation, and observation period for each of the 34 camera sites, the quality-filtering report used during dataset assembly, and the daily binary snow flags used to filter snow-contaminated observations. We also provide daily climate driver time series (temperature, precipitation, photoperiod, and vapour pressure deficit). These were obtained from the DaymetCH dataset (Federal Office of Meteorology and Climatology MeteoSwiss, 2022b; Land Change Science, WSL, 2022), which applies the Daymet interpolation software (Thornton et al.,
 375 1997) to generate daily gridded meteorological maps covering Switzerland at a 100m spatial resolution. Lastly, this folder contains two validation datasets: species-level mean phenological dates from the Swiss Phenology Network (SPN)(Federal Office of Meteorology and Climatology MeteoSwiss, 2022a) and per-tree-year visual phenology annotations across seven phenological phases.

3 Results

380 We now present the SwissPhenoCam dataset, obtained through the processing and quality filtering pipelines described previously. The complete set of ROI that were annotated yielded a total of over 14k tree-years of data. Out of this original set of candidates, we release two tree-year subsets corresponding to two quality-control levels (Tab. 1): a *full* set of 8067 tree-years, retained under lenient filtering for users who prefer to apply their own quality screening, and a smaller, analysis-ready *curated* set obtained with stricter thresholds together with the visual quality checks. Unless stated otherwise, the analyses presented

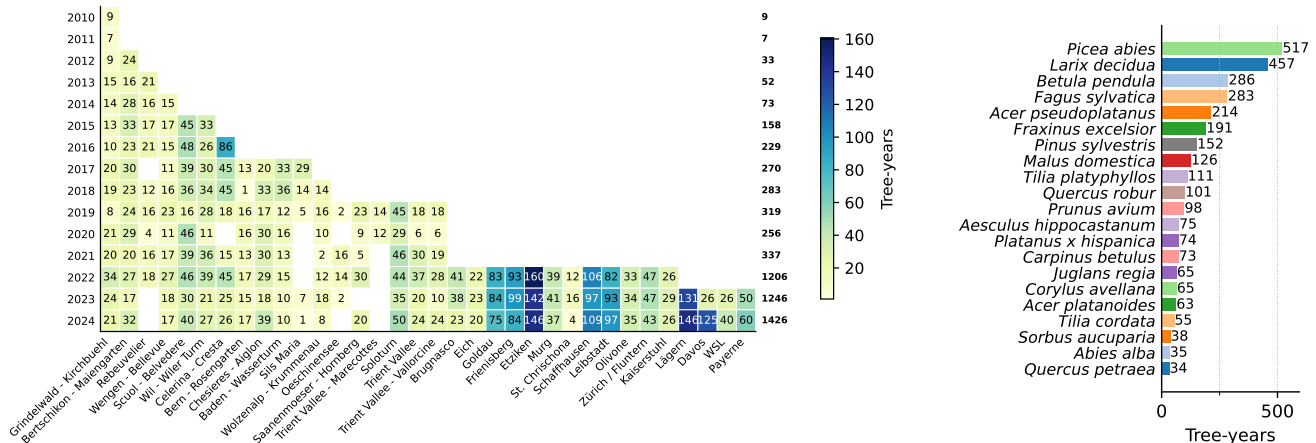


Figure 7. Distribution of ‘tree years’ across sites, years, and species. (a) Number of tree-years per site and year across all species. Cell colour encodes the count of individual tree-year records available at each site in each year, with row totals shown on the right. White cells indicate site-years with no data. (b) Ranked distribution of total tree-years per species.

below use the curated set. Within this curated set, 3843 tree-years have genus or species information, the remaining tree-years being of unidentified species. Over 20 different species are represented in our dataset, with 10 species counting each at least 100 tree-years (Fig. 7). The most represented species is *Picea abies* with 517 tree-years, followed by *Larix decidua* (457 tree-years), *Betula pendula* (286), *Fagus sylvatica* (283), *Acer pseudoplatanus* (214), and *Fraxinus excelsior* (191). Four further species—*Pinus sylvestris*, *Malus domestica*, *Tilia platyphyllos*, and *Quercus robur*—each contribute at least 100 tree-years (Fig. 7b), while the remaining 11 species each contribute between 34 and 98 tree-years. We also show on Fig. 8 how each of the ten dominant species is distributed across sites and years. Over the years, as more cameras are included in our data archive, the number of distinct sites where species were present progressively grew to reach 18 sites for the most distributed species *Betula pendula*, and 5 sites for the least distributed one *Malus domestica*. The impact of the increased number of sites is also reflected in the growth in the number of individual trees monitored each year (bold row total in Fig. 7a): from just 9 in 2010 to over 1000 individual trees from 2022. The dataset is available at <https://doi.org/10.5281/zenodo.20451225> Garnot et al. (2026).

3.1 Phenological records

We extracted green-up and green-down transition dates for all available tree-years and report the aggregated values for the 10 species with sufficient coverage across the elevation gradient (Table 2). Spring green-up timing, characterised by the 50% Green-Up date (GU_{50}), exhibits a clear and consistent delay with increasing elevation for all species. For instance, *Larix decidua* reaches GU_{50} at $DOY 98.7 \pm 6.0$ below 600 m but at $DOY 141.9 \pm 6.0$ above 1500 m—a delay of approximately 43 days. Similar elevation-driven delays are observed for all deciduous broadleaf species: *Betula pendula* GU_{50} shifts by approximately 42 days and *Fraxinus excelsior* by 22 days between the lowest and highest elevation bands in which they occur. The sole evergreen conifer in the analysis, *Picea abies*, also exhibits a green-up signal reflecting the seasonal flush of

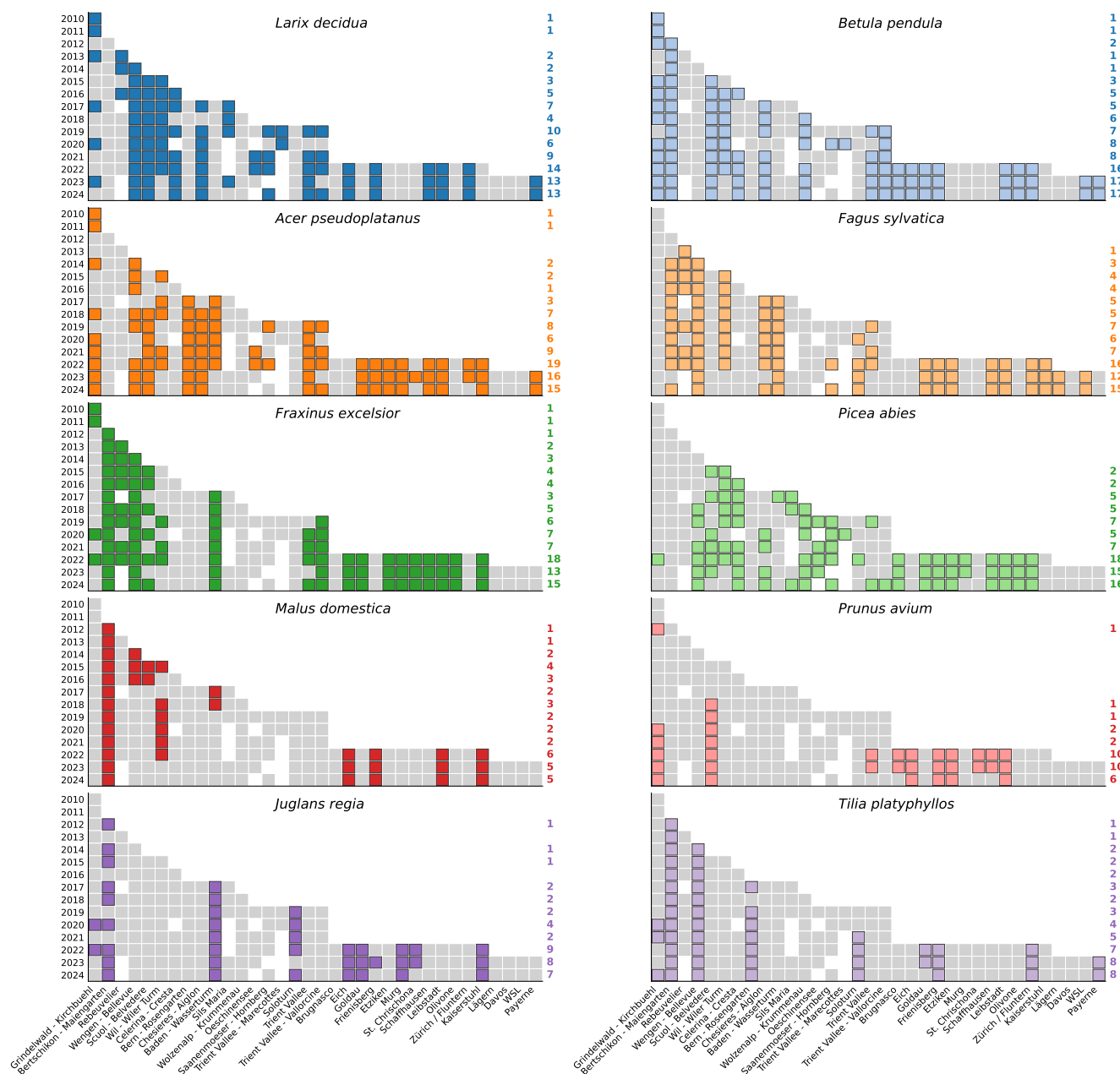


Figure 8. Distribution of species presence across sites and years in our curated dataset. Each panel shows one of the ten species with the most tree years on a site $\times$ year grid, where coloured cells indicate at least one tree-year record for that species at the given site and year, grey cells indicate the site was active but no records are available for that species, and white cells indicate no data for that site-year. Row totals on the right give the number of sites where the species is present in each year.



Table 2. Statistics of Green-Up 50% (GU₅₀) and Green-Down 25% (GD₂₅) across all years per species and elevation band. Values are mean DOY ± standard deviation; *n* is the number of tree-years. Note that only a few species are present in the highest elevations and absent species are denoted with empty cells (-).

Species	Low (<600 m)			Mid (600–1000 m)			High (1000–1500 m)			Very High (>1500 m)		
	GU ₅₀	GD ₂₅	<i>n</i>	GU ₅₀	GD ₂₅	<i>n</i>	GU ₅₀	GD ₂₅	<i>n</i>	GU ₅₀	GD ₂₅	<i>n</i>
<i>Larix decidua</i>	98.7 ± 6.0	310.2 ± 8.1	116	107.0 ± 8.7	308.6 ± 12.7	92	119.4 ± 11.2	306.7 ± 12.7	188	141.9 ± 6.0	293.6 ± 5.4	61
<i>Betula pendula</i>	104.1 ± 9.9	297.4 ± 16.9	57	108.6 ± 8.1	308.3 ± 6.3	27	123.7 ± 9.7	302.7 ± 10.0	197	146.1 ± 7.0	296.3 ± 8.4	5
<i>Acer pseudoplatanus</i>	116.2 ± 9.0	301.2 ± 11.6	72	119.2 ± 7.8	304.8 ± 9.5	28	138.1 ± 10.3	295.5 ± 8.5	112	–	–	–
<i>Fagus sylvatica</i>	114.6 ± 15.4	299.8 ± 9.9	185	119.0 ± 7.5	302.9 ± 8.6	71	138.4 ± 15.9	298.2 ± 7.8	27	–	–	–
<i>Fraxinus excelsior</i>	118.5 ± 8.4	298.9 ± 10.1	79	129.1 ± 10.8	291.3 ± 21.8	43	140.2 ± 7.9	300.6 ± 8.7	69	–	–	–
<i>Picea abies</i>	124.1 ± 10.2	296.5 ± 9.1	278	123.4 ± 12.9	291.1 ± 12.2	37	128.9 ± 23.7	297.0 ± 11.5	112	148.2 ± 15.9	288.0 ± 18.2	90
<i>Malus domestica</i>	113.9 ± 7.3	283.9 ± 14.3	69	109.8 ± 10.6	296.3 ± 13.7	52	135.7 ± 6.9	297.1 ± 11.8	5	–	–	–
<i>Prunus avium</i>	116.3 ± 18.3	295.9 ± 13.8	42	118.7 ± 6.3	299.3 ± 11.3	29	133.3 ± 9.1	297.0 ± 10.2	27	–	–	–
<i>Juglans regia</i>	133.4 ± 10.7	293.2 ± 13.1	46	134.7 ± 8.2	301.0 ± 13.2	17	136.2 ± 1.4	303.8 ± 15.8	2	–	–	–
<i>Tilia platyphyllos</i>	108.4 ± 7.3	299.9 ± 14.2	92	114.2 ± 8.5	301.0 ± 11.6	5	131.1 ± 10.2	305.8 ± 9.3	14	–	–	–

new needles, with a comparable elevation dependence but higher interannual variability (standard deviation of 10–24 days compared to 6–11 days for most deciduous species, likely reflecting the difficulty of detecting the spring needle flush against an already-green background).

In contrast, autumn green-down timing, characterised by the 25% Green-Down date (GD₂₅), shows a markedly weaker and less systematic dependence on elevation. For the majority of species, GD₂₅ values vary by fewer than 15 days across the full elevation range. *Fagus sylvatica*, for example, shows GD₂₅ dates of DOY 299.8 ± 9.9 below 600 m and DOY 298.2 ± 7.8 between 1000 and 1500 m—a difference of less than two days. The only species exhibiting a pronounced earlier green-down at higher elevations is *Larix decidua*, with GD₂₅ advancing from DOY 310.2 below 600 m to DOY 293.6 above 1500 m. Interannual variability in green-down timing is generally larger than for green-up across all species, consistent with the more gradual and environmentally complex nature of the autumn senescence process.

The asymmetric elevation responses of spring and autumn phenology result in a progressive shortening of the growing season with increasing altitude (Fig. 9). At low elevations (< 600 m), the average season length—defined as the span between the mean GU₅₀ and GD₂₅ dates—ranges from 160 days (*Juglans regia*) to 212 days (*Larix decidua*). At mid-elevations (600–1000 m), season lengths decrease moderately, ranging from 162 days (*Fraxinus excelsior*) to 202 days (*Larix decidua*). At high elevations (1000–1500 m), growing seasons are shortened by an additional 15–30 days for most species, with *Acer pseudoplatanus* reduced to 157 days and *Larix decidua* to 187 days. This compression is primarily driven by the delayed spring onset at higher elevations, while the timing of autumn green-down remains comparatively stable across elevations, with no clear elevational trend for most species.

To estimate species-specific rates of phenological change along elevational and thermal gradients, we fitted linear relationships between transition dates and both elevation and mean annual temperature (see Fig. 10). For spring phenology (GU₅₀), most species exhibit strong and consistent elevational delays, ranging from 2.4 to 4.8 days per 100 m increase in altitude. The strongest responses are observed for *Acer pseudoplatanus* (4.76, days, hm⁻¹, $R^2 = 0.81$), *Fraxinus excelsior* (4.21, days, hm⁻¹, $R^2 = 0.90$), and *Betula pendula* (3.51, days, hm⁻¹, $R^2 = 0.84$), while *Fagus sylvatica* exhibits a weaker rela-

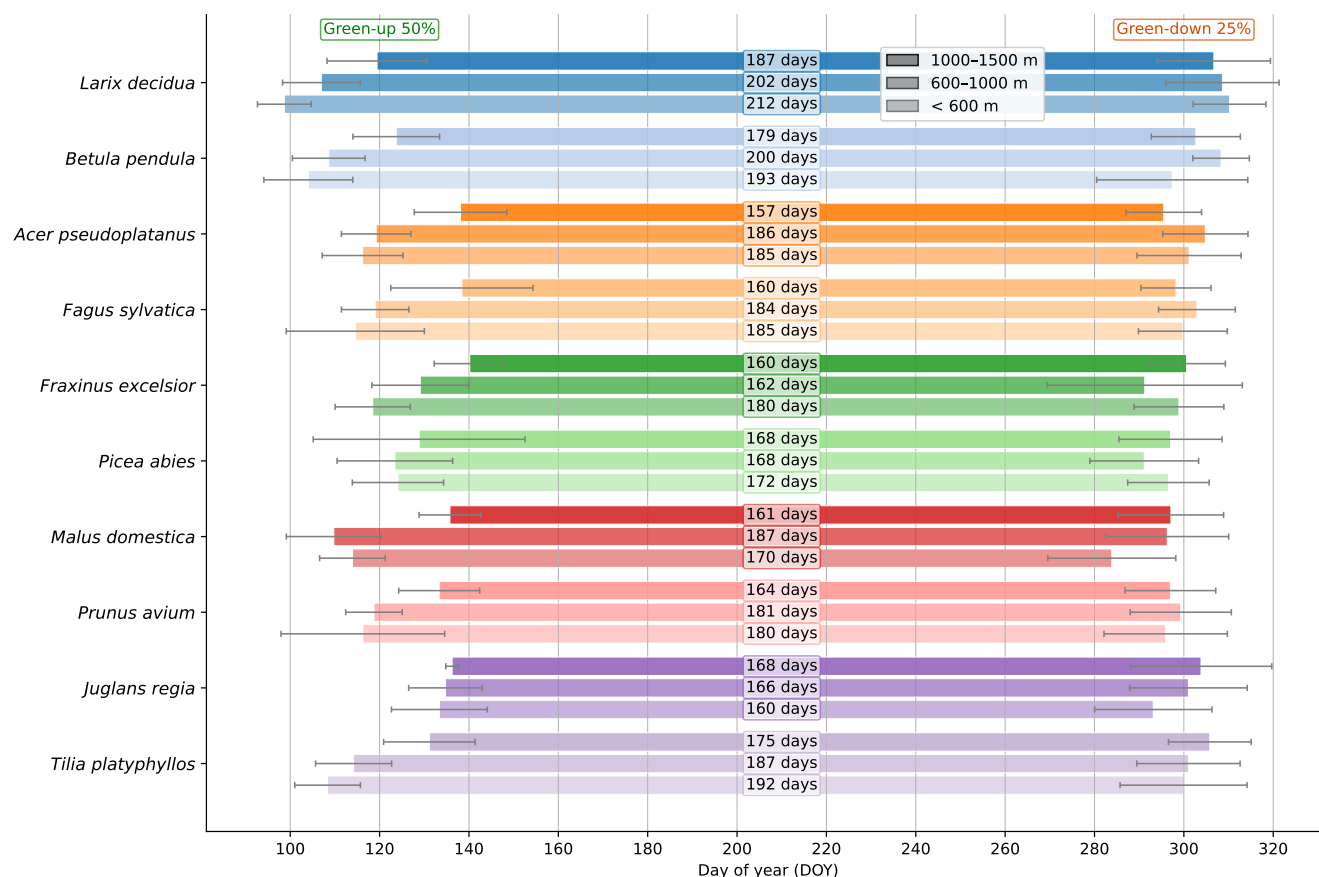


Figure 9. Cross-year average season length per species and elevation band. The horizontal bars represent the span between the average date of 50% Green Up and 25% Green Down. We show the corresponding season length in days on each bar. Each group of bars corresponds to one species (color-coded) and each of the three bars of a species corresponds to the three first elevation bands. Note the clear delaying effect of altitude on the date of green-up, especially visible for *Larix decidua*, *Acer Pseudoplatanus*, or *Fraxinus excelsior*. In contrast, the dates of green-down show neither a strong species dependence, nor a strong altitude dependence.

tionship ($2.37, \text{days}, \text{hm}^{-1}$, $R^2 = 0.17$). Correspondingly, warmer temperatures are associated with earlier spring development, with green-up advancing by approximately 4–8 days per $^{\circ}\text{C}$ for most deciduous species. The strongest temperature sensitivities are found for *Acer pseudoplatanus* ($-7.88, \text{days}, ^{\circ}\text{C}^{-1}$), *Fraxinus excelsior* ($-7.77, \text{days}, ^{\circ}\text{C}^{-1}$), and *Betula pendula* ($-6.69, \text{days}, ^{\circ}\text{C}^{-1}$), all accompanied by high coefficients of determination ($R^2 > 0.7$). In contrast, the evergreen conifer *Picea abies* shows essentially no relationship with either elevation ($-0.19, \text{days}, \text{hm}^{-1}$, $R^2 < 0.01$) or temperature ($0.56, \text{days}, ^{\circ}\text{C}^{-1}$, $R^2 = 0.01$), consistent with the weaker and more variable green-up signal one would expect to be associated with changes in the rate of evergreen canopy renewal rather than a ‘flushing event’. Similarly weak relationships are observed for *Juglans regia* and *Malus domestica*, most likely because of the relatively narrow distribution of the sites at which these species are present across elevation and mean annual temperature.



Autumn phenology (GD_{25}) exhibits markedly weaker responses to both elevation and temperature. For most species, elevational trends are smaller than ± 1 day per 100 m and explained little variance ($R^2 < 0.2$), confirming the absence of a strong systematic altitudinal effect on green-down timing. Likewise, temperature sensitivities are generally close to zero, with most models explaining less than 15% of the observed variation. Stronger responses are observed for species that had a relatively poor coverage across elevation and temperature gradients (e.g. *Malus domestica*, *Prunus avium*, and *Tilia platyphyllos*) of which are predominantly observed at relatively low elevation/high temperature locations. Overall, autumn phenology thus appears substantially less predictable from either elevation or temperature than spring phenology, indicating that senescence timing is likely governed by a broader combination of environmental drivers.

We show the aggregated G_{CC} profiles for each species in (Fig. 11). All deciduous species display the expected pattern of a low and flat winter baseline, a rapid spring green-up, an extended summer plateau, and a more gradual autumn green-down. Most broadleaved species share a characteristic spring overshoot, in which greenness spikes to its annual maximum at leaf emergence before relaxing to a lower summer plateau as foliage matures and darkens. This transient is visible in *Fagus sylvatica*, *Betula pendula*, or *Tilia platyphyllos*, but largely absent in the more rounded profiles of *Malus domestica* and *Prunus avium*. The tightness of the curve bundles reflects the consistency of phenological timing across individuals, years, and sites. Across deciduous species, we observe that green-up seems more synchronised than green-down, the larger spread of which is consistent with the greater variability in senescence timing observed in Table 2 indicating that senescence responds to a more heterogeneous set of drivers. We also note that some species such as *Fagus sylvatica* display a particularly well-synchronised green-up behaviour across individuals and years, which is coherent with the higher importance of photoperiod in the phenology of that species.

Overall, the patterns identified here are broadly consistent with previous studies of elevational and thermal controls on tree phenology (e.g. Vitasse et al. 2009; Richardson et al. 2019). While species-specific responses differ in strength and predictability, the observed relationships between delayed spring phenology and increasing elevation, as well as the comparatively weak elevational signal in autumn phenology, agree well with established findings. Continued monitoring and expanded site coverage would further improve the robustness of these estimates, particularly for species with more limited representation across the environmental gradients considered.

3.2 Validation against other sources

3.2.1 Comparison with the Swiss Phenology Network

We compared the SwissPhenoCam transition dates against independent observations from the Swiss Phenology Network (SPN) led by MeteoSwiss, in which trained citizen-science observers record phenological events including the date at which 50% of leaves have unfolded (spring) and 50% of leaves show colouration (autumn). This comparison was possible for five species observed by both networks: *Acer pseudoplatanus*, *Betula pendula*, *Fagus sylvatica*, *Larix decidua*, and *Tilia platyphyllos*. Since a tree-level matching between the two datasets is not possible, we compare phenological dates averaged per species,

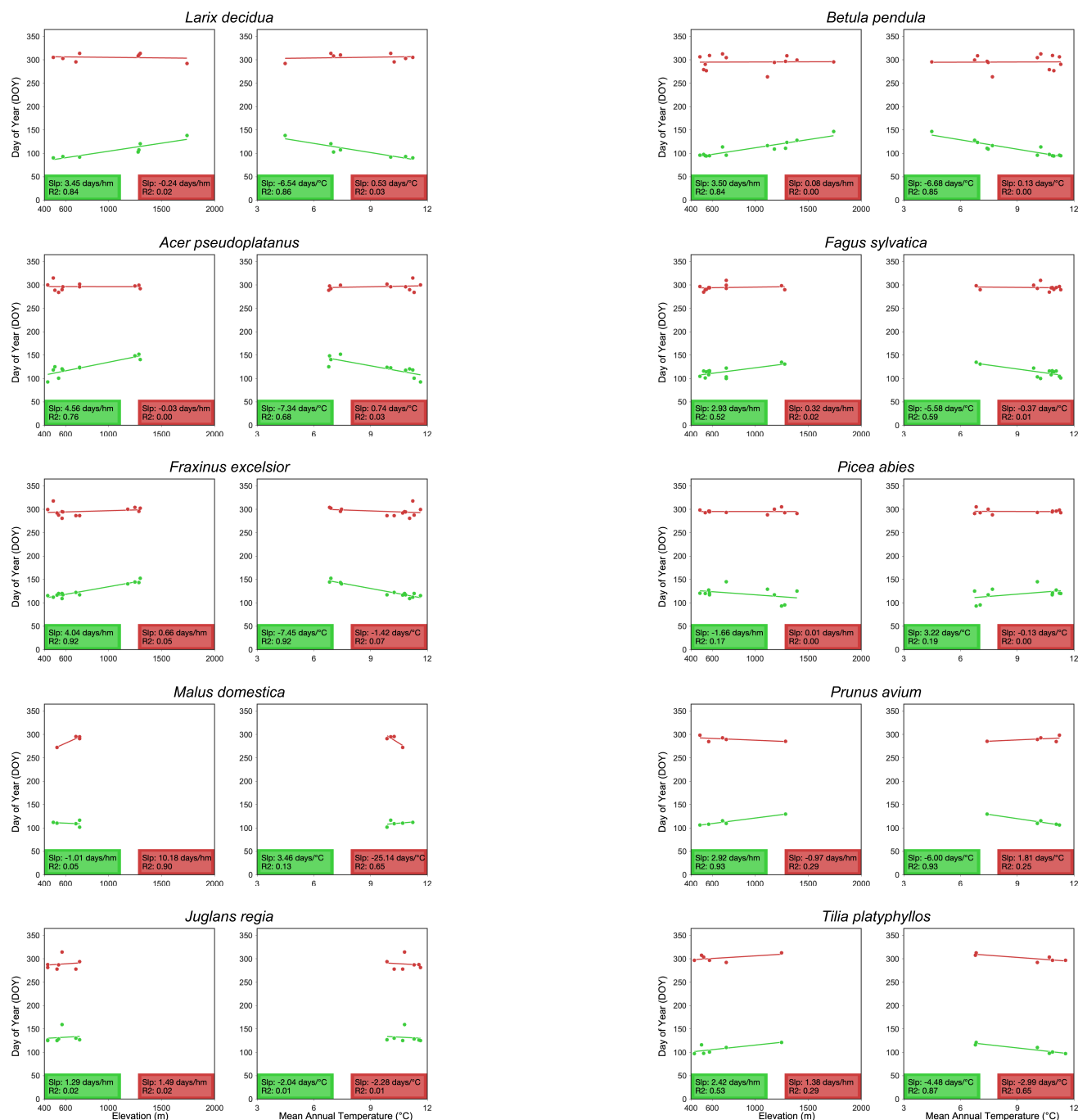


Figure 10. Trends in phenology across elevation and mean annual temperature for different species. Green elements correspond to the 50% Green Up (GU50) phase and red elements to the 25% Green Down (GD25) phase. Each point represents the median phenological transition date during 2022–2024 for all individuals of a given species at a single location. Solid lines show linear regressions fitted to the observations; the regression slope and coefficient of determination (R^2) are reported in each panel. We used tree-year data from the curated dataset with invalidity score 0. X-axis correspond to Fig. 2.

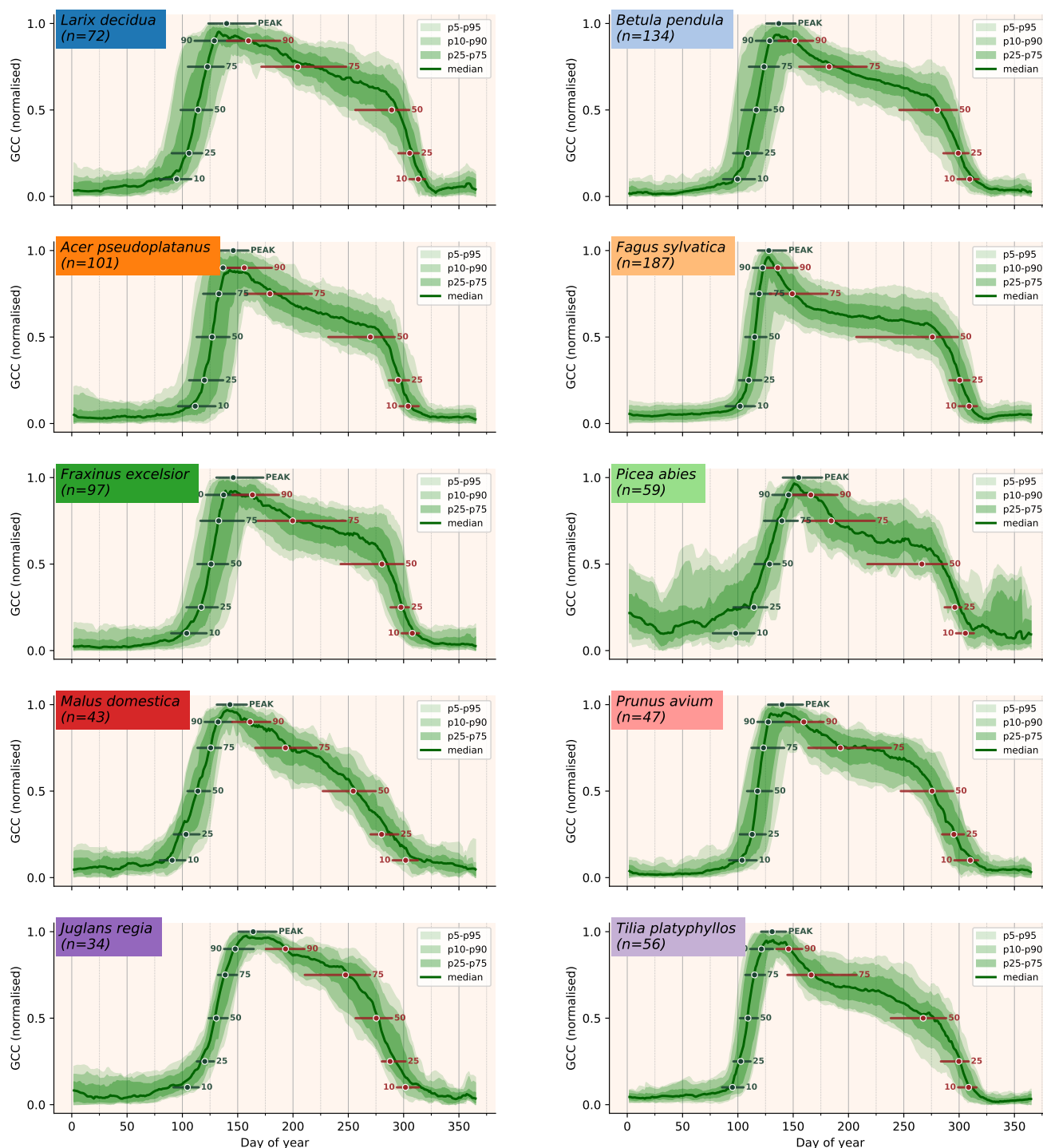


Figure 11. Average seasonal greenness profile for each species, based on min–max normalised smoothed G_{CC} (3D product). Shaded bands show the inter-tree-year variability at three levels (p5–95, p10–90, p25–75) and the solid line is the median. Horizontal markers indicate the distribution of phenological transition dates: green for green-up (GU) thresholds and peak, red for green-down (GD) thresholds. Each bar spans the mean ± 1 s.d., and the dot marks the median date. Only tree-years with a complete set of detected transitions are included; the sample size n is shown in the species label.



Table 3. Agreement between different green-up (spring, left panel) and green-down (autumn, right panel) transition dates and the MeteoSwiss SPN's mean values for leaf unfolding 50% and leaf or needle colouration 50%, respectively.

	GU 10%	GU 25%	GU 50%	GU 75%	GU 90%	GD 90%	GD 75%	GD 50%	GD 25%	GD 10%
R2	0.85	0.90	0.90	0.83	0.66	0.01	0.12	0.11	0.23	0.03
Bias	-13.76	-5.24	1.92	9.07	16.26	-133.86	-102.81	-20.62	12.61	18.05
RMSE	14.53	6.51	4.17	10.30	17.53	135.18	105.67	29.15	15.21	20.90

elevation range, and year. Hence, our comparison assesses the agreement between the two networks in capturing interannual and elevational variability in phenology at the species level, rather than the precision of individual tree-level estimates.

470 Among the different green-up thresholds, GU_{50} achieves the best overall agreement with the SPN leaf unfolding 50% metric (Table 3). Earlier thresholds (GU_{10} , GU_{25}) are systematically earlier than SPN observations, while later thresholds (GU_{75} , GU_{90}) are systematically later. The agreement between SwissPhenoCam GU_{50} and SPN 50% leaf unfolding is strong (Fig. 12a), with $R^2 = 0.90$, a bias of only 1.9 days, and an RMSE of 4.2 days (Table 3). The correlation is strong across all five deciduous species and across the full range of observed green-up dates (DOY 90–150), spanning the elevation gradient from
 475 lowland to subalpine sites.

The agreement for autumn phenology is weaker (Fig. 12b). The best-matching green-down metric is GD_{25} , which yields $R^2 = 0.22$, a bias of 12.6 days, and an RMSE of 15.2 days. The positive bias indicates that SwissPhenoCam GD_{25} dates systematically occur later than SPN 50% leaf colouration dates, which is consistent with GD_{25} representing a more advanced stage of senescence. The lower overall correlation is consistent with the greater variability in autumn phenology observed
 480 across all species in Table 2, and with the inherent difficulty of defining discrete autumn transition points from a gradual greenness decline which also leads to larger inter-observer noise. We also note that the earlier green-down thresholds, GD_{90} , GD_{75} , and GD_{50} precede the observed phenophase dates by up to 134 days and achieve a near zero R^2 . This suggests that these thresholds are not relevant to autumn phenology for single-tree greenness profiles. Indeed, due to the spring offshoot shape of the greenness curves, these thresholds tend to land on the summer plateau of individual-level greenness and do not
 485 seem to relate to leaf senescence (see Fig. 11).

3.2.2 Comparison with image-based phenophase annotation

As a complementary validation, we compared the automated greenness-based transition dates against phenological dates obtained through visual analysis of the camera imagery. A trained annotator systematically reviewed the image time series for more than a thousand monitored tree-year on screen, browsing through the sequence of images to identify the dates of 17 distinct phenophases covering the start, middle, and end of leaf emergence, flowering, fruiting, and senescence. All annotations
 490 were carried out by a single trained observer. A full description of these phenophases is available in Appendix B2, while we focus here on the subset described in Tab. 4.

We evaluated all possible pairings of G_{CC} thresholds against visual phenophases; we report the RMSE of each pairing in Tab. 5, and we highlight the best-matching pairs below. For spring, we obtain strong agreement between GU_{25} and LUG (first

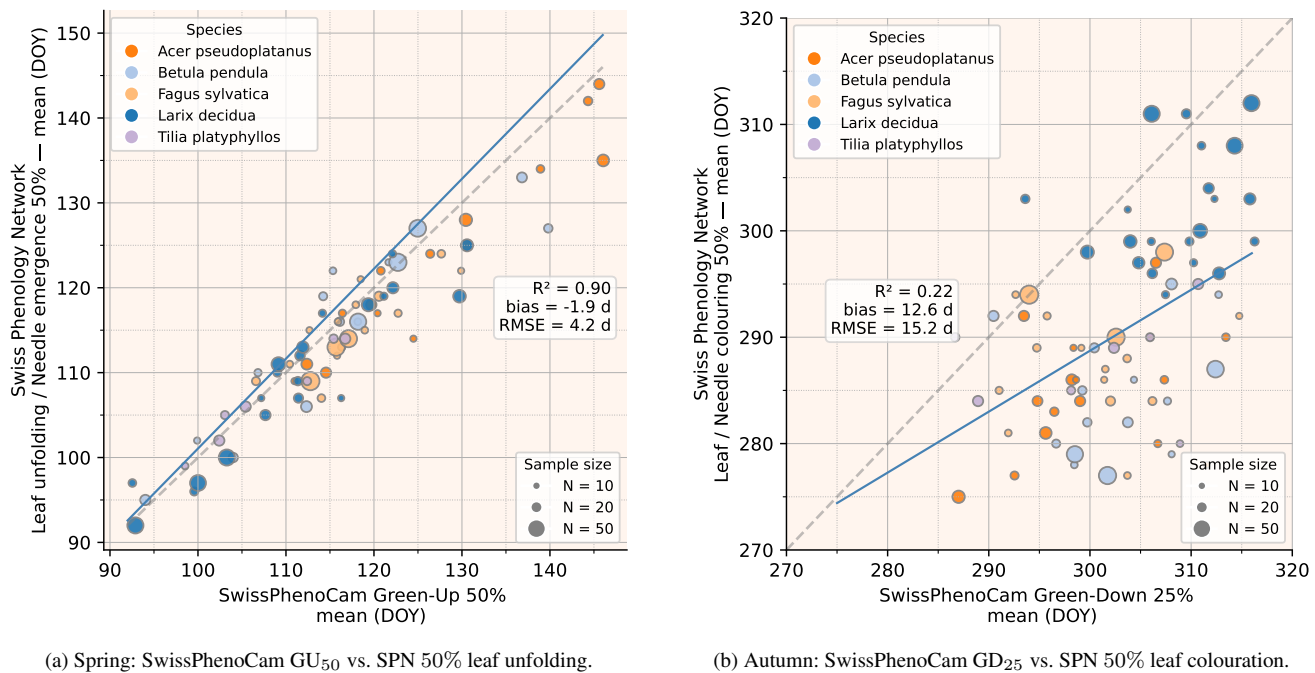


Figure 12. Comparison between SwissPhenoCam greenness-based transition dates and MeteoSwiss Swiss Phenology Network (SPN) mean phenological dates. Each point represents a species-elevation-year average, with bubble size proportional to the number of tree-years from our dataset falling in that bin. The dashed grey line indicates the 1:1 relationship and the solid blue line shows the linear regression fit.

Table 4. Phenophase abbreviations for leaf unfolding (LU) and leaf senescence (SC) used in this study.

Abbr.	Phenophase	Description
LUG	Leaf greenness	First signs of green visible on camera.
LUT	Second leaf flush	Second flush after early-spring leaf loss due to a disturbance.
LUH	Leaf unfolding (50%)	~50% of leaves unfolded; entire leaf surface visible.
LUD	Leaf development	~50% of tree covered in green; leaves halfway developed.
LUM	Leaf maturity	Leaf unfolding complete; final size reached.
SCS	Start leaf senescence	~10% of leaves discoloured (yellow/brown) or fallen.
SCH	Leaf senescence (50%)	~50% of leaves discoloured or fallen.
SCE	End leaf senescence	>90% of leaves discoloured or fallen.

sign of green), as well as between GU₅₀ and LUD (leaf development) (Fig. 13), yielding $R^2 = 0.80$ and $R^2 = 0.84$ respectively across $n = 389$ individual tree-year observations. The pairing between GU₂₅ and LUG (first sign of green visible on camera) also achieves a bias of -0.7 days, showing excellent temporal alignment. Similarly, GU₅₀ and LUD achieve a bias of 2.3 days

For autumn, the agreement between automated and visual assessments is weaker than for spring but still moderately strong (Tab. 5). The best-matching pairing is GD₂₅ with the SCE (end of colouration) phenophase, yielding $R^2 = 0.58$ across $n = 456$ observations (Fig. 13c), with a bias of 1.2 days and an RMSE of 6.8 days.

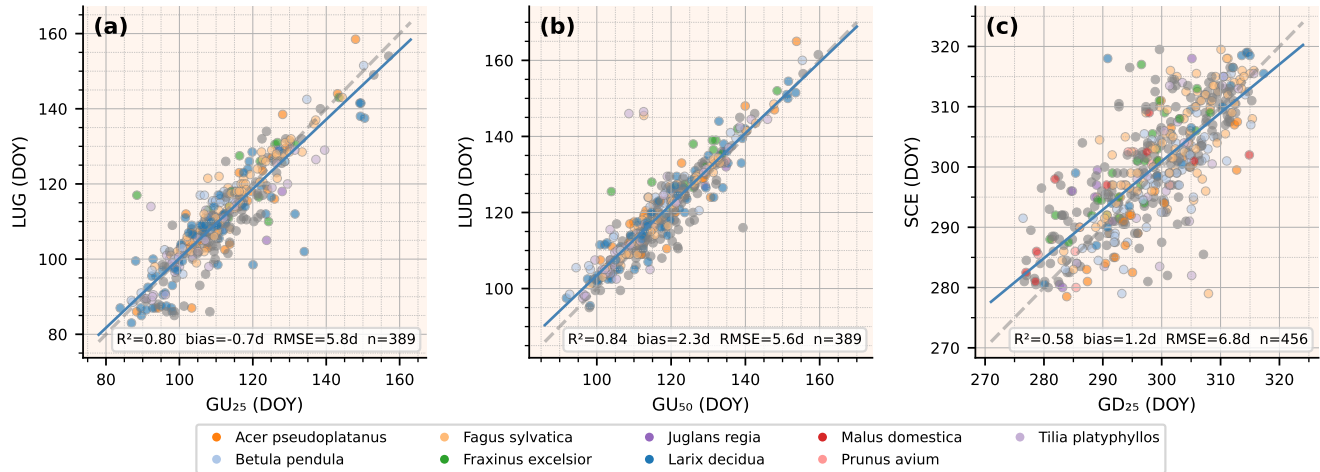


Figure 13. Comparison between automated greenness-based transition dates and expert visual annotations. Scatter plots of the best-matching pairings: for spring GU₂₅ with LUG and GU₅₀ with LUD and for autumn GD₂₅ with SCE. Each point represents an individual tree-year, coloured by species.

Table 5. RMSE (days) between SwissPhenoCam transition dates and expert visual annotations. Best pairings highlighted in **bold**.

	<i>Spring (green-up)</i>					<i>Autumn (senescence)</i>		
	LUG	LUH	LUD	LUM		SCS	SCH	SCE
GU ₁₀	11.1	14.6	18.7	33.8	GD ₉₀	117.0	130.2	139.7
GU ₂₅	5.8	7.2	10.6	25.8	GD ₇₅	94.5	106.0	115.0
GU ₅₀	9.4	6.5	5.6	19.3	GD ₅₀	33.5	35.9	41.9
GU ₇₅	17.5	14.0	10.7	15.6	GD ₂₅	23.2	11.1	6.8
GU ₉₀	26.9	23.5	20.0	17.1	GD ₁₀	31.6	18.7	10.7

3.3 Performance analysis

In this section, we further investigate the quality of our phenological data. In particular, we evaluate the relative uncertainty of different transition thresholds in Sec. 3.3.2. We then investigate the effect of tree species and image type on the quality metrics in Sec. 3.3.2. And lastly, we quantify the impact of intra-daily temporal resolution on phenophase uncertainty in Sec. 3.3.3.

505 3.3.1 Transition date uncertainty

We show the average size of the 95% Confidence Interval (CI), defined as 1.96 times the Monte Carlo uncertainty described in Algo. 3, of each phenological transition date on Fig. 14. We report these values when using the one day product in light blue and the three day product in darker blue. The one-day product results in systematically larger confidence intervals reflecting the higher noise level of this product. The uncertainty analysis reveals that transition date precision varies substantially across phenophases. GU₅₀ and GD₂₅ appear as the most stable transition dates for spring and autumn respectively, with a 95% interval

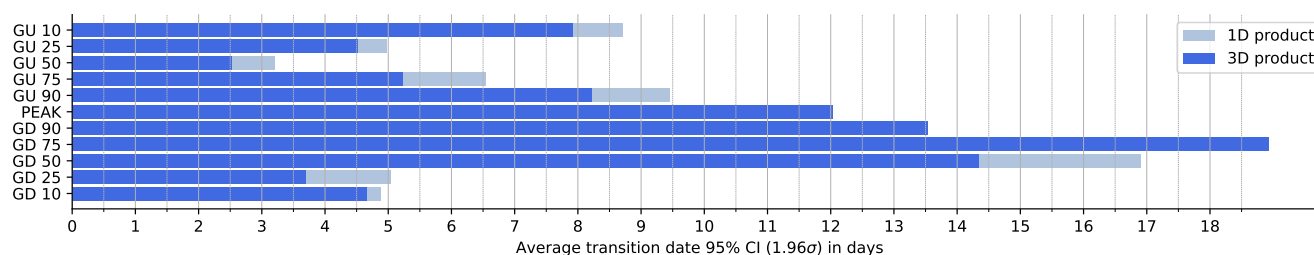


Figure 14. Average uncertainty on the transition date across the dataset. The uncertainty corresponds to the standard deviation determined through the Monte-Carlo sampling approach. We show the uncertainty values obtained when using both the one day and three day product.

of 2–4 days when using the 3D product. Next, GU₂₅ and GD₁₀ achieve slightly higher uncertainty or 3 and 5 days respectively. The least precise thresholds are the green-down phases: GD₇₅ exceeds 18 days and GD₅₀ and GD₉₀ reach 10–16 days, while GU₁₀ is approximately 6 days, which is consistent with previous observations. We therefore recommend that phenological analyses using our data are made mainly based on GU₅₀, GU₂₅, and GD₂₅, GD₁₀.

515 3.3.2 Impact of species and image type on data quality

To assess whether data quality varies across species and image types, we computed the average SNR and transition date uncertainties on a stratified subset of the dataset restricted to elevations below 1000 m, with 37 tree-years per stratum (Tab. 6). Across species, the deciduous broadleaf species all achieve SNR values between 17 and 20 decibels (dB), except for *Malus domestica* which achieves a lower SNR of 14.5 dB. *Picea abies* is also a clear outlier with an SNR of only 11.3 dB and a GU₅₀ uncertainty of 4.7 days, reflecting the reduced seasonal greenness amplitude of this evergreen species. Autumn transition dates show consistently higher uncertainty than spring dates for all species, with GD₇₅ emerging as the least precisely estimated phenophase (up to 22.5 days for *Picea abies*).

Stratifying by image type reveals a systematic quality difference: analysis images achieve an average SNR of 18.9 dB compared to 15.2 dB for panorama images. This greater noise is associated to higher uncertainties for several thresholds: GU₁₀ increases from 5.5 days (analysis) to 8.8 days (panorama). For GD₇₅, both image types show high uncertainty (17.1 and 16.3 days, respectively), with no clear advantage for analysis images at this threshold. However, the mid-amplitude thresholds most relevant for phenological monitoring remain robust: GU₅₀ uncertainty is 1.7 days for analysis images and 2.3 days for panorama images, and GD₂₅ is 3.0 vs. 4.4 days. These results confirm that despite the differences in quality associated with panoramic stitching and potential colour processing, panorama images still yield phenological transition dates with uncertainties comparable to those obtained from analysis images for some of the most robust phenophases (GU₅₀ and GD₂₅). Using higher quality image data such as the analysis images helps in narrowing down the uncertainties even further, especially on the more transient phases such as GU₁₀.



Table 6. Average quality metrics on a stratified subset of the dataset. We restrict to samples at elevations under 1000m and stratify per species and image type (panorama / analysis) with 37 tree-years for each stratum. We report the average SNR value in dB and the average 95% confidence interval on the transition date for each strata, aggregated *per species* in the top section and *per image type* in the bottom section.

	SNR (dB)	95% C.I. of Green-Up dates (1.96σ)					95% C.I. of Green-Down dates (1.96σ)				
		10%	25%	50%	75%	90%	90%	75%	50%	25%	10%
<i>Per species</i>											
Larix decidua	19.9	3.3	2.7	1.4	4.7	11.1	18.4	16.4	8.2	2.6	1.9
Betula pendula	19.0	5.5	2.2	1.4	2.4	6.3	11.8	16.9	6.3	3.2	4.7
Acer pseudoplatanus	18.9	4.8	2.1	1.2	2.8	4.1	11.9	17.4	8.7	3.1	3.3
Fagus sylvatica	17.3	7.2	2.8	1.4	1.5	1.8	4.5	13.3	19.6	3.0	3.5
Fraxinus excelsior	17.6	7.0	2.8	1.7	2.5	4.5	12.7	18.7	12.1	3.2	4.3
Picea abies	11.3	12.4	11.6	4.7	9.9	11.9	15.4	22.5	22.0	5.0	6.0
Malus domestica	14.5	6.7	4.1	2.8	4.4	6.8	14.0	14.3	10.6	6.7	9.6
Juglans regia	16.2	12.2	6.3	2.5	5.3	10.6	18.7	15.5	4.2	4.3	5.6
<i>Per image type</i>											
analysis	18.9	5.5	3.6	1.7	3.0	5.2	10.8	17.1	9.7	3.0	3.5
panorama	15.2	8.8	4.0	2.3	4.5	7.7	14.7	16.3	14.2	4.4	6.0

3.3.3 Impact of temporal resolution

Some site-years of our image archive contain a single observation per day while others have up to one image every 30min (Fig. 4). To evaluate the impact this had on the quality of the estimated transition dates, we performed a subsampling experiment on deciduous tree-year time series using the three-day product with 1000 Monte Carlo iterations (Fig. 15). We progressively reduced the number of observations per day from the maximum of 15.7 (one every 30 minutes) down to 1.4 per day and recomputed the GU_{50} and GD_{25} uncertainties at each level.

For GU_{50} , the median 95% confidence interval remains approximately 0.5 days across all temporal resolutions, indicating that the typical-case precision is largely insensitive to the sampling rate. However, the spread of the uncertainty distribution widens substantially at lower resolutions: the 95th percentile of the confidence interval increases from approximately 1 day at the full 30-minute resolution to approximately 5 days at the lowest sampling rate of 1.4 observations per day. A similar pattern is observed for GD_{25} , where the median uncertainty shifts modestly from approximately 1.0 to 1.2 days while the tail of the distribution expands from about 2 to 5 days.

These results indicate that reducing the temporal resolution primarily degrades the worst-case performance rather than the typical-case precision. Sites with lower temporal sampling—including the panorama-image sites that historically captured only one image per day—can therefore still yield reliable transition dates for the majority of tree-years, but are more susceptible to occasional large uncertainties. This supports the inclusion of lower-resolution panorama imagery in the dataset while highlighting the benefit of the ongoing migration towards 30-minute sampling across all sites.

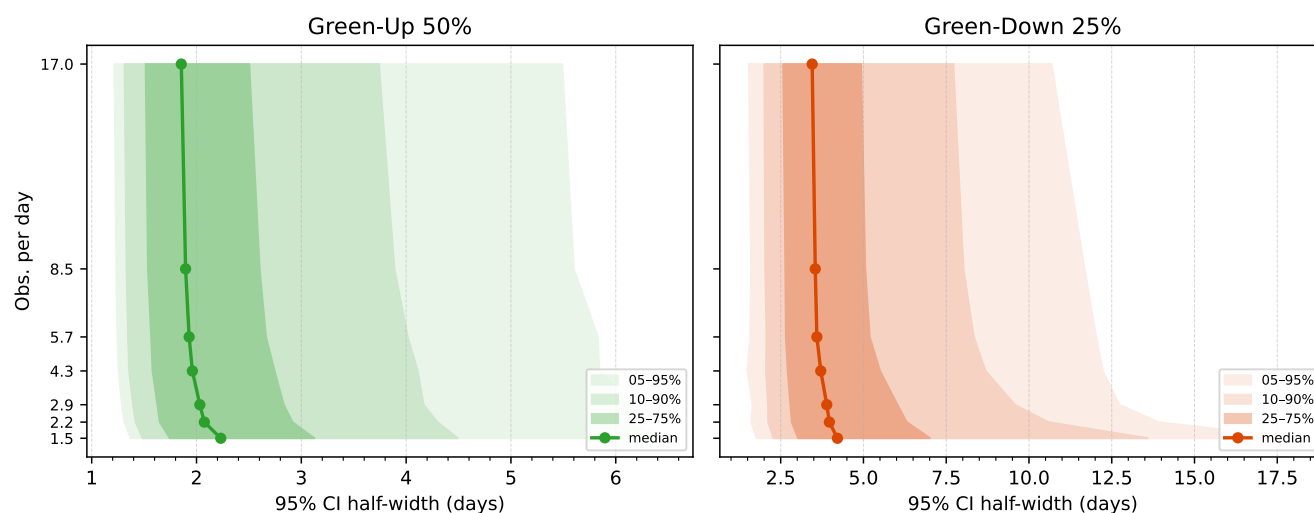


Figure 15. Impact of intra-day temporal resolution on transition date uncertainty. For 214 deciduous tree-year time series (three-day product, 1000 Monte Carlo iterations), we progressively subsampled the number of observations per day and recomputed the 95% confidence interval for GU₅₀ (left) and GD₂₅ (right). The dark shading shows the 25th–75th percentile range and the light shading the 5th–95th percentile range of the uncertainty distribution.

550 4 Discussion

The SwissPhenoCam dataset represents a significant step forward in observing vegetation phenology by combining high-frequency imagery with tree-level data across elevation gradients and diverse biogeographic zones in Switzerland. By using existing camera networks, this approach demonstrates how such infrastructures can be repurposed to generate ecologically meaningful information at relatively low additional cost. As such, the network offers substantial opportunities for further research on the interaction between (changing) environmental conditions and phenology.

4.1 Advancing phenological monitoring across scales

Phenological observations involve trade-offs between spatial coverage, temporal resolution, and biological detail, with ground observations offering detailed but sparse spatial coverage and satellites providing broad but coarse signals. Just like other PhenoCam networks, SwissPhenoCam addresses this gap by delivering continuous, high-frequency measurements at intermediate spatial scales, enabling robust characterization of seasonal dynamics. The network's main strengths lie in the following aspects: first, its focus on individual trees, which enables the analysis of intra-site variability and species-specific phenological responses that are often obscured in canopy-aggregated datasets; and second, the geographic focus on Switzerland introduces strong environmental gradients over short distances, offering unique opportunities to study phenological responses to elevation, temperature, and microclimatic variability. These characteristics complement existing datasets, such as those from the PhenoCam network (V1.0–V3.0), which emphasize a broad coverage across biomes but typically operate at coarser (i.e. canopy-level) ecological resolution.



While the use of third-party cameras introduces limitations in terms of standardized setup and data quality (e.g., the absence of reflectance reference panels, temporal frequency, and image resolution), this may also pave the way towards a more spatially continuous monitoring. As third-party camera footage is expected to become increasingly available in the near future, this may enable more cost-effective and extensive monitoring at a global scale. Consequently, failing to make use of this growing source of information could become an increasingly missed opportunity. By integrating different levels of data quality (i.e. from MeteoSwiss and third-party Roundshot cams), our approach might lay the groundwork for the broader use of non-dedicated cameras in phenology monitoring across a much wider range of imaging sources of varying quality. Ultimately, such a spatially more dense network could allow for the spatial mapping of phenology through interpolation across high- and lower-quality monitoring locations through interpolation, as is already common in weather monitoring. In such an integrated network, the key objective becomes accurate spatial predictions across the landscape, rather than precision at individual monitoring sites.

4.2 Opportunities for ecological and climate research

The dataset provides a valuable resource for investigating the drivers and consequences of phenological variability. Phenology plays a central role in regulating ecosystem productivity, carbon cycling, and land–atmosphere interactions, and is considered an important indicator of the biological effects of climate change (Jetz et al., 2019). By capturing detailed temporal trajectories of canopy greenness, SwissPhenoCam enables the detection of subtle shifts in phenophase timing, including earlier spring onset or delayed autumn senescence, which have been widely observed in temperate ecosystems.

Furthermore, the dataset’s high temporal resolution and spatial specificity make it particularly well suited for disentangling the relative importance of environmental drivers such as temperature, photoperiod, and moisture availability. In mountainous regions like Switzerland, where climatic conditions can vary dramatically over short distances, such analyses are critical for improving our understanding of phenological controls and for testing process-based models.

In addition, SwissPhenoCam provides an important benchmark for evaluating satellite-derived phenology products. Previous PhenoCam studies have demonstrated strong agreement between camera-derived transition dates and satellite observations, while also highlighting the limitations of satellite data in resolving fine-scale variability and rapid phenological transitions. High-frequency phenocam data may therefore serve as a reference for validating satellite-based metrics, particularly in heterogeneous and topographically complex environments such as those covered by the SwissPhenoCam network.

4.3 Methodological considerations and limitations

Despite its strengths, several limitations should be considered when interpreting the dataset. First, the use of cameras not originally designed for ecological monitoring introduces variability in image quality, viewing geometry, and illumination conditions. While quality control procedures mitigate these effects, residual noise and biases may influence derived greenness indices. Similar challenges have been documented in previous PhenoCam datasets, where issues such as camera configuration, white balance, and field-of-view changes can affect data quality and require careful interpretation.

Second, RGB-based indices such as the green chromatic coordinate (G_{CC}) provide an indirect proxy for vegetation activity. Although widely used and generally robust, these indices can be influenced by factors such as illumination changes, snow



600 cover, or background elements within the field of view. Recent developments incorporating additional spectral information, such as near-infrared bands (e.g. cameraNDVI in PhenoCam V3.0), suggest potential pathways for improving the sensitivity and interpretability of phenocam-derived metrics .

Third, while the dataset includes detailed annotations for individual trees and forest patches, accurate species identification and consistent region-of-interest delineation remain challenging, particularly in complex scenes, e.g., where trees are partially
 605 standing in front of each other. These challenges highlight the importance of continued methodological development, including automated segmentation and classification approaches.

We believe, however, that these points are not of sufficient importance to undermine the above mentioned opportunities.

4.4 Future perspectives

The SwissPhenoCam dataset is designed as a living resource, and its value will increase as longer time series become avail-
 610 able and additional sites are incorporated. Future developments could include the integration of complementary data sources, such as meteorological measurements, flux tower observations, or satellite products, enabling more comprehensive analyses of ecosystem processes. To support this integration, project sites were specifically selected where existing monitoring infrastruc-
 615 ture was already available, allowing Roundshot Livecams to be co-located with dendrometers and sap-flow sensors installed on individual trees through the TreeNet network (see Zweifel et al. 2021), as well as with flux towers and phenological gardens located within the cameras' fields of view. Future work could also expand analyses from individual trees to groups of trees and entire forest stands, for which regions of interest have already been delineated, enabling monitoring across multiple spatial scales. In addition, the dataset could support the development of approaches for detecting disturbances and anomalies, such as premature senescence, drought-induced canopy scorching, or damage caused by late spring frosts (e.g., as in Spafford et al. 2023). These developments would further broaden the applicability of the dataset for ecosystem health monitoring and climate
 620 impact assessments.

Moreover, advances in computer vision and machine learning offer promising opportunities to automate the extraction of phenological information from imagery, including species classification, phenophase detection, and uncertainty quantification. Such approaches could further enhance the scalability and reproducibility of phenocam-based monitoring.

Finally, the dataset provides a foundation for expanding phenological research in complex terrain, where traditional observa-
 625 tion methods face significant limitations. By combining high temporal resolution, spatial detail, and broad geographic coverage, SwissPhenoCam contributes to ongoing efforts to better understand and predict ecosystem responses to environmental change.

5 Conclusions

The SwissPhenoCam dataset establishes a country-scale, tree-level phenological record for Switzerland, comprising nearly 5,900 tree-years of greenness time series across 21 species and 34 sites, with an archive extending up to 15 years. Validation
 630 against the Swiss Phenology Network and expert validations of the images confirm high accuracy and robustness.



The most consistent ecological signal emerging from the dataset is a pronounced asymmetry between spring and autumn phenological responses to elevation. Spring green-up is delayed by up to 43 days between lowland and subalpine sites — a gradient that is coherent across all monitored deciduous species — whereas autumn green-down shows little systematic variation with altitude, differing by fewer than 15 days for most species across the full elevation range. This asymmetry means that growing season length is compressed primarily at the spring end as elevation increases, rather than from both ends simultaneously. This finding has also direct implications for how we interpret and project climate change impacts on mountain forest ecosystems: Seasonal differences in warming intensity with elevation (e.g.; highest spring warming in mid-elevations around 1000 m a.s.l. but highest autumn warming in the lowland (Scherrer et al., 2026)) might lead to altitude-dependent changes in growing season length. Such differential responses affect carbon uptake dynamics, water cycling, and the phenological synchrony between trees and their associated fauna, all of which are sensitive to the timing and duration of the active growing season.

More broadly, the dataset addresses a persistent gap in phenological observation: the mismatch between the coarse spatial (and, depending on clouds, also the coarse temporal) resolution of satellite-derived products and the sparsity of traditional ground-based records. By providing species-resolved, individual-tree time series at high temporal frequency across a topographically complex landscape, SwissPhenoCam offers a uniquely suited benchmark for evaluating and calibrating remote sensing phenology products in heterogeneous terrain, and for constraining process-based models that require species-specific parameterisation. As a living resource — designed to grow as the camera network expands and the archive deepens — it is well positioned to capture the interannual variability and long-term trends that are essential for detecting and attributing phenological change in a warming climate.

6 Code and data availability

Data described in this manuscript can be accessed at <https://doi.org/10.5281/zenodo.20451225> (Garnot et al., 2026) and is visualized on our website <https://swissphenocam.ch> (login information for reviewing purposes is shared with the editor) . Our complete code is also available on github and archived at <https://doi.org/10.5281/zenodo.20435338> (VSainteuf, 2026)



Appendix A: Visual checks

The primary objective of the visual checks is to make sure that the observed changes in greenness and the associated phenological transition dates belong to a single tree and are not influenced by other factors. To this end, we generated a report for each tree year that we have in our dataset (See Fig. A1). Tree-year reports were assigned the labels 'polygon issue', 'background-color issue', 'time series issue', and 'canopy issue' depending on whether these issues were there. In addition to this, tree-years were assigned an 'invalidity score' (0-5) which is a (subjective) assessment of the extent to which these issues affect the greenness (G_{CC}) time series and the extracted metrics of phenology. An invalidity score of '0-1' would correspond to a situation in which no major issues were identified, '3-4' to a situation in which a part of the time series is affected (e.g. spring phenology is OK, but autumn phenology cannot be trusted due to, e.g., a lack of data), and '5' to a situation in which all parts of the time series and its associated metrics of phenology are affected. In quite a few cases it was possible to fix the identified issues. We therefore chose for the iterative process described in section 2.2.4. An example of the distribution of invalidity scores across our dataset during the last iteration (in which time series issues were the main remaining source of invalidity) can be found in Fig. A2.

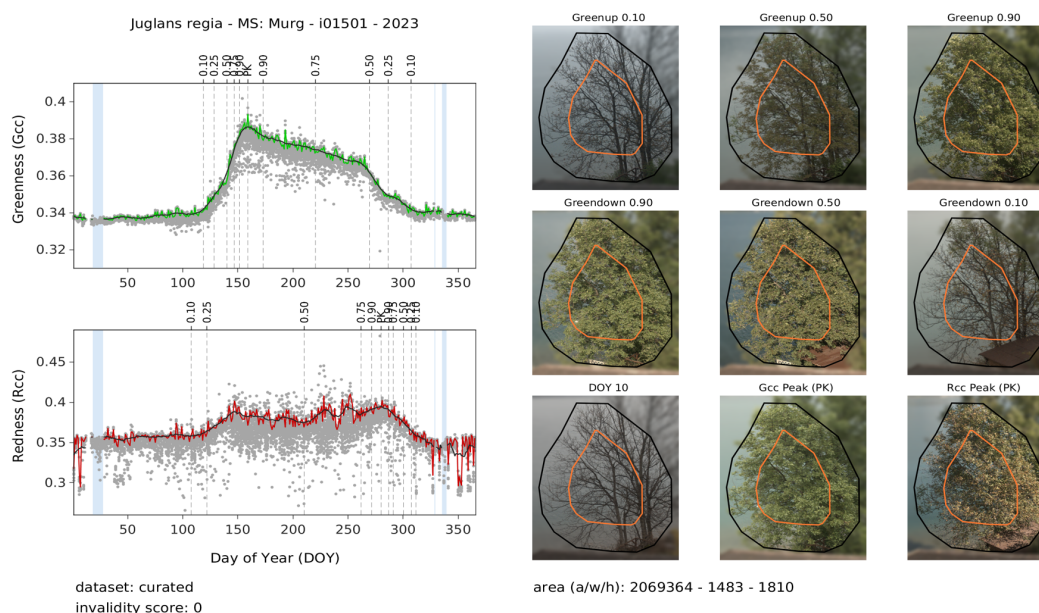


Figure A1. Example of a tree-year report. In the top left it shows the species name, location, tree ID, and the year. The top left panel shows the greenness across the year of the segment containing the tree. Striped lines in this panel indicate the phenophases. The bottom left panel shows the redness across the year. On the right the image segment with (a part of) the tree is depicted at different phenophases. Analysis were done for the part of the segment that is indicated with the orange line.

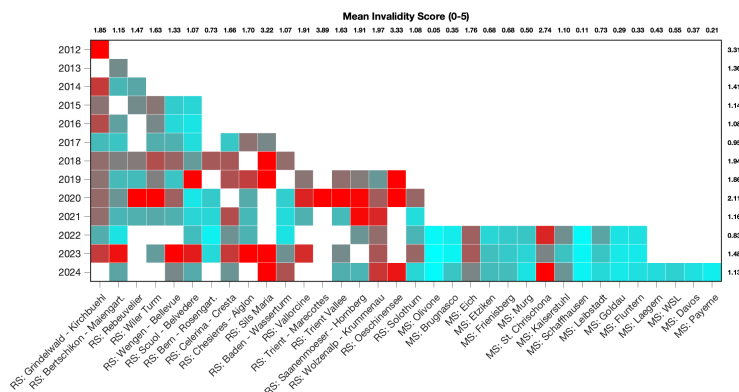


Figure A2. Example of the distribution of invalidity scores across our dataset during the last iteration (see section 2.2.4), i.e. before more strict filtering criteria were applied (see section 2.2.5).



A1 Time series issues

Data availability within a tree year might be poor in a way that affects metrics of phenology. This may occur, for example, when there is a lack of information on the baseline greenness (i.e. in the winter period when the tree has no leaves), when it is difficult to define a single highest peak in greenness (i.e. a lack of seasonality in the time series), or when jumps in raw data availability affect the smoothed greenness time series. Time series issues remained the most common reason for higher invalidity scores in our dataset after reducing polygon size and applying the snow filter (see section 2.2.4 and Fig. A3) and are more commonly observed during specific years (2020 and 2023) during which image acquisition was lower and at certain locations. Examples of tree year reports with time series issues can be found in Figs. A4 - A5.

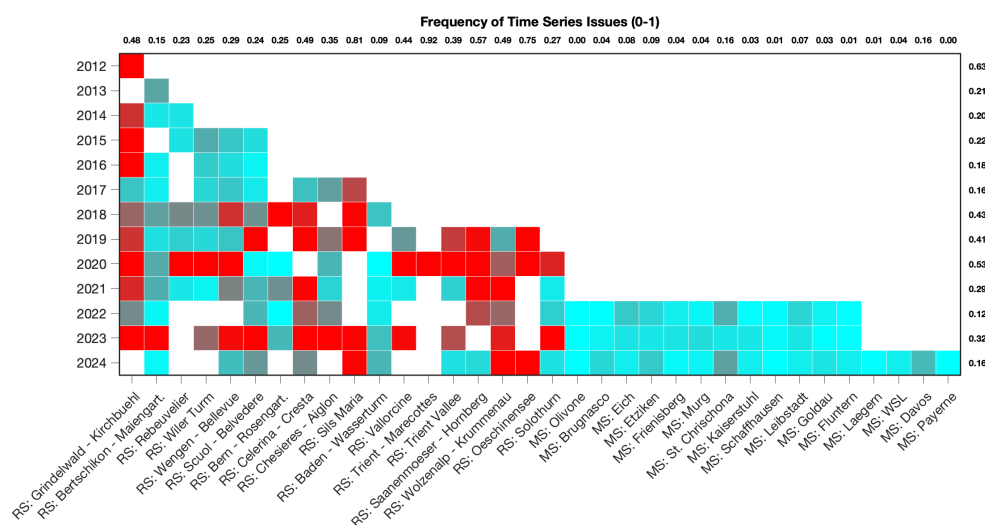


Figure A3. Frequency of time series issues per location across years during the last iteration (see section 2.2.4), i.e. before more strict filtering criteria were applied (see section 2.2.5).

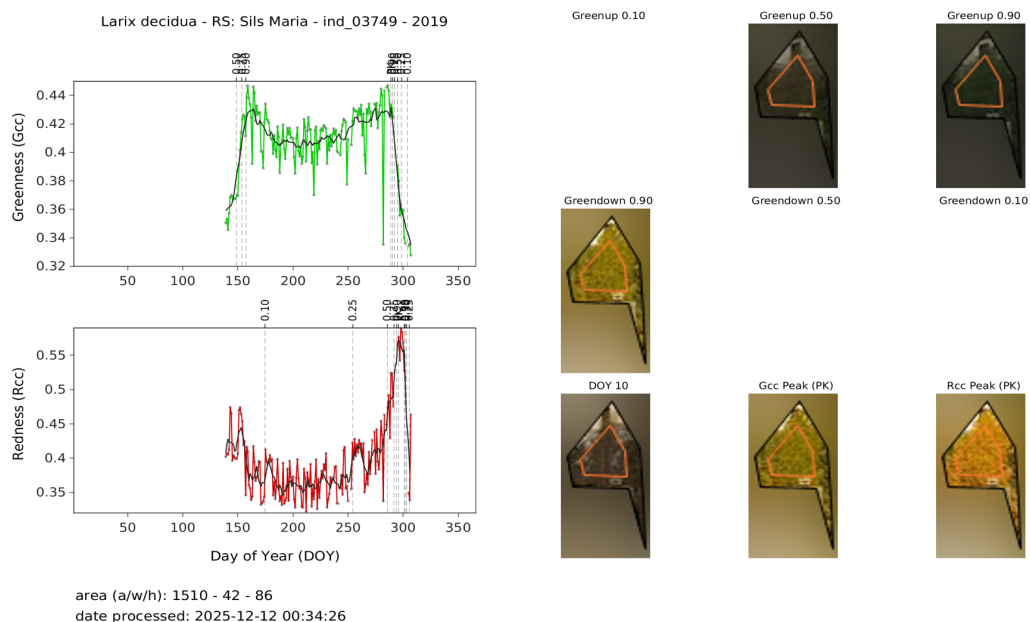


Figure A4. Example of a tree year with time series issues: there is no clear baseline greenness (i.e. in the winter period) because of missing data, and it is difficult to define a single highest peak in greenness; there seems to be two, one around day 160 and around day 290. Invalidity score 4-5, mainly because of the lack of baseline.

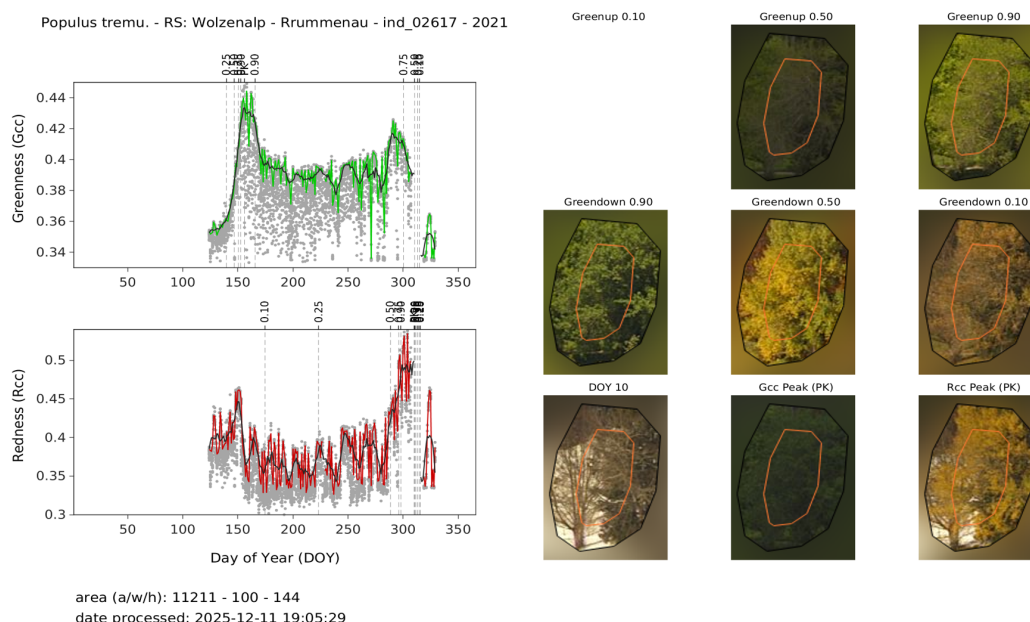


Figure A5. Example of a tree year with time series issues: there is no clear baseline greenness (i.e. in the winter period) because of missing data and there is a gap during the greendown phase. Things seem to be ok during the greenup phase; invalidity score 2-3.

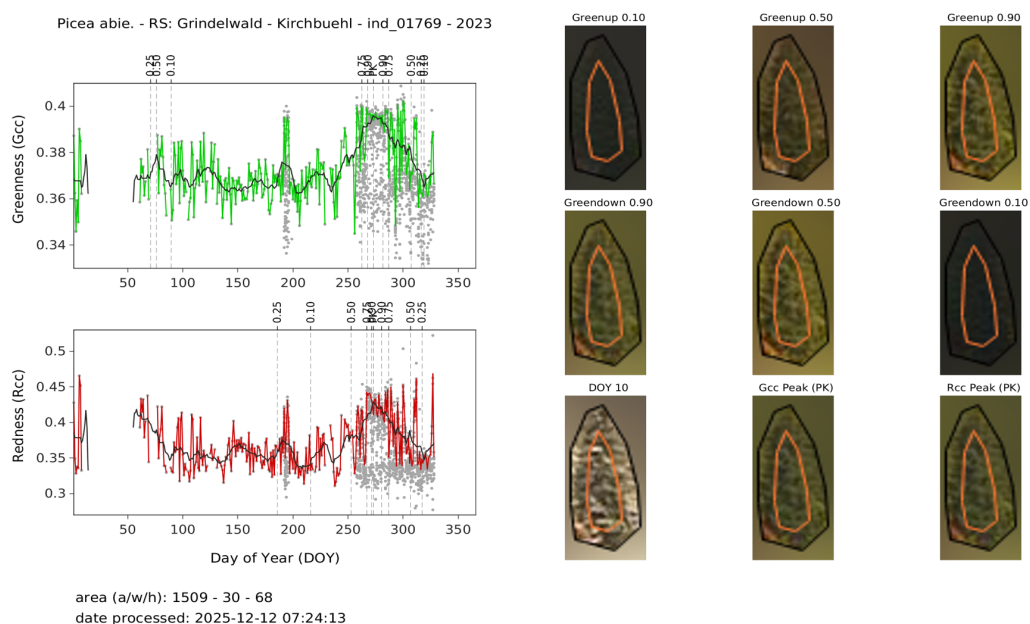


Figure A6. Example of a tree year with time series issues: there is a strange increase in greenness at the end of the year, possibly related with an increase in available raw data points (the grey dots). There is also a lack of seasonality/difficulty to identify a single highest peak. The invalidity score therefore is 5.

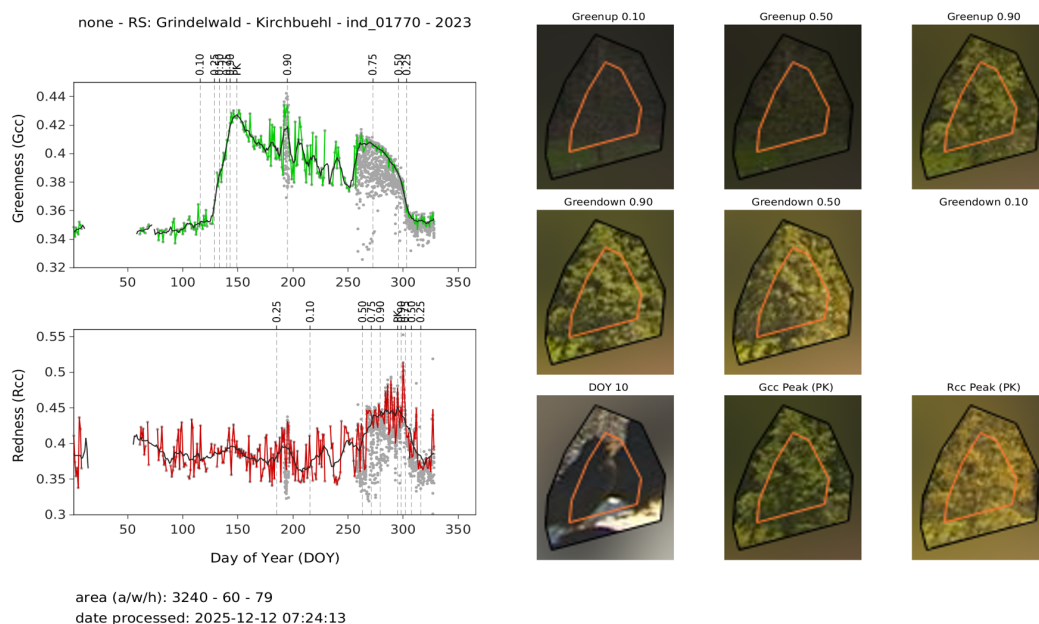


Figure A7. Example of a tree year with time series issues: there is a strange increase in greenness at the end of the year, possibly related with an increase in available data points (the grey dots). Phenophases during greenup still seem to be ok though. Invalidity score 2-3.



675 A2 Background issues

When there is something behind a deciduous tree that is green as well, this can be an issue. In many cases this happens when there is a free-standing tree in a grassland, but it can also happen when a deciduous tree is standing in front of an evergreen or other tree with a longer growing season. It is not always easy to estimate the extent to which background color changes affect results. To be on the safe side, an invalidity score of 3 or higher is applied. Background issues were more common during the
 680 initial iterations of our quality checks, but many examples were excluded based on statistical criteria, e.g. because the trees with severe background issues are likely to fail criteria on season length and amplitude. They remained fairly common, however, at certain locations (see Fig. A8). Examples of tree year reports with background issues can be found in Figs. A9 - A10.

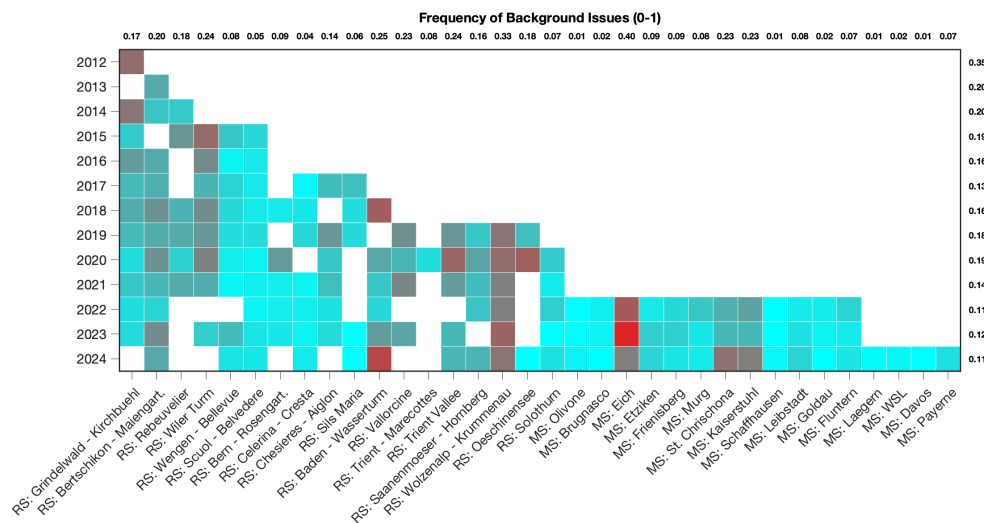


Figure A8. Frequency of background issues per location across years during the last iteration (see section 2.2.4), i.e. before more strict filtering criteria were applied (see section 2.2.5).

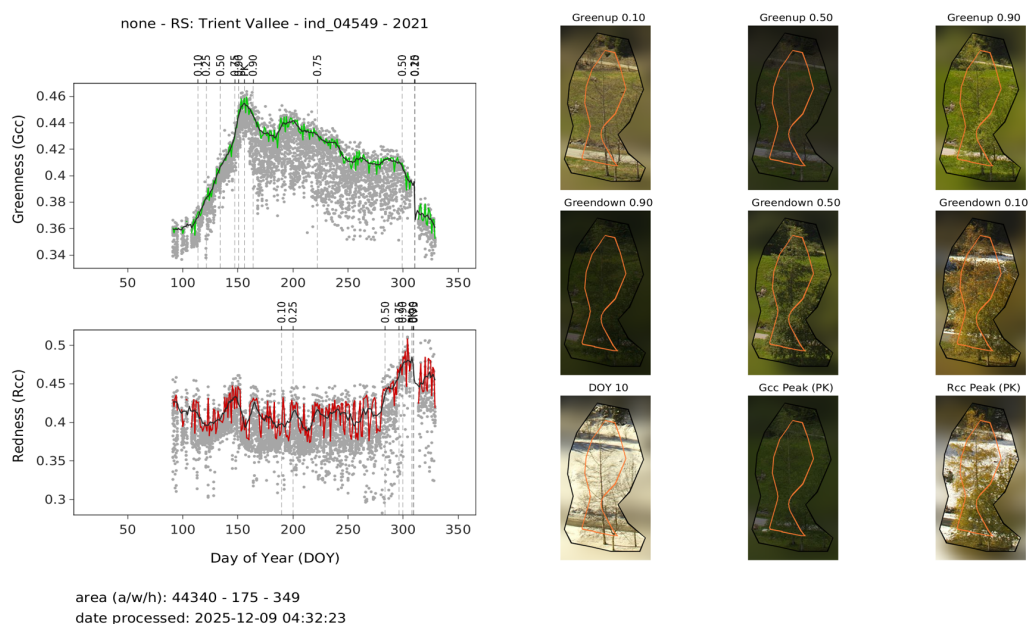


Figure A9. Example of a tree year with a strong background issue. The tree appears to have the most leaves in the Greendown 0.5 panel. In the greenup 0.9 panel there are only very few leaves. The greenness curve likely is influenced by the color of the grass in the background. Invalidity score 5.

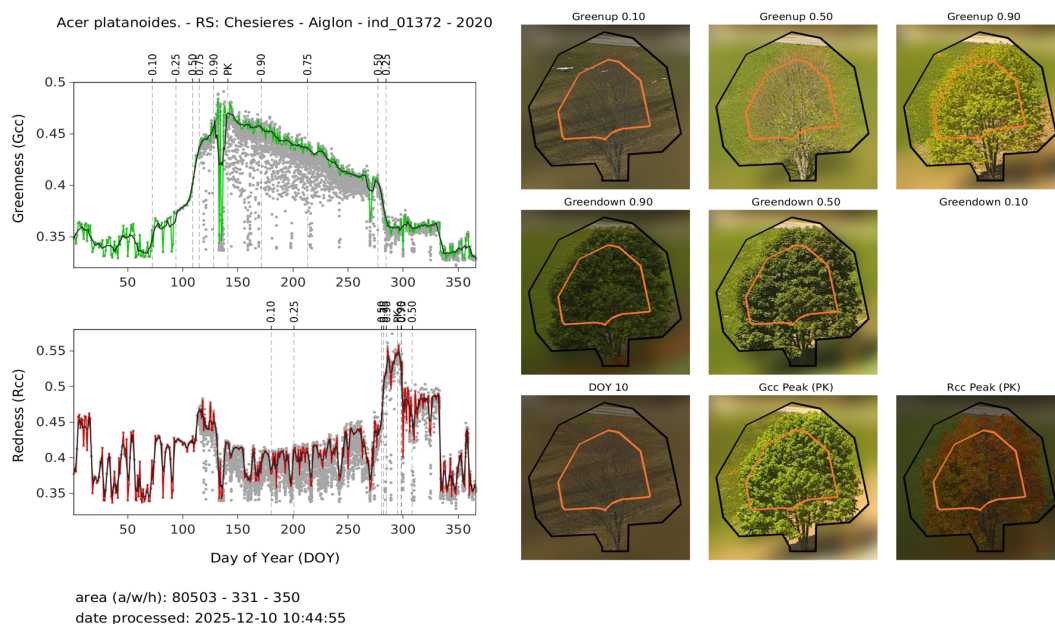


Figure A10. Example of a tree year with a weaker background issue. Invalidity score 3-4.



A3 Polygon issues

When the polygon (i.e. Region of Interest) contains more than just a part of the single tree we want to study, we are dealing with a ‘polygon issue’. This could either be because this single tree is not properly inside the polygon, but also because there is more than one tree inside the polygon. If less than half the (orange) polygon contains the tree of interest the worst invalidity score 5 is assigned. The invalidity score decreases as a larger portion of this polygon contains the same individual tree. Polygon issues very common during the initial iterations of our quality checks, but were largely addressed by shrinking the polygon to 1/3 of the original size (see section 2.2.4). Statistics after the last iteration can be seen in Fig. A11. Examples of tree year reports with polygon issues can be found in Figs. A12 - A14. Polygon issues do not have to remain across all years of a certain tree (e.g. because trees may grow over the years).

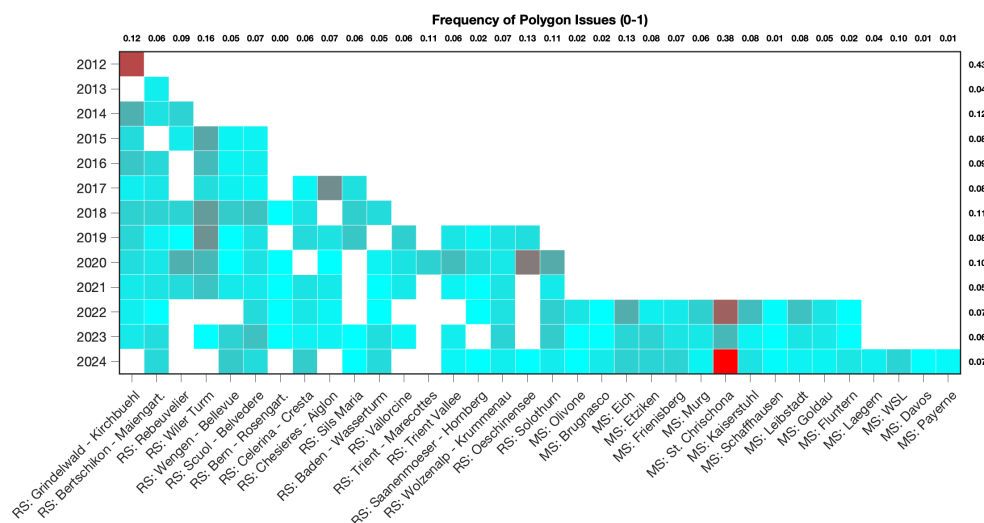


Figure A11. Frequency of polygon issues per location across years during the last iteration (see section 2.2.4), i.e. before more strict filtering criteria were applied (see section 2.2.5).

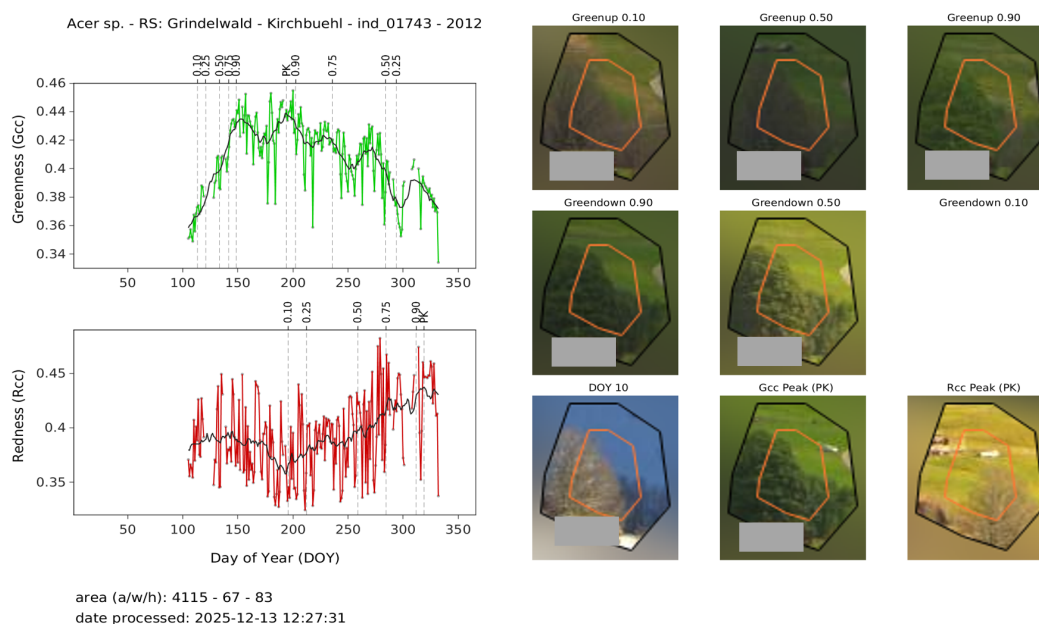


Figure A12. Example of a tree year with a polygon issue. The tree of interest occupies roughly 60% of the internal (orange) polygon that is used for greenness extraction. Grey blocks cover areas where houses are visible. Invalidity score 4.

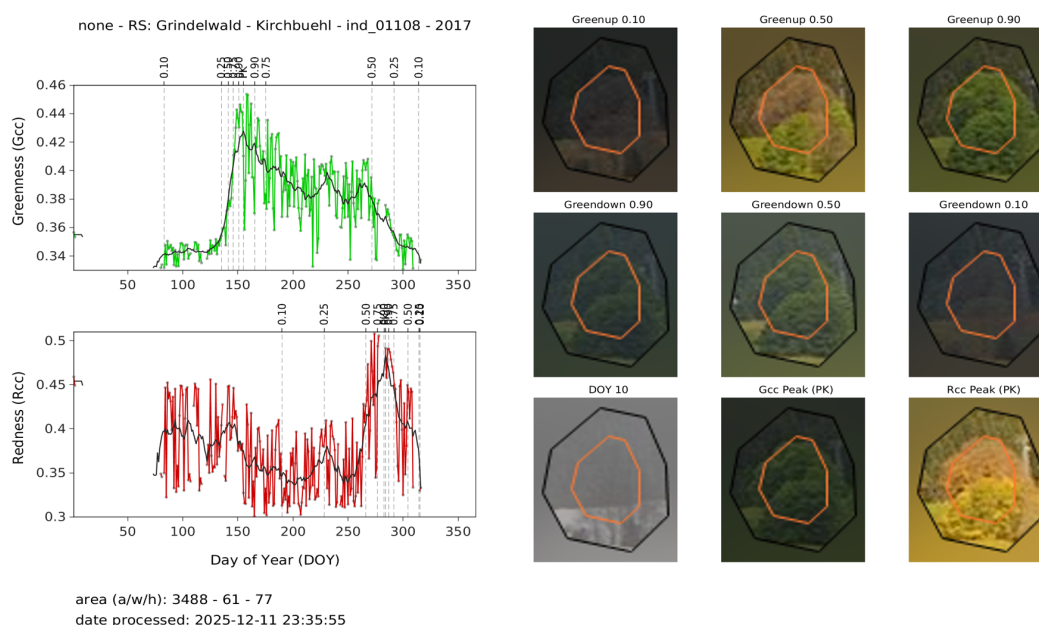


Figure A13. Example of a tree year with a polygon issue. There are multiple, different trees inside the polygon. The tree of interest may occupy slightly more than 50% of the internal (orange) polygon that is used for greenness extraction. Invalidity score 4-5.

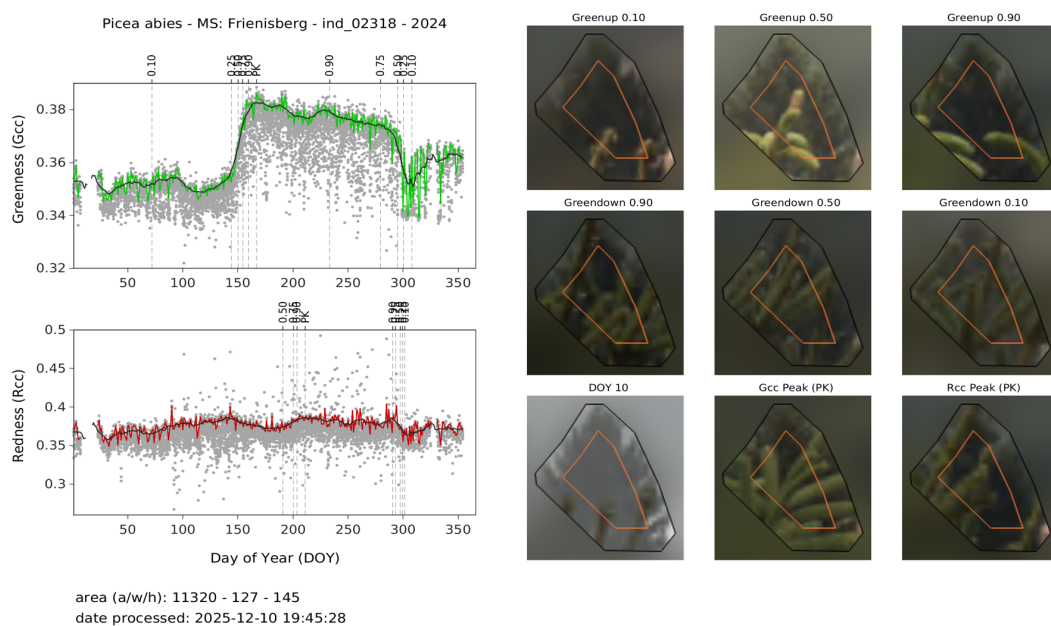


Figure A14. Example of a tree year with a polygon issue. A branch of another tree has grown in front of the tree of interest. Invalidity score 5.



A4 Canopy issues

Canopy issues occur when (a part of) the tree has died or was removed during the year. For example due to trimming, summer drought, or tree death. To some extent this is similar to a ‘polygon issue’, but this may require a different type of fix. Canopy issues were fairly uncommon already during the first iteration. Statistics after the last iteration can be seen in Fig. A15. Examples of a tree year report with canopy issues can be found in Fig. A16.

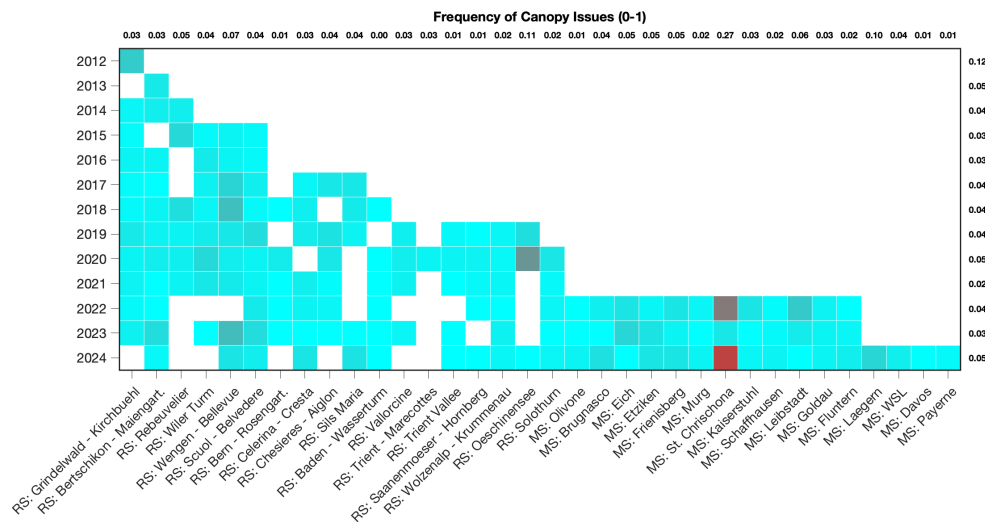


Figure A15. Frequency of canopy issues per location across years during the last iteration (see section 2.2.4), i.e. before more strict filtering criteria were applied (see section 2.2.5).

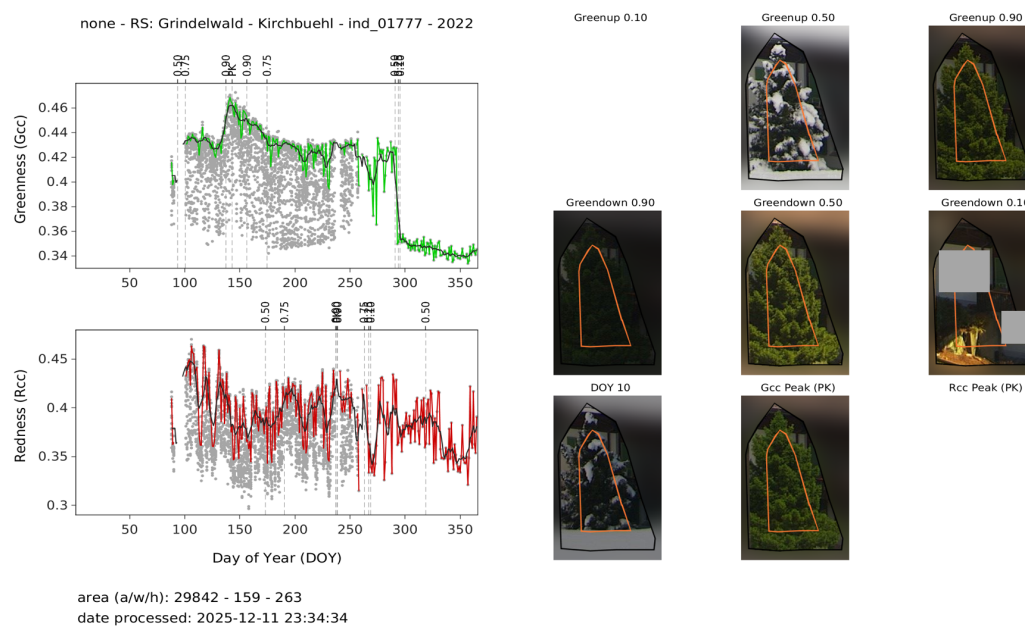


Figure A16. Example of a tree year with a canopy issue. The tree was removed around day 290. It is missing in the greendown 0.10 image, and there is a strong drop in greenness around this day. Invalidity score 5. Grey areas block housing. This tree year also has other issues.



A5 Weather issues

It could be that frequently returning snow or fog is affecting the greenness time series. During the first iterations of our visual checks, drops in greenness due to the presence of snow were a common phenomenon. This was largely addressed by applying a snow filter (see section 2.2.4). We also checked for the possibility that frequently returning fog affects our results but this was not a common issue. Weather issues were very common during the first iterations of our data curation efforts but were largely addressed by implementing a snow filter. Statistics after the last iteration can be seen in Fig. A17. Examples of a tree year report with a weather issue can be found in Fig. A18. In Fig. A19 you find the same report after applying the snow filter.

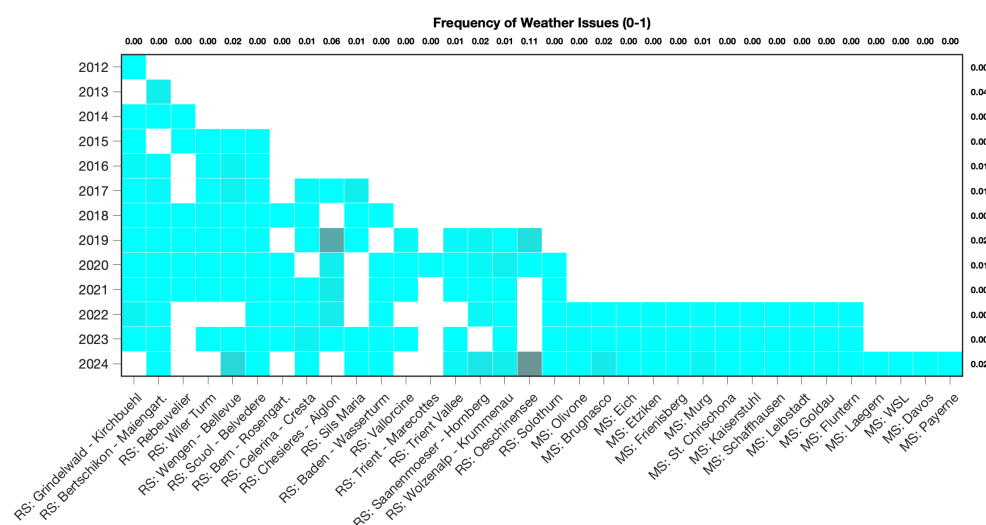


Figure A17. Frequency of weather issues per location across years during the last iteration (see section 2.2.4), i.e. before more strict filtering criteria were applied (see section 2.2.5).

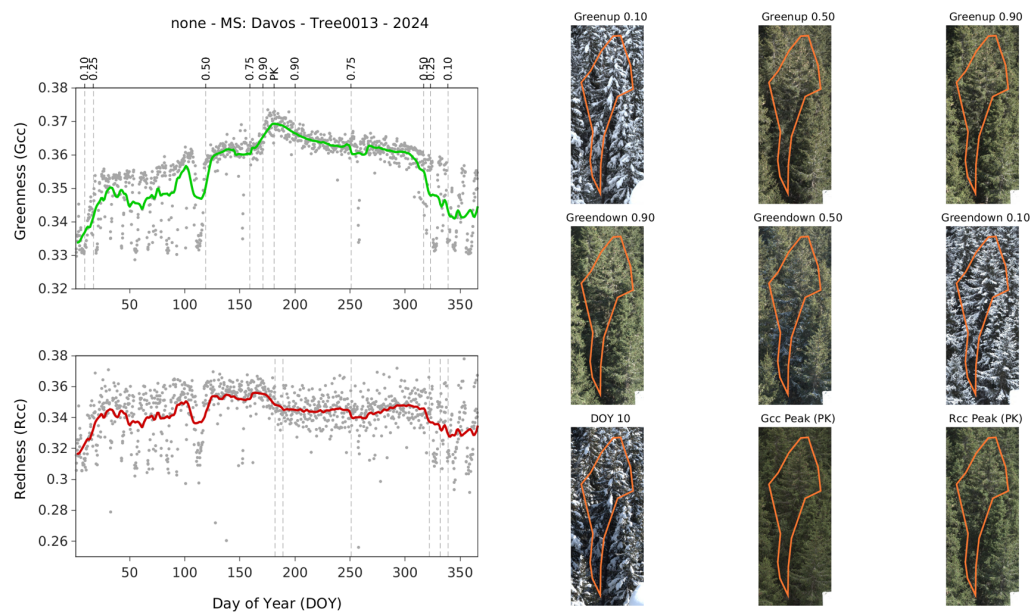


Figure A18. Example of a tree year with a weather issue.

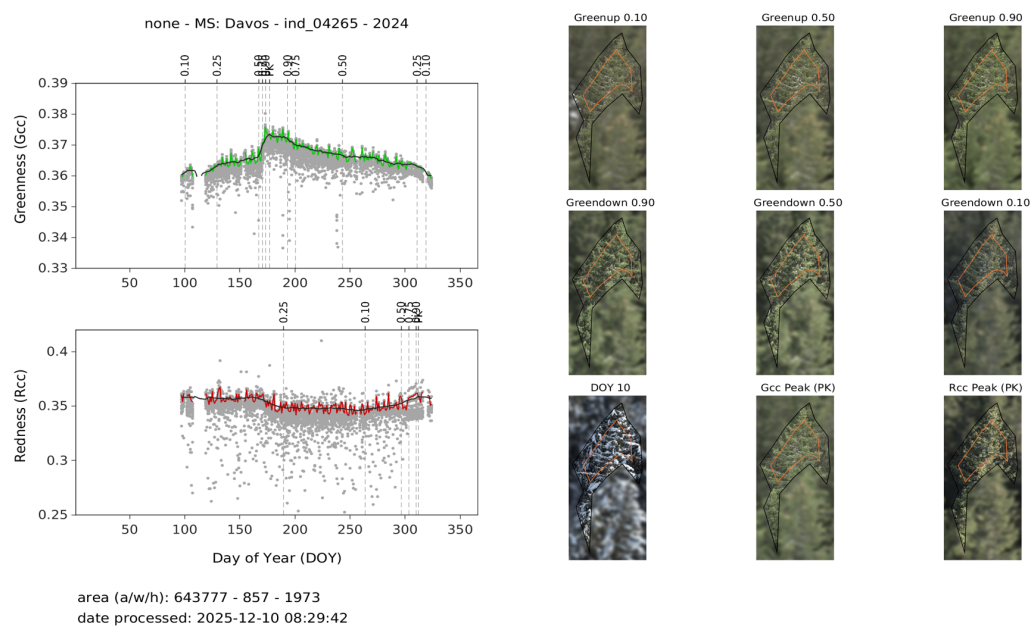


Figure A19. Example of the same tree year as in A18 with a weather issue that was fixed.



A6 Multiple issues

705 It could be that there are multiple issues that can be flagged simultaneously. When there are multiple issues this affects the invalidity score.

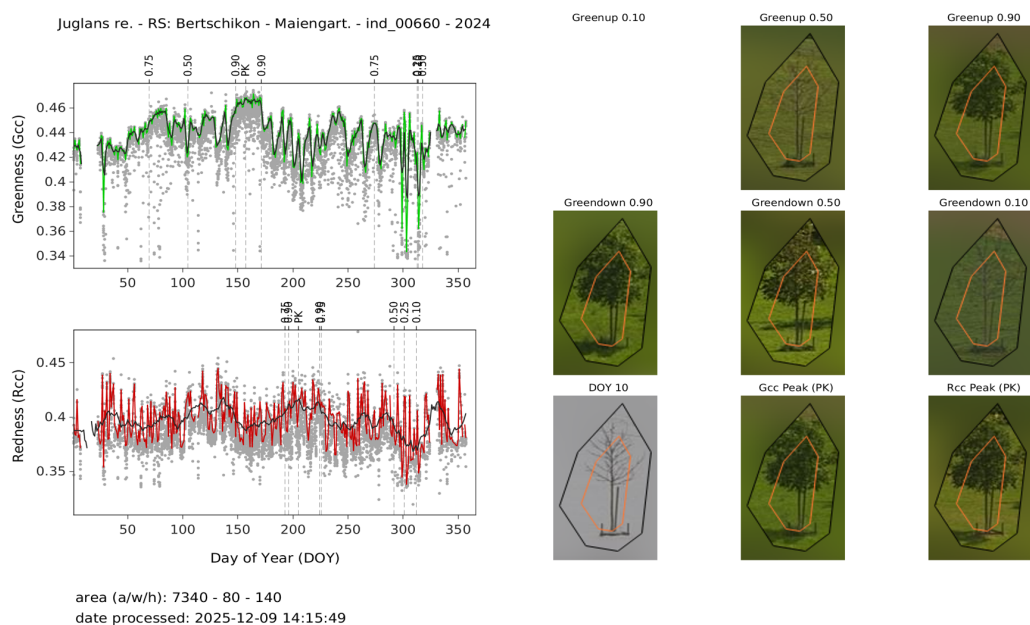


Figure A20. Example of a tree year with multiple (a time series, background, and polygon) issues. Invalidity score 5 is assigned.



Appendix B: Additional technical details

B1 Implementation details of the snow detector

Snow detector The presence of snow on the camera images leads to outliers in the extracted chromatic coordinates. It is therefore important to flag images with snow and discard them. To that aim, we used the Qwen2-VL-2B-Instruct (Wang et al., 2024) Vision-Language Model (VLM). This foundation model is composed of an image analysis component and a text-understanding component, both of which are trained on large amount of image and text pairs to develop the ability to perform tasks on images via written user instructions. We gave the model the following prompt : *"Does this webcam image show visible snow on the foreground ground, vegetation, or structures? Answer only with 'yes' or 'no'."* The images of our webcam archive were too large to be processed in a single pass of the VLM. Instead, we subdivided each image into square patches of size 750 pixels for panorama images and 2000 pixels for analysis images as shown on Fig. B1. For panorama images, we only used the lower row of patches as the top rows typically contain only sky or faraway landscape. For each patch, the VLM made a binary prediction for the presence of snow as instructed by our prompt. We then aggregated all patch-level predictions into a camera-level *snow index* by taking the average prediction across all patches. The *snow index* takes values between 0 and 1 and we consider the image as snowy if the snow index is superior or equal to 50%. This aggregation enables some robustness to the occasional false positives (see Fig. B1b) or false negatives (see Fig. B1c) that can occur at patch level. We evaluated the accuracy of this snow detection pipeline on 1000 randomly selected camera images that were manually annotated for presence of snow. Out of these images, 252 were positively labelled as containing snow after visual inspection. On this image set, our snow detector — predicting snow iif $snow\ index \geq 50\%$ — achieved an overall accuracy of 98% and an F1-score on the snow class of 95%, reaching a similar performance level as the snow detection pipeline used in the PhenoCam Network (Young et al., 2025).

Daily snow flag We used this snow detector to compute a binary snow flag for each day of observation on each camera site. When available, we selected three images per day, equally spread from sunrise to sunset, and used a minimum of one image per day. We ran the snow detector on these images, yielding one to three snow index values per day of observation. For cameras taking analysis images, we average the snow index values obtained from the different viewing angles into a single value since they correspond to the same landscape. We then take the average daily snow index value and apply the 50% threshold to obtain a binary snow flag. Lastly, we apply a temporal closing of one day: if a day is predicted as without snow but is preceded and succeeded by snowy days, we flip its flag to snowy. With this process, we obtain a daily binary snow flag for each site-year of our dataset. We show an example of a snow flag for a site-year on Fig. B1e, where we can see that the long winter snow period is correctly flagged as well as a shorter flash-snow event in the middle of October.

B2 Definition of the visual phenophases

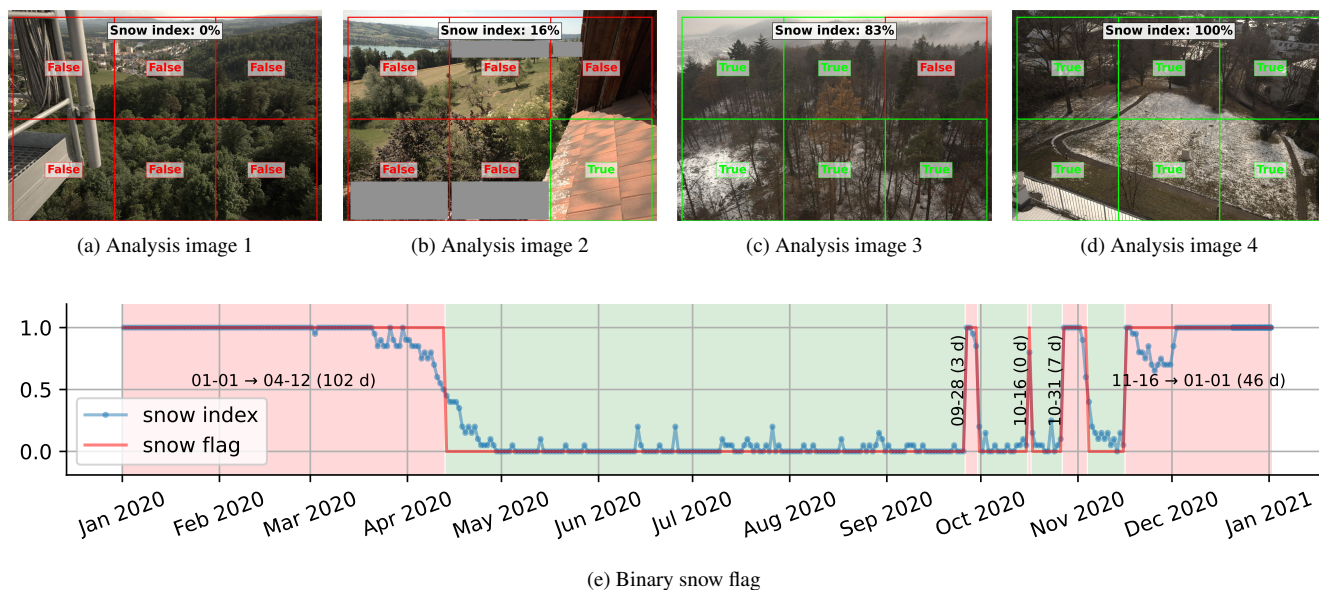


Figure B1. Examples of snow detection.

Table B1: Phenophases used in this study including the abbreviation for the phenophase, the explanation, the corresponding MeteoSwiss and BBCH phase, and whether the phase is present in deciduous (D) and/or evergreen (E) species.

Abbr.	Phenophase	Explanation	BBCH	MeteoSwiss	D/E
LUG	Leaf greenness	First signs of green and/or leaves of different colour on camera.	10–13	BEB/BEA	D/E
LUT	Second flush	Second signs of green on camera after a disturbance which caused the leaves to die in early spring and reflush.	–	–	D
LUH	Leaf unfolding (50%) / needle emergence (50%)	~50% of the leaves of the individual tree, i.e. on average about two leaves per bud, have unfolded so that the entire leaf surface and the leaf base are visible in high resolution trees.	13	BEA	D/E
LUD	Leaf development / needle development	~50% of the tree is covered in green, i.e. leaves are halfway developed.	15	–	D/E
LUM	Leaf maturity	Leaf unfolding or needle elongation complete. Final size is reached.	19	–	D/E
BLS	Start of flowering	First signs of flowers on camera, i.e. approximately three flowers on a single tree very close to the camera and ~10% of the flowers opened completely at a distant tree.	60	BLB	D

Continued on next page



Table B1 continued from previous page

Abbr.	Phenophase	Explanation	BBCH	MeteoSwiss	D/E
BLH	Flowering (50%)	~50% of the flowers on the tree or in the stand are open, or the flowers have already wilted again.	65	BLA	D
BLE	End of flowering	When no flowers are visible anymore; all flowers have wilted. This might overlap with leaf defoliation.	69	–	D
FRS	Start of fruit ripening	The first individual fruits of the individual tree have reached their normal stage of ripeness and have thus taken on their assumed final colouration.	86	FRB	D
FRH	Fruit maturity (50%)	~50% of the fruits from the tree(s) are mature, i.e. they have either fallen from the tree individually or taken on their assumed final colouration.	87	FRA	D
PRS	Start premature disturbance discolouration	When leaves start to discolour even though it is not expected yet (e.g. during summer), occurring much earlier as a result of various disturbances.	–	–	D
SCS	Start leaf senescence	~10% of the mature leaf area of the individual tree discoloured (yellow or yellow-brown to red-brown) and/or fallen off — species specific.	92/93	BVB	D
SCH	Leaf senescence (50%)	~50% of the mature leaves of the individual tree are discoloured in autumn (yellow or yellow-brown to red-brown) or fallen off.	94	BVA	D
SCE	End leaf senescence	>90% of leaves have either discoloured or fallen off.	–	–	D
DRP	Start premature leaf drop	Leaf drop due to hail, gale-force winds, or pests, either in spring or in autumn.	–	–	D
DRH	Leaf drop (50%)	~50% of the leaves have already fallen off.	95	BFA	D
DRE	End leaf drop	>90% of leaves have already fallen off.	97	–	D

Author contributions. Conceptualization: VSFG and JJJ. Data Collection: MdB, BP, CS, YV. Data curation: VSFG, JJJ. Formal analysis: VSFG and JJJ. Funding acquisition: JDW, JJJ, YV, and AG. Investigation: VSFG, JJJ, and MdB. Methodology: VSFG and JJJ. Project administration: VSFG and JJJ. Resources: AG and JDW. Software: VSFG and JJJ. Supervision: LS, YV, CS, BP, RZ, AG, and JDW.

740 Visualization: VSFG and JJJ. Writing (original draft preparation): VSFG and JJJ. Writing (review and editing): all authors.



Competing interests. The authors declare no competing interests.

Acknowledgements. This work was funded by MeteoSwiss/GCOS-CH. AI tools were used to edit the text and generate the figures of the present manuscript.



References

- 745 Brügger, R. and Vassella, A.: Pflanzen im Wandel der Jahreszeiten, Geographica Bernensia, Bern, Switzerland, 2003.
 Bundesamt für Umwelt: Datenbeschreibung Biogeographische Regionen der Schweiz, Datenbeschreibung / technischer bericht, Bundesamt für Umwelt (BAFU), Bern, Schweiz, 2020.
 Caparros-Santiago, J. A., Rodriguez-Galiano, V., and Dash, J.: Land surface phenology as indicator of global terrestrial ecosystem dynamics: A systematic review, *ISPRS Journal of Photogrammetry and Remote Sensing*, 171, 330–347, 2021.
- 750 Cleland, E. E., Chuine, I., Menzel, A., Mooney, H. A., and Schwartz, M. D.: Shifting plant phenology in response to global change, *Trends in ecology & evolution*, 22, 357–365, 2007.
 Cleverly, J., Eamus, D., Edwards, W., Grant, M., Grundy, M. J., Held, A., Karan, M., Lowe, A. J., Prober, S. M., Sparrow, B., et al.: TERN, Australia's land observatory: addressing the global challenge of forecasting ecosystem responses to climate variability and change, *Environmental Research Letters*, 14, 095 004, 2019.
- 755 Denny, E. G., Gerst, K. L., Miller-Rushing, A. J., Tierney, G. L., Crimmins, T. M., Enquist, C. A., Guertin, P., Rosemartin, A. H., Schwartz, M. D., Thomas, K. A., et al.: Standardized phenology monitoring methods to track plant and animal activity for science and resource management applications, *International journal of Biometeorology*, 58, 591–601, 2014.
 Federal Office of Meteorology and Climatology MeteoSwiss: Swiss Phenology Network, <https://www.meteoswiss.admin.ch/services-and-publications/applications/measurement-values-and-measuring-networks.html#param=messnetz-phaenologie&table=false>,
 760 2022a.
 Federal Office of Meteorology and Climatology MeteoSwiss: DaymetCH, data source, 2022b.
- Fu, Y. S., Campioli, M., Vitasse, Y., De Boeck, H. J., Van den Berge, J., AbdElgawad, H., Asard, H., Piao, S., Deckmyn, G., and Janssens, I. A.: Variation in leaf flushing date influences autumnal senescence and next year's flushing date in two temperate tree species, *Proceedings of the National Academy of Sciences*, 111, 7355–7360, 2014.
- 765 Garnot, V. S. F., Lever, J. J., de Boer, M., Sigg, C., Pietragalla, B., and Vitasse, Y.: SwissPhenoCamDataset, <https://doi.org/10.5281/zenodo.20451225>, data set, 2026.
 Hastie, T.: The elements of statistical learning: data mining, inference, and prediction, 2009.
- Jeong, S.-J., HO, C.-H., GIM, H.-J., and Brown, M. E.: Phenology shifts at start vs. end of growing season in temperate vegetation over the Northern Hemisphere for the period 1982–2008, *Global change biology*, 17, 2385–2399, 2011.
- 770 Jetz, W., McGeoch, M. A., Guralnick, R., Ferrier, S., Beck, J., Costello, M. J., Fernandez, M., Geller, G. N., Keil, P., Merow, C., et al.: Essential biodiversity variables for mapping and monitoring species populations, *Nature ecology & evolution*, 3, 539–551, 2019.
 Keenan, T. F., Gray, J., Friedl, M. A., Toomey, M., Bohrer, G., Hollinger, D. Y., Munger, J. W., O'Keefe, J., Schmid, H. P., Wing, I. S., et al.: Net carbon uptake has increased through warming-induced changes in temperate forest phenology, *Nature Climate Change*, 4, 598–604, 2014.
- 775 Kharouba, H. M., Ehrlén, J., Gelman, A., Bolmgren, K., Allen, J. M., Travers, S. E., and Wolkovich, E. M.: Global shifts in the phenological synchrony of species interactions over recent decades, *Proceedings of the National Academy of Sciences*, 115, 5211–5216, 2018.
 Kumar, A., Noolu, G. S. S., Khare, S., and Rossi, S.: A comparison of PhenoCam and satellite indices with in-situ observations for black spruce in the boreal forest of Quebec, Canada, *Ecological Informatics*, 88, 103 137, 2025.
 Land Change Science, WSL: DaymetCH, data processing, 2022.



- 780 Liu, G., Chuine, I., Denéchére, R., Jean, F., Dufrêne, E., Vincent, G., Berveiller, D., and Delpierre, N.: Higher sample sizes and observer
 inter-calibration are needed for reliable scoring of leaf phenology in trees, *Journal of Ecology*, 109, 2461–2474, 2021.
- Menzel, A., Sparks, T. H., Estrella, N., Koch, E., Aasa, A., Ahas, R., Alm-Kübler, K., Bissolli, P., Braslavská, O., Briede, A., et al.: European
 phenological response to climate change matches the warming pattern, *Global change biology*, 12, 1969–1976, 2006.
- Nasahara, K. N. and Nagai, S.: Review: Development of an in situ observation network for terrestrial ecological remote sensing: the Pheno-
 logical Eyes Network (PEN), *Ecological Research*, 30, 211–223, 2015.
- 785 Parmesan, C. and Yohe, G.: A globally coherent fingerprint of climate change impacts across natural systems, *nature*, 421, 37–42, 2003.
- Peltoniemi, M., Aurela, M., Böttcher, K., Kolari, P., Loehr, J., Karhu, J., Linkosalmi, M., Tanis, C. M., Tuovinen, J.-P., and Arslan, A. N.:
 Webcam network and image database for studies of phenological changes of vegetation and snow cover in Finland, image time series from
 2014 to 2016, *Earth System Science Data*, 10, 173–184, 2018.
- 790 Peñuelas, J. and Filella, I.: Responses to a warming world, *Science*, 294, 793–795, 2001.
- Richardson, A. D.: Tracking seasonal rhythms of plants in diverse ecosystems with digital camera imagery, *New Phytologist*, 222, 1742–
 1750, 2019.
- Richardson, A. D., Andy Black, T., Ciais, P., Delbart, N., Friedl, M. A., Gobron, N., Hollinger, D. Y., Kutsch, W. L., Longdoz, B., Luyssaert,
 S., et al.: Influence of spring and autumn phenological transitions on forest ecosystem productivity, *Philosophical Transactions of the*
 795 *Royal Society B: Biological Sciences*, 365, 3227–3246, 2010.
- Richardson, A. D., Keenan, T. F., Migliavacca, M., Ryu, Y., Sonnentag, O., and Toomey, M.: Climate change, phenology, and phenological
 control of vegetation feedbacks to the climate system, *Agricultural and Forest Meteorology*, 169, 156–173, 2013.
- Richardson, A. D., Hufkens, K., Milliman, T., Aubrecht, D. M., Chen, M., Gray, J. M., Johnston, M. R., Keenan, T. F., Klosterman, S. T.,
 Kosmala, M., et al.: Tracking vegetation phenology across diverse North American biomes using PhenoCam imagery, *Scientific data*, 5,
 800 1–24, 2018a.
- Richardson, A. D., Hufkens, K., Milliman, T., and Frolking, S.: Intercomparison of phenological transition dates derived from the PhenoCam
 Dataset V1. 0 and MODIS satellite remote sensing, *Scientific reports*, 8, 5679, 2018b.
- Richardson, A. D., Hufkens, K., Li, X., and Ault, T. R.: Testing Hopkins’ bioclimatic law with PhenoCam data, *Applications in Plant*
Sciences, 7, e01 228, 2019.
- 805 Scherrer, S. C., Isotta, F. A., and Kotlarski, S.: Elevation-dependent warming in Switzerland: Observed signals and dataset limitations, *Journal*
of the European Meteorological Society, 4, 100 026, 2026.
- Schwartz, M. D., Ault, T. R., and Betancourt, J. L.: Spring onset variations and trends in the continental United States: past and regional
 assessment using temperature-based indices., *international Journal of Climatology*, 33, 2013.
- Schwartz, M. D. et al.: *Phenology: an integrative environmental science*, vol. 132, Springer, 2003.
- 810 Seyednasrollah, B., Young, A. M., Hufkens, K., Milliman, T., Friedl, M. A., Frolking, S., and Richardson, A. D.: Tracking vegetation
 phenology across diverse biomes using Version 2.0 of the PhenoCam Dataset, *Scientific data*, 6, 222, 2019.
- Spafford, L., MacDougall, A. H., Vitasse, Y., Filippa, G., Richardson, A., Steenberg, J., and Lever, J. J.: Leaf phenology as an indicator of
 ecological integrity, *Ecosphere*, 14, e4487, 2023.
- Spafford, L., Lever, J. J., Gessler, A., Zweifel, R., Pietragalla, B., Wegner, J. D., Garnot, V. S. F., Sigg, C., and Vitasse, Y.: Stability and
 815 transferability of broadly trained phenology models in a changing climate, *Agricultural and Forest Meteorology*, 372, 110 685, 2025.



- Templ, B., Koch, E., Bolmgren, K., Ungersböck, M., Paul, A., Scheifinger, H., Rutishauser, T., Busto, M., Chmielewski, F.-M., Hájková, L., et al.: Pan European Phenological database (PEP725): a single point of access for European data, *International journal of biometeorology*, 62, 1109–1113, 2018.
- Thornton, P. E., Running, S. W., and White, M. A.: Generating surfaces of daily meteorological variables over large regions of complex
 820 terrain, *Journal of hydrology*, 190, 214–251, 1997.
- Vitasse, Y., Porté, A. J., Kremer, A., Michalet, R., and Delzon, S.: Responses of canopy duration to temperature changes in four temperate tree species: relative contributions of spring and autumn leaf phenology, *Oecologia*, 161, 187–198, 2009.
- VSainteuf: VSainteuf/SwissPhenoCam-greenness-processing: initial release (init), <https://doi.org/10.5281/zenodo.20435338>, software, 2026.
- 825 Wang, P., Bai, S., Tan, S., Wang, S., Fan, Z., Bai, J., Chen, K., Liu, X., Wang, J., Ge, W., et al.: Qwen2-vl: Enhancing vision-language model's perception of the world at any resolution, *arXiv preprint arXiv:2409.12191*, 2024.
- Wilson, K. B. and Baldocchi, D. D.: Seasonal and interannual variability of energy fluxes over a broadleaved temperate deciduous forest in North America, *Agricultural and Forest Meteorology*, 100, 1–18, 2000.
- Wingate, L., Ogée, J., Cremonese, E., Filippa, G., Mizunuma, T., Migliavacca, M., Moesinger, L., Wohlfahrt, G., Rastetter, E., Toomey, M.,
 830 et al.: Interpreting canopy development and physiology using a European phenology camera network at flux sites, *Biogeosciences*, 12, 5995–6015, 2015.
- Xie, Y., Civco, D., and Silander, J.: Species-specific spring and autumn leaf phenology captured by time-lapse digital cameras. *Ecosphere* 9: e02089, 2018.
- Young, A. M., Milliman, T., Hufkens, K., Ballou, K., Coffey, C., Begay, K., Fell, M., Javadian, M., Post, A. K., Schädel, C., et al.: Tracking
 835 vegetation phenology across diverse biomes using Version 3.0 of the PhenoCam Dataset, *Earth System Science Data Discussions*, 2025, 1–42, 2025.
- Zhang, X., Friedl, M. A., and Schaaf, C. B.: Global vegetation phenology from Moderate Resolution Imaging Spectroradiometer (MODIS): Evaluation of global patterns and comparison with in situ measurements, *Journal of Geophysical Research: Biogeosciences*, 111, 2006.
- Zweifel, R., Etzold, S., Basler, D., Bischoff, R., Braun, S., Buchmann, N., Conedera, M., Fonti, P., Gessler, A., Haeni, M., et al.: TreeNet—the
 840 biological drought and growth indicator network, *Frontiers in Forests and Global Change*, 4, 776 905, 2021.