Slovenská ekologická spoločnosť pri SAV
v spolupráci
s Ústavom krajinnej ekológie SAV, v. v. i., Bratislava
a Katedrou ekológie a environmentalistiky FPVaI UKF v Nitre

EKOLOGICKÉ ŠTÚDIE

Ročník 16 **Číslo 2/2025**

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ASSESSING THE EFFECTIVENESS OF PHENOCAM-BASED VEGETATION INDICES TO ANALYSE SPRING PHENOLOGY IN BAB FOREST

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Abstract: *Forest phenology monitoring is crucial to understand the response of vegetation growth to climatic change. This study analyzed the effectiveness of vegetation indices in extracting start of season (SOS) with Phenocam-derived phenometrics at the forested LTER site Bab, Slovakia (https://deims.org/79e10639-dd60-4f30-9c43-7b2bae0f359a). The single logistic regression model was applied to the smoothed time series for the year 2024 for each vegetation index to determine SOS and a threshold value of 10% of the seasonal amplitude was used to extract the spring green-up. Model performance was validated with the coefficient of determination (R^2) and root mean square error (RMSE). The study assessed that GCC has detected the earliest SOS in both woody and herbaceous layers than ViGreen and VARI, while ExR recorded a delayed onset due to its high sensitivity to non-vegetative parts. The study assessed that GCC has shown the strongest fit R^2 value 0.81, RMSE 0.04 for woody, and R^2 0.84, RMSE 0.05 for herbs, whereas ExR shown poor effectiveness due to its sensitivity to non-vegetative elements. The study highlighted the robust performance of GCC in extracting early SOS, while ViGreen and VARI were more effective during mid to late season transitions. The study highlighted the importance of selecting apposite indices for specific vegetation layers and to utilize the Phenocam-derived indices for precise phenological monitoring under illumination and canopy conditions.*

Keywords: *Phenocam imagery, Forest phenology, Vegetation indices, Green Chromatic Coordinate (GCC), Single logistic model and Seasonal dynamics, LTER*

Introduction

Phenology is one of the most sensitive indicators of vegetation growth responses to climate change (Way and Montgomery, 2015). Phenological events such as leaf unfolding, flowering, and leaf senescence has influenced the plant growth and ecosystem processes including carbon, water cycling and species interactions (Piao et al., 2019; Richardson, 2019). Shifts in the timing of these phenological events can cause far-reaching consequences for forest functioning and biodiversity. Therefore, monitoring the vegetation phenology has been the main focus of ecological research over the past two decades (Tang et al., 2016).

Although satellite-based remote sensing provides long-term records of phenological changes to monitor fine-scale shifts and phenological dynamics (Melaas et al., 2018). According to some studies satellite data is not considered enough to assess the phenological dynamics, which highlighted the need for near-surface approaches for the high-resolution monitoring at the ecosystem level (Bolton et al., 2020; Rodriguez-Galiano et al., 2015). The Phenocams are now popular for their high-resolution monitoring of phenological phases. These phenology cameras can provide daily images from which different vegetation indices could be derived, including the Green Chromatic Coordinate (GCC), Visible Atmospherically Resistant Index (VARI), Visible Greenness (ViGreen), and Excess Red (ExR) (Klosterman et al., 2014; Richardson, 2019; Sonnentag et al., 2012). These indices are increasingly used to track seasonal dynamics of forest phenology, particularly the start and end of the growing season, and playing a significant role to quantify year-to-year variability (Jönsson et al., 2010). The performance of these indices still has some uncertainties, which indices are most suitable for different vegetation types and canopy layers (Antonio et al., 2019).

Temperate forests draw a clear functional line between the canopy and the floor. Herbaceous understory species typically break dormancy early in spring, taking advantage of the brief window of strong light before the canopy closes. Woody species, by contrast, tend to leaf out later and do so more gradually, a pattern reported across sites and years (Basler & Körner, 2012; White et al., 2009). What remains less explored is how well Phenocam-derived indices capture these staggered phenologies when both layers are assessed within the same plots. Only a handful of studies have attempted side-by-side comparisons of woody and herbaceous transitions using the same camera data sources (Tian et al., 2021). With that gap in view, the present study examines two oak-hornbeam forest plots, A73 and P35, which differ in vegetation structure and thus offer a useful contrast for testing layer-specific phenological signals. We applied four commonly used vegetation indices GCC, VARI, ViGreen, and ExR to both woody and herbaceous layers (Figure 1) and used a single logistic model with a 10% amplitude threshold to estimate the start of season. This study aimed to evaluate the reliability of these indices for detecting SOS in both woody and herbaceous layers and to identify which indices can provide the most reliable estimates for long-term forest phenological monitoring.

Fig. 1. *Selection of phenological regions of interest (ROI) in plot A73. The left photo (05.04.2024) highlights the ROI for the woody layer (red rectangle), targeting the woody layer. The right photo (27.04.2024) highlights the ROI for the herbaceous layer (blue rectangle).*

Research Site

Báb forest is located in western Slovakia, in Nitra region, Nitra district (Figure. 2). The site is located in Podunajská nížina lowland in altitude 160-210 m. This area belongs to warm climatic region, it is typical by long, warm and dry summers, short, moderately warm, dry winters with very short snow cover. The average annual temperature varies between 9 and 10 °C, average temperatures in July are from 18 to 20.5 °C and in January -1 to -3 °C). The average annual precipitation is 500-600 mm (Lapin et al. 2002). In tree layer of the forest dominate oaks (*Quercus robur, Q. petraea, Q.cerris*) with admixture of *Carpinus betulus* and *Acer campestre*. In the herbaceous layer prevail *Melica uniflora, Pulmonaria officinalis, Asperula odorata, Hedera helix* and *Mercurialis perennis*. The studied permanent plots include native oak-hornbeam forest.

Fig. 2. *Research Site Bab forest.*

Methodology

We used Wachman Rio 4G (https://www.wachman.eu/de/p-197/wachman-rio-4g) cameras for phenological observations installed in Bab site in 2024 with an active daily period from 09:00 to 17:00, taking a picture every hour. Cameras are installed at a height about 5 meters. Their north-northwest orientation minimizes lens flare and shadowing from the sun throughout the year. The variability in the selection of a suitable color vegetation index across different image acquisition times and growth phases was evaluated. The procedure for downloading the data files and calculating RGB-based vegetation indices from the files was developed using Python programming language. First, images were divided into zones of interest to separate the woody and herbaceous layers for detailed analysis. Greenness Indices were then computed using normalized channels to effectively map vegetative regions. After cropping a specific region of interest from the GI map, we applied a crucial processing step: a threshold of 0.4. This value, established through testing, served to create a binary mask by removing all pixels with a GI score lower than 0.4. This step is critical because it isolates true green vegetation, aligning with the expected increase in greenness during the phenological development. The final step involved counting the remaining green pixels to quantify the vegetation coverage.

To monitor vegetation phenology across the study sites, we used four phenocam-based vegetation indices (VIs): GCC (Green Chromatic Coordinate), ExR (Excess Red), VARI (Visible Atmospherically Resistant Index), and ViGreen (Vegetation Greenness Index). These indices are derived from the red, green, and blue (RGB) channels of near-surface digital cameras and are commonly used to track seasonal changes in canopy greenness.

GCC (Green Chromatic Coordinate) is one of the most widely used color-based VIs, especially within the PhenoCam network. It represents the relative contribution of the green channel to the total RGB reflectance and is calculated as:

$$GCC = G/R + G + B \quad (1)$$

where R, G, and B denote the red, green, and blue color channels, respectively. GCC is highly sensitive to changes in canopy greenness and is particularly effective for monitoring leaf emergence and senescence (Richardson et al., 2007).

ExR (Excess Red) uses only the red and green channels and is particularly useful when NIR information is unavailable, such as in camera-based or high-resolution RGB satellite imagery. It is defined as:

$$EXR = (1.4 \times Red) - Green \quad (2)$$

ExR highlights changes in red reflectance associated with chlorophyll breakdown during late-season leaf coloration (Klosterman et al., 2014).

VARI (Visible Atmospherically Resistant Index) is designed to enhance the vegetation signal from RGB imagery by emphasizing green reflectance while minimizing atmospheric effects on the red and blue channels. It is calculated as:

$$VARI = G + R - B/G - R \quad (3)$$

VARI has been shown to perform well under variable illumination and atmospheric conditions (Treitz, 2001).

ViGreen (Vegetation Greenness Index) emphasizes the green channel but normalizes it to improve contrast between vegetation, background, and senesced material. Its general form is:

$$ViGreen = G/R\gamma + B\delta \quad (4)$$

where γ and δ are empirically derived parameters to optimize contrast between vegetation and background (Antonio et al., 2019).

The computing process for greenness indices was consisted of several steps. Firstly, band normalization for images. Secondly, all images were masked by the ROI to calculate the band color channel information for each pixel. The mean of greenness indices value was computed. Greenness indices were calculated for ROI within each image during the day time 11:00 AM – 3:00 PM, in which the camera could have better light conditions for exposure.

The raw data, or pre-processed vegetation indices were further processed for their time series. To reduce noise and detect seasonal cycles from high-frequency data, the time series data of all greenness indices was smoothed using a 10-day moving window method (Schieber et al., 2017). This approach is generally effective for minimizing day-to-day variation due to weather related scene illumination changes or digital image format. A specific smoothing and interpolating method were applied to the time series vegetation indices for key phenological events extraction.

To determine the SOS for woody and herbaceous vegetation layers, a single logistic regression model was applied to the time series of vegetation indices. The model was fitted to the spring green-up phase, as this period represented the most distinct phenological transition. SOS was defined as the date at which the fitted logistic curve reached 10% of the seasonal amplitude a biologically meaningful threshold for the initiation of vegetation greenness (Klosterman et al., 2014; Liu and Zhang, 2020).

We performed the model fitting for each plot and vegetation layer, and the resulting logistic curves were evaluated for accuracy. To validate the performance of the fitted models, the coefficient of determination (R^2) was calculated, which served as an indicator of the model's goodness of fit (Zhang et al., 2003). High R^2 values indicated that the logistic regression fitted to the time series data of greenness index.

Results

We focused on the forested LTER site Bab, Slovakia (LTER Bab site) to analyse the spring 2024 phenological dynamics for both woody (trees and shrubs) and herbaceous layers shown in Figure 3 and Figure 4. Our goal was to assess how different RGB-based vegetation indices GCC, ExR, VARI, and ViGreen performed in detecting the start of the season (SOS) for these two vegetation layers. To achieve this, we used two analytical approaches. For both woody and herbaceous layer, standard index calculations were applied across four indices to estimate SOS, using a single logistic regression model with a 10% amplitude threshold. Data smoothing and pre-processing were performed to minimize noise and fluctuations caused by lighting and shadow effects. Our observations showed a clear seasonal pattern in both layers. In the herbaceous layer, growth commenced in the first week of April in both plots and reached peak greenness around mid-May.

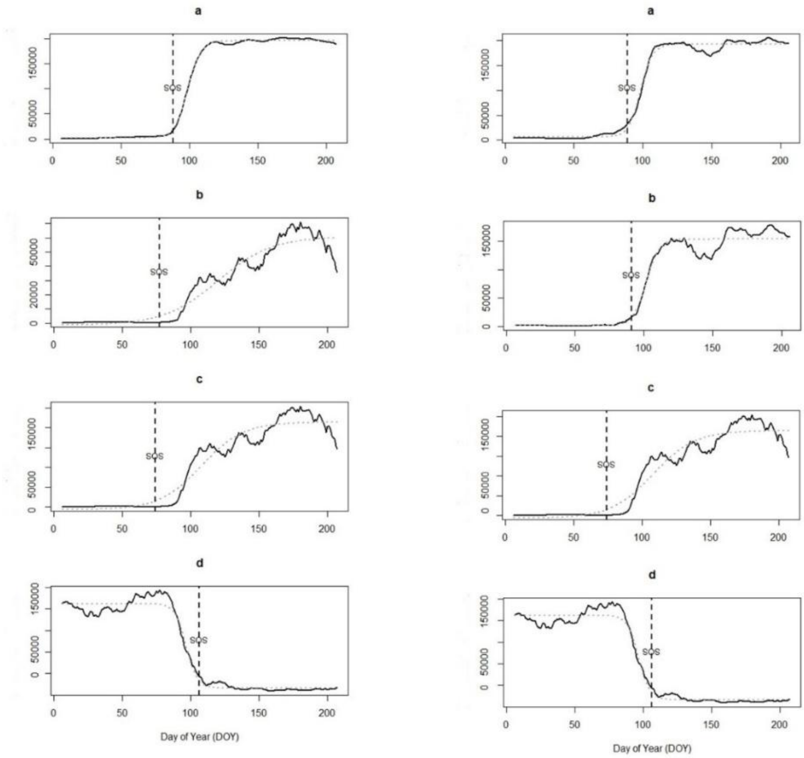

Fig. 3. *Start of the season of Woody layer. Legends in right column are representing Plot P35 and left column representing Plot A73. In both columns, a) representing GCC, b) Vigreen, c) VARI and d) ExR. Smoothe and Black line is representing the trend line, the grey dotted line is the model fitting curve and grey dashed line is representing the start of the season in all indices.*

Figure 3 have shown that woody layer also began its spring growth in early April, with minor differences between indices in SOS detection. GCC identified the earliest onset with SOS occurring during the first week of April on day 91 in P35 and day 90 in A73. While, VARI and ViGreen detected later SOS day 97 in P35 and day 96 in A73, which reflected their higher sensitivity to non-vegetative components. Whereas, ExR shown the different patterns of SOS day 104 in P35 and day 106 in A73 due to its responsiveness to soil background and dry vegetation rather than green biomass.

In Figure 4 in Herbaceous layer, SOS showed a similar trend. GCC captured the earliest onset on day 59 in A73 and day 63 in P35, while VARI, ViGreen, and ExR indicated slightly delayed green-up (ranging from day 66 to 70). These differences have shown the layer-specific behaviour of indices with GCC being particularly effective at detecting early-season vegetative growth, whereas the other indices were influenced more strongly by non-vegetated areas, shadows, or early-stage senescence. Despite the careful pre-processing, all indices were still affected by environmental noise. Canopy shadows has significantly impacted the herbaceous layer and caused some variability in pixel classification, while sunlight brightness significantly affected the woody layer. These factors highlighted the importance of interpreting Phenocam-based indices with an awareness of site-specific light conditions and canopy structure.

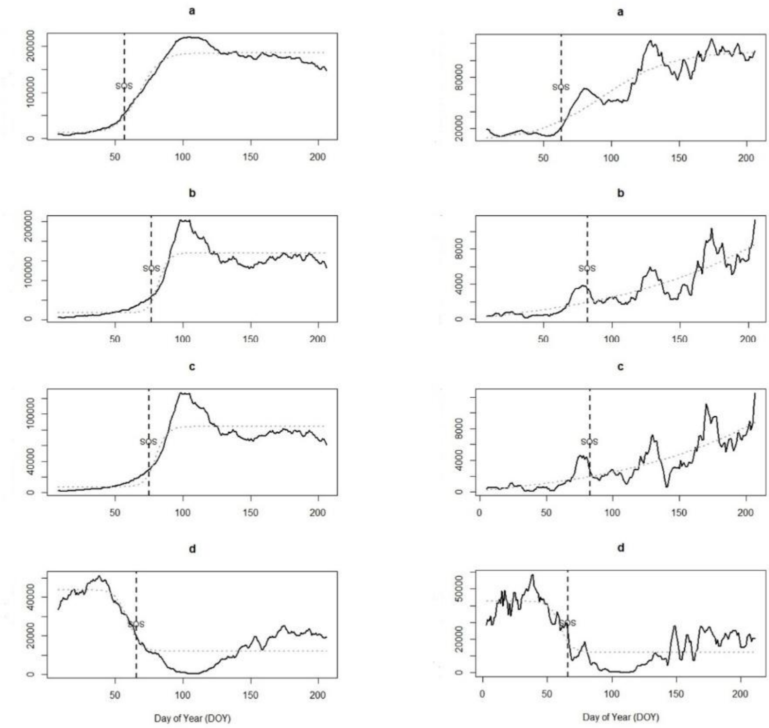

Fig. 4. *Start of the season of Herbaceous layer. Legends in right column are representing Plot P35 and left column representing Plot A73. In both columns, a) representing GCC, b) Vigreen, c) VARI and d) ExR. Smooth and Black line is representing the trend line; the grey dotted line is the model fitting curve and grey dashed line is representing the start of the season in all indices.*

The comparison of GCC, VARI, ViGreen, and ExR in detecting SOS for both woody and herbaceous layers highlighted distinct patterns in plotted time series with the numeric summary Table 1. In the woody layer, GCC identified the earliest green-up on day 91 in plot P35 and day 90 in plot A73 and highlighted its sensitivity to chlorophyll-rich vegetation components and its robustness in detecting the onset of photosynthetic activity (Shi et al., 2019). VARI and ViGreen detected SOS later, while ExR lagged furthest behind and showed a different behaviour on days 104 and 106 and showing its high responsiveness to soil background and dry plant material. This delay is visible in the curves, where the ExR increase more slowly in early spring as compared to the sharp GCC rise. While in the woody layer, SOS estimates have shown some differences among indices, GCC has consistently detected the earliest onset of green-up on day 90–91 and ExR showing the latest onset on day 104–106. Whereas, model fitting performance was indicated by R^2 and RMSE values, which confirmed the reliability of GCC R^2 0.81, RMSE 0.04 and in VARI, R^2 0.76, RMSE 0.15, while ExR showed weak performance as compared to others R^2 0.26, RMSE 0.73. Vigreen displayed moderate performance assessed greening onset slightly later than GCC R^2 0.73, RMSE 0.13. These results suggest that GCC can provided the most reliable and robust estimate of SOS for the woody layer and closely reflected the timing of green-up in Table 1.

Tab. 1. *Seasonal Growth phases and day of the year (DOY) of Vegetation in all indices*

	Indeces	**Plot-A73**	**Plot-P35**	**R2 Value**	**R2 Value**	**RMSE**
Woody Layer	GCC	90	91	0.81	0.04	91
	Vigreen	93	91	0.73	0.13	91
	VARI	87	92	0.76	0.15	92
	ExR	106	104	0.26	0.73	104
Spring Herbs	GCC	57	63	0.84	0.05	57
	Vigreen	71	68	0.76	0.18	71
	VARI	74	67	0.78	0.17	74
	ExR	70	66	0.31	0.76	70

In the herbaceous layer, GCC has performed effectively in detecting green-up than VARI, ViGreen, and ExR. The SOS for herbs was observed earlier in the plots compared to woody vegetation as ecologically understory herbs often respond faster to warming temperatures and increasing light availability before canopy growth (Sonnentag et al., 2012; Tang et al., 2023). Phenological patterns were observed generally earlier and more variable between indices. The model fitting confirmed the reliability of GCC for the herbaceous layer as R^2 was 0.84, and RMSE was 0.05, whereas ExR showed low goodness-of-fit and indicated substantial deviation from the observed green-up. VARI and Vigreen performed moderately, with R^2 values between 0.76 and 0.78, which shows the general trend but with a higher deviation as compared to GCC.

Conclusion

Phenocam-based vegetation indices are effective for analysing phenological changes in both woody and herbaceous layers of hornbeam forests. In the comparative assessment of greenness indices, GCC worked as the most reliable for detecting the start of season. GCC captured early greening clearly and produced strong model fits across plots. VARI and Vigreen also worked effectively and shown general phenological trends, but they had slight delays or small deviations. In contrast, ExR was less suitable because it showed high variability and did not match well with observed phenological events. This study suggested that the right vegetation index should be considered according to the characteristics of the vegetation layer. The study emphasized that the selecting suitable indices and curve-fitting methods can improve the monitoring of phenological phases. This approach has proved effective in detecting seasonal changes more accurately and shown how different vegetation layers respond to environmental factors.

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