Decadal High-Resolution Monitoring of Climate-Driven Phenological Shifts Across Diverse Vegetation Zones of the Great Himalayan National Park Conservation Area

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Abstract: Vegetation phenology is a sensitive indicator of climate change, particularly in mountainous ecosystems where elevation-driven climatic gradients strongly influence growing season dynamics. This study examined the spatial and inter-annual variability of the Start of Season (SoS), End of Season (EoS), and Length of Season (LoS) across distinct vegetation zones of the Great Himalayan National Park Conservation Area (GHNPCA) from 2015 to 2025. To achieve a decadal timeline, an integrated multi-sensor Enhanced Vegetation Index (EVI) time series was developed on Google Earth Engine, utilizing Landsat 8 (2015–2017) and Sentinel-2 (2018–2025) surface reflectance data. Minimum temperature (Tmin) and precipitation data from ERA5-Land and CHIRPS were topographically downscaled to 30 m using orographic gradients and analyzed to quantify climatic controls. Results showed pronounced altitudinal gradients, with earlier SoS, later EoS, and longer LoS in low-elevation forests, and short, thermally constrained seasons in alpine zones. Pre-season Tmin increases strongly advanced SoS, while precipitation effects were spatially heterogeneous and topographically mediated. These findings highlight the need for elevation and plant functional type specific monitoring to improve phenological projections mitigate the risks of trophic mismatches and guide climate adaptation strategies in the Himalaya.

Keywords: Climate drivers, Google Earth Engine, Himalaya, Phenology, Sentinel-2

1. Introduction

Phenology is the study of recurring biological events in plants, such as bud burst, leaf emergence, and senescence and their relationship with environmental drivers (Lieth, 1974; de Beurs & Henebry, 2004; Cleland et al., 2007; Schwartz, 2003). Vegetation phenology provides vital information about past, present, and potential future ecosystem states (Nietupski et al., 2021), as its timing is strongly influenced by temperature and precipitation (Richardson et al., 2013; Chen et al., 2019). In vegetation science, phenology plays a critical role in regulating carbon, water, and nutrient cycles (White et al., 2009) and is widely recognized as a sensitive bio-indicator of climate change, disturbance, and ecosystem health (Myneni et al., 1997; Huete et al., 2006; Linderholm, 2006; Richardson et al., 2013). By linking life-cycle events to climatic drivers, phenology offers critical insights into ecosystem functioning, biodiversity, and carbon dynamics (White & Nemani, 2006). Rising temperatures have driven widely documented shifts in plant phenology, typically manifesting as earlier springs and delayed autumn senescence (Berra & Gaulton, 2021). Consequently, these altered timelines significantly impact vegetation dynamics and fundamental ecosystem processes (Forkel et al., 2016). Understanding and assessing phenological dynamics is therefore essential for studying plant responses to climate change (Moore et al., 2016).

Phenology is among the most visible and extensively studied biological indicators of climate change, with consistent evidence across diverse biomes showing earlier onset of spring and delayed autumn senescence, leading to longer growing seasons (Song et al., 2025; Yin et al., 2024; Piao et al., 2019; Morisette et al., 2009; Richardson et al., 2013). These shifts, driven primarily by temperature and precipitation variability, significantly alter the start (SoS), peak (PoS), and end (EoS) of the growing season (Song et al., 2025; Yin et al., 2024). In seasonal snow environments, earlier snowmelt advances spring phenology (Chang et al., 2024). While such shifts can enhance carbon sequestration potential, they may also increase vulnerability to frost, heat stress, or drought (Guillevic et al., 2002; Peñuelas & Filella, 2009). Ultimately, these changes cause cascading effects on species interactions, productivity, biodiversity, and climate feedbacks (Baldocchi et al., 2001; Richardson et al., 2013; Keenan et al., 2014; Helman, 2018; Pomara et al., 2024). Satellite-derived Land Surface Phenology (LSP) datasets have revealed hemispheric-scale trends, including the advancement of maturity and senescence dates in the Northern Hemisphere over recent decades (Wu et al., 2023). Because interannual variability in phenological events reflects the combined influence of temperature, precipitation, and disturbance regimes (Schwartz et al., 2006; White et al., 2009), relying on short-term observations can be misleading. Therefore, continuous, high-resolution monitoring is essential for accurately predicting these dynamics under ongoing climate change (Li et al., 2022).

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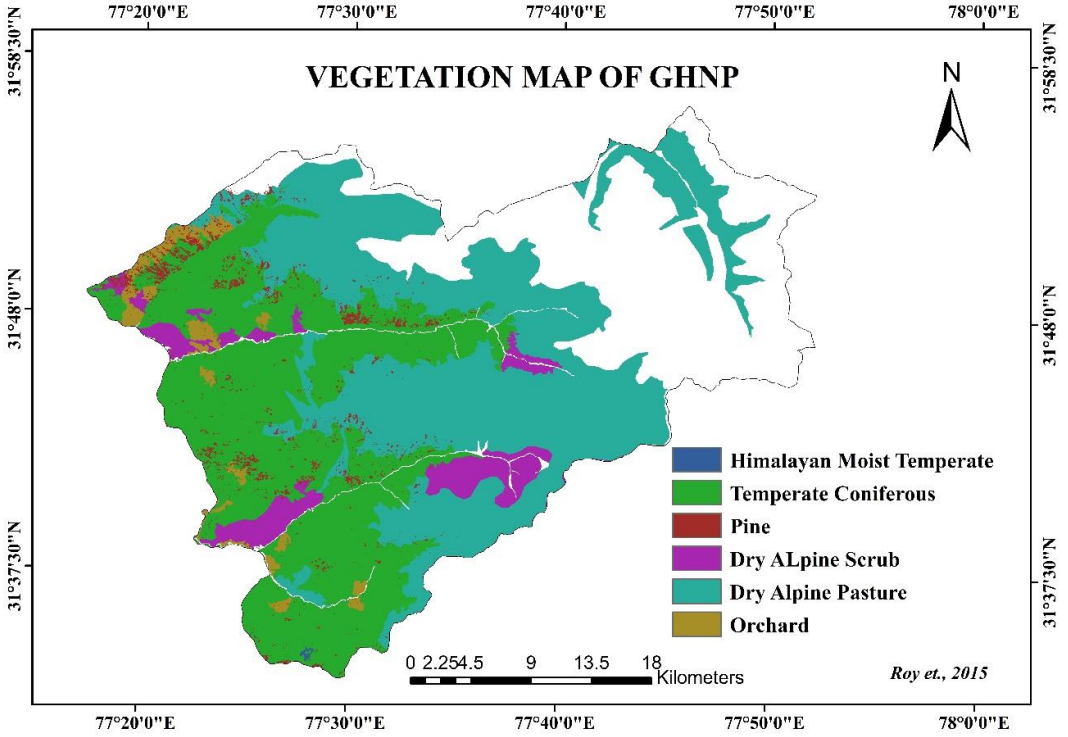
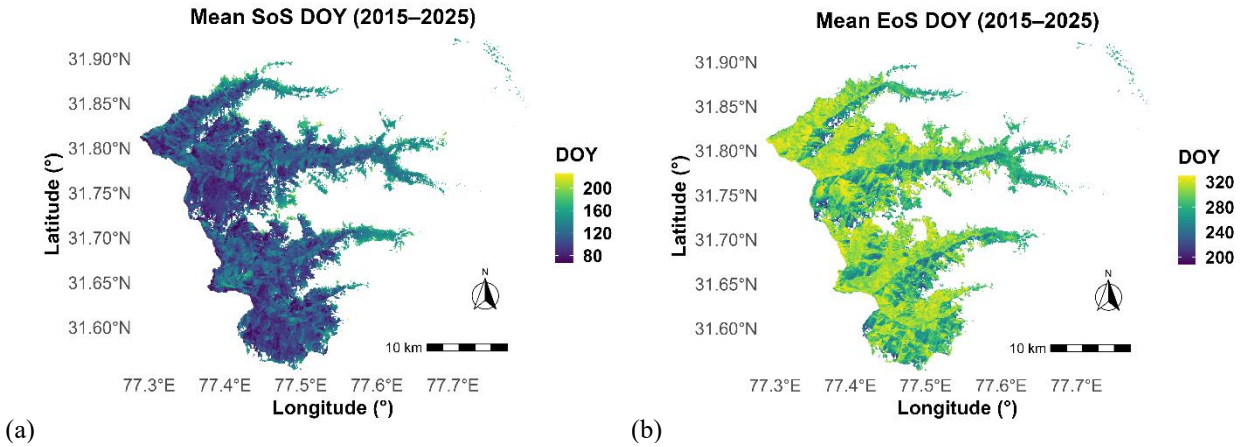


Figure 1: Vegetation map of the Great Himalayan National Park Conservation Area based on the classification done by Roy et al., (2015).

The Himalaya, a Global Biodiversity Hotspot, is among the most climate-sensitive regions due to its steep elevation gradients and complex microclimatic influences (Shrestha, 1999). Phenological responses in this region are shaped by localized variations in temperature, precipitation, and solar radiation, where both altitudinal gradients and species composition play significant roles (Chang et al., 2024; Yin et al., 2024). These dynamics make phenology a valuable indicator of climate change in the region (Negi et al., 2012), as evident in cases such as the early flowering and fruiting of *Rhododendron arboreum* (Gaira et al., 2014). While historical studies have examined the phenology of Himalayan forests (Negi, 1989; Rawal et al., 1991; Negi and Singh, 1992), explicit, spatially contiguous links to long term climate change remain limited (Singh and Negi, 2016). Much of this research has relied on localized in situ observations, offering high accuracy but poor spatial coverage. Insights from global mountain studies confirmed that vegetation is highly responsive to climate variability. This sensitivity highlights the need for high resolution remote sensing paired with fine scale climatic data. Together, these tools are essential to accurately capture complex, topography driven dynamics across the Himalaya (Chang et al., 2024; Yin et al., 2024).

Although elevation shapes mountain climates, high-altitude phenology strongly depends on vegetation characteristics like leaf longevity and whether a species is needle-leaved or broadleaved, deciduous or evergreen (Wullschleger et al., 2014; Křenová et al., 2022). Generalizing metrics like the SoS and EoS across an entire elevation belt lacks ecological validity because it ignores this high spatial heterogeneity. For example, due to micro-topography like slope orientation, a south-facing slope may support evergreen oaks with year-round foliage, while an adjacent north-facing slope at the exact same altitude hosts birch woodlands with a compressed 5-to-6-month growing season (Ustin & Gamon, 2010). Therefore, accurately monitoring climate-driven phenological shifts requires explicitly analyzing responses by specific vegetation classes rather than relying purely on simple elevational gradients (Terasaki Hart et al., 2025; Andreatta et al., 2025).

Traditional phenology monitoring dates back to the 9th century (Richardson et al., 2013) and typically involves direct plant observation by scientists or trained volunteers (Schwartz, 2013; Kosmala et al., 2016), often following standardized phenological staging protocols such as the BBCH scale (Templ et al., 2018; Antala et al., 2025). These ground-based observations provide detailed, unambiguous records of phenophases at the individual or species level, capturing subtle transitions in plant growth stages that satellites may miss (Donnelly et al., 2017). Historical monitoring networks, such as the Pan-European Phenology Project (PEP725) and USA National Phenology Network (USA-NPN), have been instrumental in producing robust datasets for calibrating and validating remote sensing metrics (White et al., 2009; Hmimina et al., 2013; Hanes, 2013). While utilizing standardized scales like BBCH alongside citizen science participation can enhance data volume and spatial representation (Polgar and Primack, 2011; Templ et al., 2018; Kudo, 2020; Guo et al., 2024), in situ monitoring is highly resource-intensive, spatially limited, and costly (Richardson et al., 2009; Morellato et al., 2016). This is particularly true for continuous, decadal retrospective studies in rugged, inaccessible high-altitude ecosystems like the Himalaya, where establishing permanent long-term validation plots



(a) (b)

Figure 2: Mean Start and End of Season across the GHNPCA (2015–2025): (a) SoS, and (b) EoS.

across diverse vegetation zones remains logistically prohibitive (Pomara et al., 2024; Zhao et al., 2024). Consequently, these constraints underscore the critical need for robust, data-driven satellite methodologies such as dynamic inflection-point thresholds to achieve comprehensive, regional scale assessments when extensive ground validation is unfeasible.

Satellite imagery has revolutionized phenology research by enabling monitoring across otherwise inaccessible areas (Nietupski et al., 2021). LSP is defined as the characterization of seasonal patterns in vegetation greenness derived from satellite reflectance data over time (de Beurs and Henebry, 2004). LSP commonly uses Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1973) and Enhanced Vegetation Index (EVI) (Huete et al., 2002), with EVI offering distinct advantages in dense canopies by reducing background soil and atmospheric noise (Gitelson, 2004). These datasets enable detection of phenological patterns, interannual variability, and climate driven trends from regional to global scales (Helman, 2018; Song et al., 2025; Girardello et al., 2024). High-resolution imagery, sensor data fusion, and improved temporal frequency have enhanced the capacity for fine-scale phenological detection (Tian et al., 2024). Meanwhile, LSP metrics such as SoS and EoS have been applied to assess productivity, disturbance, and resilience (Cleland et al., 2007; Rodriguez-Galiano et al., 2015).

Nonetheless, several critical challenges persist. Because satellite sensors capture all objects within a pixel's instantaneous field of view, the resulting "mixed pixel" effect can severely complicate the interpretation of the vegetation signal (Richardson et al., 2012). Other ongoing limitations include spatial resolution mismatch with highly heterogeneous vegetation communities, persistent cloud contamination, and the inherent differences between landscape-level canopy greenness and the true physiological phenophases observed on the ground (Broich et al., 2015; Nijland et al., 2016; Richardson et al., 2018; Gašparović et al., 2024).

Consequently, selecting appropriate datasets and extraction methodologies requires carefully balancing temporal and spatial resolution to ensure that the resulting phenological estimates are both ecologically meaningful and mathematically robust (Nietupski et al., 2021).Historically, sensors like the Advanced Very High Resolution Radiometer (AVHRR) of 5km spatial resolution offer multi-decadal continuity for continental to global-scale monitoring (White & Nemani, 2006; Wu et al., 2023), while MODIS (500 m) and Visible Infrared Imaging Radiometer Suite (VIIRS) provide daily observations suitable for intra-annual phenology estimation (Zhang et al., 2018; Yin et al., 2024; Pomara et al., 2024; Song et al., 2025). However, in highly heterogeneous mountainous terrain, these coarse pixels often fail to capture species-specific phenological signals. Landsat (30 m) offers high spatial detail but has a limited temporal frequency (16-day revisit), restricting its ability to capture rapid interannual phenological patterns (Fisher et al., 2006; Tian et al., 2024; Li et al., 2022). Sentinel-2, operational since 2016, offers 10 m resolution with an improved 5 day revisit frequency, making it particularly suitable for detailed phenology mapping in heterogeneous landscapes (Xie et al., 2023; Guo et al., 2024). To bridge these temporal and spatial gaps, emerging approaches such as spatiotemporal data fusion (Tian et al., 2024), machine learning based prediction (Gašparović et al., 2024), and multi-sensor integration (Girardello et al., 2024) have enhanced detection capabilities across complex landscapes. In addition, proximal sensing tools, such as phenocams and hyperspectral spectroradiometers, are deployed to provide high-frequency site-specific data for calibration and validation (Antala et al., 2025).

2. Materials and Methods

2.1 Study Area

The Great Himalayan National Park Conservation Area (GHNPCA), located in the Kullu district of Himachal Pradesh, was selected for conducting the LSP study (Figure 1). Himachal Pradesh exhibits strong spatial and seasonal temperature variability. Mean annual temperature values range from below 15°C in higher valleys to around 25°C in southern and western districts. Long-term records (1951–2013) indicate a slight but statistically insignificant warming trend in both maximum and minimum temperatures. The state receives an average annual rainfall of about 1284 mm, largely from the southwest monsoon (66%), but long-term records (since 1951) show a statistically significant decline in both total rainfall and the number of rainy days (SAPCC, 2021). Kullu district, centrally located in Himachal Pradesh, is bounded by the

Pir-Panjal range and shaped by glacial and fluvial processes, with climates ranging from subtropical to alpine that support diverse vegetation; it experiences mild-hot summers, cold winters, year round rainfall from the southwest monsoon, and snowfall from western disturbances (Verma, 2022).

The Park encompasses nearly 1171 km^2 area and lies between 31^0 38' 28" N to 31^0 51' 58" N lat. and 77^0 20" 11"E to 77^0 45' 52" E longitude. The altitude ranges from 1344 m to 6248 m. The dominant tree species in the region is Silver fir (*Abies pindrow*) which is distributed throughout the Western Himalayas in an altitudinal range of 2250 m to 3350 m (2100 m in cool ravines to 3650 m on warmer aspects). It frequently co-occurs with spruce (*Picea smithiana*) and deodar or blue pine. The cones ripen from late September to early November (Masoodi et al., 2018). Himalayan blue pine (*Pinus wallichiana*) is distributed in the moist temperate forest type of the Western and Central Himalayas, between altitudes of 1800-3000 m. Sometimes it may ascend to 3600 m and descend to 1200 m, making it the conifer with the widest altitudinal range. At higher altitudes, it is associated with deodar and silver fir (conifers), Kharsu and Mohru oak, Birch, Rhododendron, and Ulmus. Cones ripen and release seed from late September to early November. The Himalayan Cedar or Deodar (*Cedrus deodara*) ranges between 1220 m and 3050 m altitude, where the altitudinal range is higher on the southern aspect compared to the northern aspect. Flowering and pollination in *Quercus floribunda* occur during April, followed immediately by seed setting. The fruits grown in the following summer lead to maturation during the August to September (Ralhan et al., 1985).

2.2 Remote Sensing Data – Time Series Phenology Analysis

A threshold-based phenological analysis was conducted using Sentinel-2 Level-2A surface reflectance imagery on the Google Earth Engine (GEE) platform to estimate the Start of Season (SoS), End of Season (EoS), and Length of Season (LoS). To extend the analysis to a decadal time scale, a multi-sensor approach was adopted, using Landsat 8 Collection 2 Tier 1 Level-2 surface reflectance imagery for the 2015–2017 period and Sentinel-2 Level-2A surface reflectance imagery for the 2018–2025 period. Landsat 8 provided 30 m spatial resolution, while Sentinel-2 provided 10 m spatial resolution with improved revisit frequency, enabling detailed phenology mapping in the heterogeneous mountain landscape (Pomara et al., 2024). Scenes were filtered by cloud cover (<70%) and snow cover (<90%) using the QA_PIXEL band and Scene Classification Layer (SCL), following masking practices in alpine and temperate forest phenology studies (Antala et al., 2025). Spectral bands were scaled to surface reflectance, and the Enhanced Vegetation Index (EVI) was calculated:

$$EVI = 2.5*((NIR-Red))/(NIR+6*Red-7.5*Blue+1)$$

$where,$
$NIR = Near\text{-}InfraRed\ band$
$Red = Red\ band$
Blue = Blue band

where *NIR*, *Red*, and *Blue* correspond to the Sentinel-2 bands. EVI was selected because of its reduced sensitivity to soil background and atmospheric effects, particularly in dense and topographically complex vegetation cover (Pettorelli et al., 2005). To reduce noise and fill gaps, a 30 day compositing window was applied, and missing observations were replaced with mean values from adjacent windows. Cubic Hermite spline interpolation was used to generate a continuous daily time series, consistent with large-scale phenology assessments. To accurately capture phenological transitions across heterogeneous terrain, the Derivative (Inflection Point) Method was applied at the pixel level. Rather than relying on empirical amplitude baselines, this data-driven approach identifies transition dates by calculating the daily rate of change (first derivative) of the smoothed EVI curve (Shang et al., 2017). Specifically, the SoS was defined as the day of the year exhibiting the maximum positive rate of change (the inflection point) during the ascending green-up phase. Conversely, EoS was defined as the day corresponding to the maximum negative rate of change during the descending senescence phase. Pixels with EVI < 0.25 were classified as snow-contaminated or invalid and excluded from analysis, as recommended for snow-affected alpine regions (Antala et al., 2025). LoS was calculated as the difference between the EoS and SoS in day of year (DOY) format.

2.3 Climatic Drivers of Phenological Transitions

Daily minimum temperature (Tmin) data were obtained from ERA5-Land (ECMWF/ERA5_LAND/HOURLY) and aggregated from hourly records to daily minima (°C) using Google Earth Engine (GEE). Precipitation data were sourced from CHIRPS (UCSB-CHG/CHIRPS/DAILY) and expressed in millimetres/day. Both datasets were filtered for the period 2014-12-01 to 2026-01-01 to ensure full coverage. Because the coarse native resolutions of ERA5-Land (11.1 km) and CHIRPS (5.5 km) are insufficient for assessing highly localized phenological responses in complex mountain terrain, both datasets were topographically downscaled to a 30 m spatial resolution using a 30 m SRTM Digital Elevation Model (DEM). For Tmin, a dynamic environmental lapse rate was calculated daily by linearly regressing the coarse ERA5-Land temperatures against a spatially aggregated DEM; this thermal gradient was then applied directly to the 30 m DEM to produce high-resolution temperature surfaces. For precipitation, an orographic gradient was similarly established using CHIRPS and the aggregated DEM, and a residual correction method was applied—where coarse residuals were calculated, resampled using bilinear interpolation, and added back to the 30 m topographic prediction to conserve mass. Following downscaling, the datasets were clipped to the GHNPCA extent. Finally, a stable-pixel mask was applied—retaining only locations with valid SoS and EoS estimates for all 11 consecutive years (2015–2025)—to ensure the statistical robustness of the long-term trend and correlation analyses (Pomara et al., 2024).

To extract climatic metrics, two temporal extraction approaches were used: (1) Event-day extraction where the Tmin and precipitation value closest to each SoS/EoS date were identified and (2) Window-based aggregation where

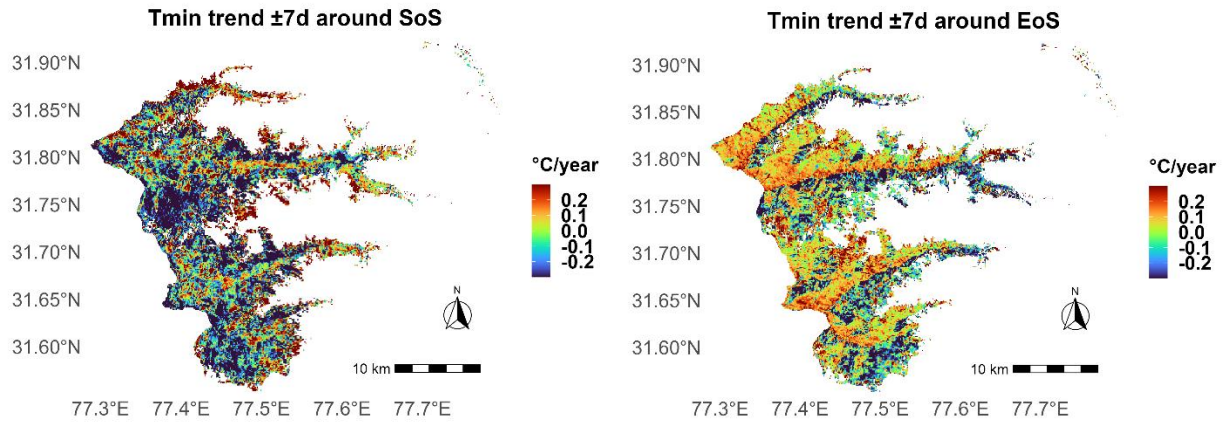


Figure 3: Spatial trends in minimum temperature (Tmin) during ±7-Day windows around SoS and EoS in the GHNPCA (2015–2025)

the mean Tmin and cumulative precipitation were calculated within a ±7-day symmetric window around SoS and EoS, following established vegetation climate linkage protocols (Cleland et al., 2007). Temporal trends in phenology and climate metrics were calculated using per-pixel linear regression (`ee.Reducer.linearFit()`) in GEE, with slopes expressed in days/year for phenological shifts and °C/year or mm/year for climatic trends. Pearson's correlation coefficients were computed pixel-wise across the decadal time series to quantify the strength and direction of climate phenology relationships, consistent with continental-scale LSP analyses (Pomara et al., 2024). All statistical analyses, spatial data processing, and visualization were conducted in GEE and R studio. To address the high ecological heterogeneity of the landscape, the resulting trend and correlation rasters were exported and stratified by specific vegetation classes and elevation bands in RStudio. Post-processing, categorical extractions, statistical summaries, and visual mapping were executed using the R packages terra (high-performance raster processing), *dplyr* and *tidyr* (data manipulation and aggregation), ggplot2 and patchwork (graphical visualization and paneling), and ggspatial (map scale and north arrow integration).

3. Results and Discussion

3.1 Spatial and Interannual Patterns of Phenology

The 10-year (2015–2025, excluding 2017) mean distribution of SoS, EoS, and LoS across the GHNPCA demonstrated clear topography-driven gradients (Figure 2; Table 1). SoS occurred earliest in the low-elevation valleys (1000–1500 m), primarily located in the western periphery of the park, with a decadal mean ranging from DOY 81 to 126 (Table 2). Conversely, SoS was progressively delayed at higher elevations (≥4000 m) in the eastern and northern alpine ridges, where SoS generally occurred much later, between DOY 135 and 189. Conversely, EoS was latest in the western valleys, extending to DOY 313, and advanced significantly in alpine zones (≥4000 m), where senescence consistently began before DOY 277 (ranging from DOY 236 to 276; Table 2). Consequently, the low-elevation zones experienced extended growing seasons (LoS), while the high-elevation zones were restricted to highly compressed growing seasons. These patterns corroborate the observed spatial gradients of delayed greening and shorter growing seasons in snow-dominated high-elevation environments reported in previous studies (Figure 2; Table 2).

Spatial overlays of the vegetation and elevation maps reveal that distinct Plant Functional Types (PFTs) strongly mediate these phenological responses along the altitudinal gradient. The low-elevation zones (1000–2500 m) are dominated by Himalayan Moist Temperate and Pine forests, alongside isolated orchards. Among these, Himalayan Moist Temperate forests exhibited the earliest spring onset (annual mean SoS ranging from DOY 76 to 122) and delayed senescence (EoS up to DOY 312), resulting in the longest extended growing seasons (>200 days) (Table 2). Pine forests, occupying similar lower altitudes, showed a slightly delayed SoS (DOY 98–145) but maintained a comparably late EoS. In stark contrast, the high-altitude zones (>3000 m) are characterized by Dry Alpine Scrub and Dry Alpine Pasture. Dry Alpine Pasture, which dominates the highest and most rugged terrain (≥4000 m), exhibited the most constrained phenological window, with the latest green-up (SoS DOY 114–183) and the earliest senescence (EoS generally between DOY 257 and 321). Dry Alpine Scrub acts as a transitional ecotone, showing intermediate but highly compressed LoS values compared to the temperate forests.

Overall, LoS patterns across the landscape were dictated by the combined influence of altitude-driven and PFT-specific SoS and EoS. This finding is consistent with earlier Himalayan phenology studies, which have linked LoS variation to temperature and snow-cover duration (Negi et al., 2012; Chang et al., 2024). Interannual variability revealed high standard deviations in spring phenology across multiple zones (e.g., an SoS SD of ±68.99 days in 2016 for Himalayan Moist Temperate forests; Table 2), suggesting significant sensitivity to anomalous pre-season climatic events. In contrast, the high-elevation zones exhibited tighter interannual control over EoS. This indicates that autumn senescence in alpine ecosystems is strictly bounded by the rapid onset of harsh freezing temperatures, whereas spring green-up is more likely driven by fluctuating pre-season temperature and precipitation conditions.

Table 1: Annual mean and standard deviation of phenological metrics (SoS, EoS, LoS) in GHNPCA

Metric	Year	Mean (doy)	Sd (± days)	1000 – 1500 m	1500 – 2000 m	2000 – 2500 m	2500 – 3000 m	3000 - 4000 m	>4000 m
SoS	2015	129.11	22.96	126.46	123.47	123.45	125.77	138.86	165.08
SoS	2016	128.37	68.85	96.71	98.89	102.68	119.81	166.42	171.68
SoS	2018	101.3	40.29	105.13	108.3	104.97	101.17	96.45	189.15
SoS	2019	104.75	26.43	88.98	95.75	102.81	104.88	108.47	164.55
SoS	2020	149.87	48.54	111.56	106.59	113.60	113.97	170.24	157.02
SoS	2021	142.24	52.39	112.43	108.37	110.71	103.44	163.59	156.61
SoS	2022	141.53	43.35	141.67	132.52	125.89	114.77	155.93	135.65
SoS	2023	172.77	60.54	114.08	116.89	130.79	143.70	198.87	184.93
SoS	2024	163.62	58.75	139.35	131.59	132.32	129.96	187.42	166.27
SoS	2025	99.81	32.43	88.71	92.83	99.6	100.55	100.93	142.94
EoS	2015	301.13	33.34	313.95	309	302.56	298.34	301.16	276.97
EoS	2016	276.12	67.35	310.7	302.03	288.73	267.81	269.03	253.16
EoS	2018	275.17	59.99	302.11	293.92	281.23	268.23	273.52	250.16
EoS	2019	301.19	26.43	306.8	303.52	300.42	298.84	303.88	302.73
EoS	2020	286.87	28.23	302.06	297.93	298.34	301.53	279.56	282.86
EoS	2021	290.02	31.71	313.28	309.31	306.30	305.17	280.47	283.41
EoS	2022	272.06	29.60	296.09	296.58	288.67	281.47	262.78	278.62
EoS	2023	278.33	29.00	277.71	286.39	283.75	281.98	274.97	289.42
EoS	2024	282.34	26.60	287.69	293.38	291.74	288.08	276.86	288.81
EoS	2025	298.24	38.62	306.23	308.88	304.15	293.97	295.85	286.26
LoS	2015	172.02	40.79	187.49	185.52	179.12	172.57	162.31	111.89
LoS	2016	147.75	87.08	213.99	203.15	186.05	148	102.6	81.48
LoS	2018	173.87	79.53	196.97	185.61	176.25	167.05	177.06	61.01
LoS	2019	196.43	44.26	217.82	207.77	197.61	193.95	195.41	138.18
LoS	2020	137.00	70.07	190.50	191.34	184.74	187.55	109.32	125.84
LoS	2021	147.79	75.76	200.85	200.94	195.58	201.73	116.88	126.8
LoS	2022	130.52	61.64	154.42	164.06	162.79	166.69	106.85	142.98
LoS	2023	105.56	72.28	163.63	169.50	152.96	138.27	76.10	104.49
LoS	2024	118.72	72.84	148.33	161.78	159.42	158.13	89.44	122.54
LoS	2025	198.43	55.26	217.52	216.05	204.55	193.42	194.92	143.32

3.2 Climatic Trends Around Phenological Transitions

The decadal analysis (2015–2025) of microclimatic trends during the ±7-day windows around phenological transitions revealed complex, topographically mediated interactions (Figure 3). Across the GHNPCA, the SoS advanced significantly, particularly in low- to mid-elevation Temperate Coniferous and Himalayan Moist Temperate forests (advancing by -2.50 and -2.28 days yr^{-1}, respectively). Interestingly, the minimum temperature (Tmin) specifically during this shifting SoS window exhibited a localized cooling trend, decreasing by -0.14 to -0.33 °C yr^{-1} across elevation bands. This cooling within the transitional window, coupled with a strong positive correlation between Tmin and SoS (r = +0.70 to +0.86), indicates that as broader seasonal warming drives early snowmelt, the onset of growth is pushed into earlier, inherently colder temporal windows of the spring.

High altitude ridges (≥4000 m) showed the most pronounced SoS window Tmin decreases (-0.33 °C yr^{-1}), highlighting strict thermal bounding in alpine zones. Late-season (EoS) patterns exhibited a slight delay (extension) in lower elevations (+0.82 to +2.39 days yr^{-1}) despite

Table 2: Annual mean and standard deviation of phenological metrics (SoS, EoS, LoS) in the GHNPCA by vegetation class (HMT = Himalayan Moist Temperate; TC = Temperate Coniferous; DAS = Dry Alpine Scrub; DAP = Dry Alpine Pasture)

Metric	Year	Mean (doy)	Sd (± days)	HMT	TC	Pine	DAS	DAP	Orchard
SoS	2015	129.09	22.96	122.67	128.18	128.06	130.67	140.05	125.57
SoS	2016	128.43	68.99	86.09	124.58	145.09	121.05	183.43	110.83
SoS	2018	101.24	40.27	76.99	96.8	98.94	133.45	115.36	94.03
SoS	2019	104.72	26.42	87.53	102.73	104.64	112.93	125.28	93.25
SoS	2020	109.08	28.91	89.14	107.32	110.17	117.86	126.42	96.93
SoS	2021	102.49	32.38	80.82	99.26	102.88	119.32	125.32	90.55
SoS	2022	95.54	28.39	76.93	91.03	98.38	121.18	114.37	89.7
SoS	2023	112.57	51.93	89.11	108.88	118.65	123.37	151.55	92.2
SoS	2024	103.93	38.26	80.45	99.97	105.97	117.26	138.2	91.48
SoS	2025	99.76	32.43	78.6	97.25	102.33	111.83	117.04	91.19
EoS	2015	301.18	33.34	312.27	296.58	317.24	317.27	302.73	321.33
EoS	2016	276.06	67.51	304.66	266.99	306.95	306.16	283.58	313.45
EoS	2018	275.39	59.9	278.8	269.91	292.55	297.98	267.15	307.94
EoS	2019	301.29	26.39	308.08	299.06	309.32	306.7	302.31	314.07
EoS	2020	303.14	23.34	314.82	303.42	308.51	299.65	296.1	309.32
EoS	2021	303.88	24.45	305.77	302.17	309.69	310.74	298.54	317.26
EoS	2022	304.18	24.19	308.27	303.19	307.41	309.49	296.18	315.8
EoS	2023	303.06	28.76	310.3	302.21	309.38	302.44	299.18	314.57
EoS	2024	306.53	23.55	313.06	305.64	311.42	308.12	303.27	315.55
EoS	2025	298.35	38.62	307.9	295.48	304.79	307.66	299.52	313.96
LoS	2015	172.09	40.77	189.6	168.4	189.18	186.6	162.68	195.76
LoS	2016	147.63	87.21	218.57	142.41	161.86	185.11	100.15	202.61
LoS	2018	174.15	79.46	201.81	173.11	193.61	164.53	151.79	213.91
LoS	2019	196.57	44.22	220.55	196.33	204.68	193.77	177.04	220.82
LoS	2020	194.06	45.49	225.68	196.11	198.33	181.78	169.68	212.4
LoS	2021	201.39	47.6	224.95	202.91	206.8	191.42	173.23	226.7
LoS	2022	208.63	42.54	231.34	212.16	209.04	188.32	181.82	226.09
LoS	2023	190.49	64.21	221.2	193.33	190.73	179.08	147.63	222.37
LoS	2024	202.6	50.66	232.62	205.68	205.45	190.86	165.08	224.08
LoS	2025	198.59	55.23	229.29	198.24	202.46	195.83	182.48	222.77

marginal cooling during the EoS window (-0.01 to -0.15 °C yr^{-1}). These patterns reinforce the dominant role of Tmin in driving phenological shifts in the park (Figure 3). The spatial uniformity suggests that regional-scale elevation-dependent warming, a well-documented phenomenon in the Himalayas (Shrestha, 1999; Yin et al., 2024), is driving the overall phenological shift, while the specific transition windows capture the micro-climatic realities of these new timings.

Precipitation trends during the ±7-day window around SoS (Figure 4) ranged from -1.08 to +2.58 mm yr^{-1}, showing distinct spatial variability across the GHNPCA. Increases were concentrated along mid-elevation valleys and parts of the western boundary (e.g., +2.58 mm yr^{-1} in Moist Temperate forests), while decreases occurred mainly in high-elevation ridges (≥4000 m; -1.08 mm yr^{-1}) and exposed aspects. These spatial differences suggest that topography has a significant influence on pre-season precipitation. Increased precipitation in the pre-season window can locally amplify early green-up by providing essential moisture, as evidenced by the negative

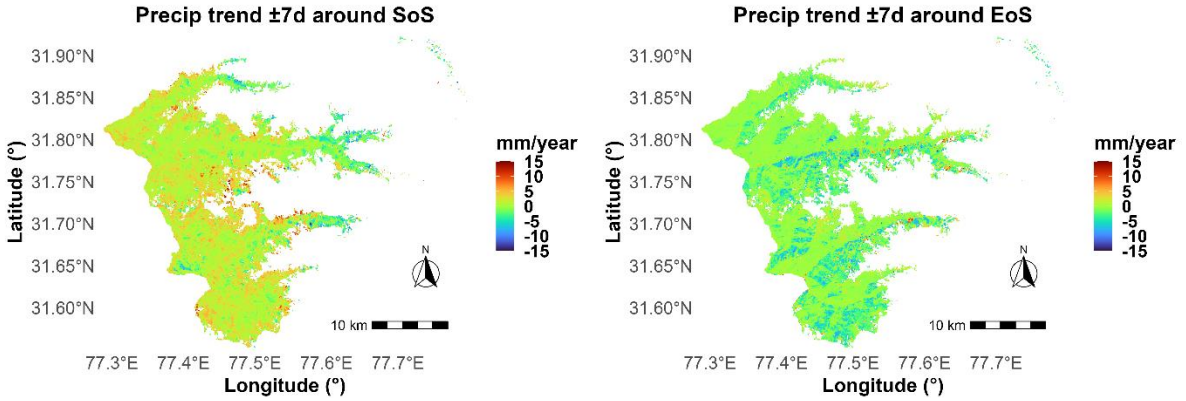


Figure 4: Spatial trends in precipitation during ±7-Day windows around SoS and EoS in the GHNPCA (2015–2025)

correlation (r = -0.21) between precipitation and SoS in temperate zones.

During the EoS window (Figure 4), trends exhibited widespread drying across most vegetation zones (ranging from -0.51 to -1.53 mm yr^{-1}). High-altitude areas still showed pockets of decline, potentially accelerating senescence where soil moisture is already a limiting factor. Conversely, late-season moisture retention from earlier in the year may prolong canopy activity and extend LoS in water-limited low-elevation forests.

Overall, precipitation acts as a secondary yet significant driver of phenological variability in GHNPCA. While Tmin exerts the dominant influence on SoS and EoS timing, spatially variable precipitation trends can locally amplify or counteract temperature-driven responses, emphasizing the need to incorporate both climatic drivers in phenology–climate assessments for mountainous ecosystems (Shrestha, 1999; Yin et al., 2024).

3.3 Climate–Phenology Relationships

The correlation between minimum temperature (Tmin) within the ±7-day window and SoS (Figure 5) was predominantly strong and positive across the GHNPCA, with large areas exhibiting correlation coefficients greater than 0.6. This correlation indicates that higher pre-season Tmin is consistently associated with earlier SoS dates, reflecting the strong thermal control over the initiation of the growing season in these temperate and alpine systems. The spatial uniformity of these positive correlations suggests that temperature is a primary driver of SoS variability across elevations, with only limited areas showing weaker or near-zero correlations, likely due to local microclimatic or snow persistence effects. The findings align with temperature-driven phenology responses in other temperate and alpine systems (Richardson et al., 2013; Chang et al., 2024).

In contrast, correlations between Tmin and EoS (Figure 5) were generally weak and negative across much of the study area, with values close to zero in many areas. This pattern suggests that late-season Tmin has a lesser influence on the timing of senescence compared to SoS, with other factors, such as soil moisture status, photoperiod, and species-specific senescence physiology, likely playing a more dominant role. These results confirm that Tmin is a strong and consistent predictor of SoS, whereas its influence on EoS is weaker and spatially variable. This asymmetry highlights the necessity of considering distinct controlling mechanisms when modelling the onset and cessation of the growing season in mountainous ecosystems.

Scatterplots of phenology trends against Tmin trends (Figure 6) confirmed that areas with the highest Tmin warming rates experienced the most significant SoS advancements. In contrast, EoS–Tmin relationships were negative, indicating potential threshold effects where warming accelerates senescence in already moisture-limited areas. Precipitation - phenology relationships were more variable. Pre-season precipitation was positively correlated with delayed SoS in some mid-elevation forests (r > 0.4), likely due to snow cover persistence or cloud shading effects. Late-season precipitation showed modest positive correlations with EoS in western valleys but had a negligible influence in higher elevations. Trend scatterplots indicated that increases in pre-season precipitation generally delayed SoS, while increases in late-season precipitation slightly extended EoS.

3.4 Ecological Implications

The observed warming-driven advancement of SoS and extension of LoS in low-elevation Himalayan Moist Temperate and Coniferous forests suggests potential increases in seasonal carbon uptake, consistent with findings from other temperate coniferous and mixed forest systems (Forkel et al., 2016; Keenan et al., 2014). However, earlier onset also raises the risk of exposure to late-spring frost events, particularly in years with high interannual variability. Additionally, a prolonged LoS coupled with the widespread drying observed during the late-season EoS window may intensify late-summer water stress, especially under declining monsoon precipitation in parts of the park (Peñuelas and Filella, 2009).

At higher elevations, shorter LoS and weaker climate phenology coupling indicate that snow persistence, short thermal windows, and low soil temperatures remain the primary constraints on vegetation green phase. In these alpine zones, the abrupt return of harsh freezing temperatures dictates rapid senescence. These contrasting elevation-dependent responses highlight the need for PFT-specific modelling and monitoring to better predict forest

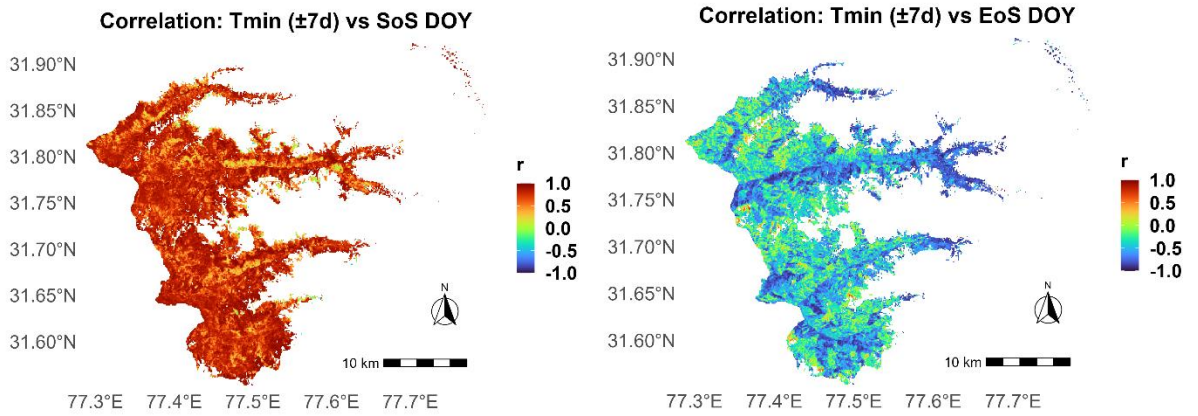


Figure 5: Spatial correlation between minimum temperature (±7 Days) and phenological metrics (SoS and EoS) in the GHNPCA (2015–2025)

dynamics in the Himalaya under continued climate change. The results also underline the importance of integrating both temperature and precipitation metrics in phenological modelling. While Tmin is the dominant driver of SoS, precipitation variability, particularly in the pre-season, can moderate or override the effects of temperature. This has important implications for future projections, as shifts in precipitation regimes could modify or reverse temperature-driven trends in phenology.

4. Conclusion

This study presents a high-resolution decadal assessment of vegetation phenology across diverse forests of the GHNPCA from 2015 to 2025, combining Landsat-8 and Sentinel-2 derived land surface phenology metrics with topographically downscaled climatic drivers from the ERA5-Land and CHIRPS datasets. Spatial patterns in the SoS, EoS, and LoS revealed strong elevation and vegetation dependent gradients. Specifically, low-elevation valleys exhibited earlier green-up, later senescence, and extended growing seasons, whereas alpine and subalpine zones were restricted to short, thermally constrained seasons..

Consistent warming trends in minimum temperature during pre and late-season windows emerged as the dominant climatic driver, strongly advancing SoS and, in some areas, extending EoS. In contrast, precipitation influences were spatially heterogeneous and largely mediated by topography. Delays in SoS associated with pre-season precipitation were likely linked to snow persistence or reduced insolation, while late-season precipitation modestly extended EoS in water-limited sites.

These results highlight the intricate relationship between temperature and precipitation in shaping phenological dynamics in mountainous ecosystems. While warming driven LoS extensions in lower elevations may enhance seasonal carbon uptake, they also heighten vulnerability to late frost and late summer drought stress. At higher elevations, phenology remains constrained by snow cover and short thermal windows. In these zones, exceptionally tight pre-season thermal bounding dictating the strict limits of the growing phase. Beyond these direct physiological impacts, such shifts carry profound implications for the broader Himalayan ecosystem. Asynchronous phenological responses across different elevations and plant functional types risk triggering trophic mismatches, potentially disrupting plant-pollinator interactions and the foraging dynamics of endemic herbivores. Furthermore, altered growing seasons may significantly impact regional ecohydrology by modifying evapotranspiration rates, cascading into changes in downstream water availability. Ultimately, these

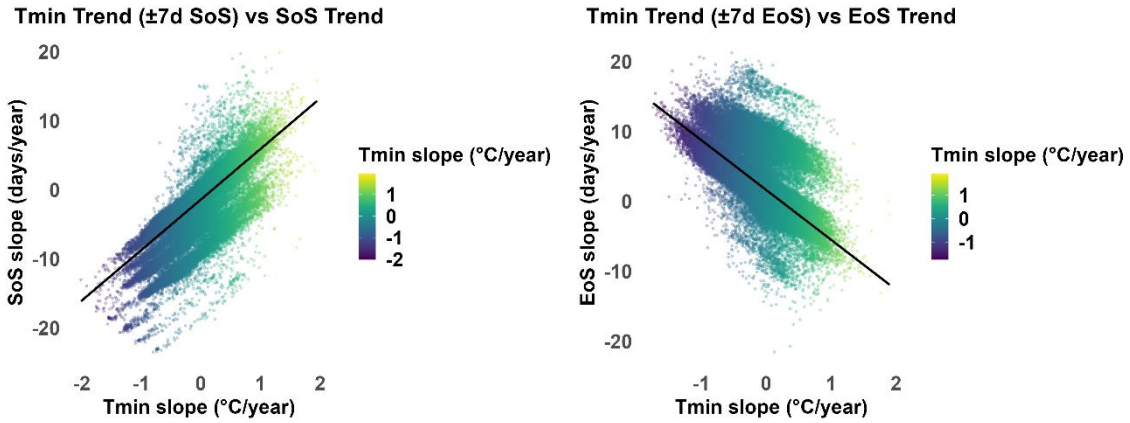


Figure 6: Relationships between Tmin trends (±7 Days) and phenological trends (SoS and EoS) in the GHNPCA (2015–2025)

uncoupled climate-phenology shifts threaten to alter the fundamental composition of Himalayan forests over time.

A primary limitation of this study is the absence of direct in situ field validation (e.g., BBCH scale observations), as maintaining continuous ground-monitoring sites across the extreme topography of the GHNPCA over a decade is logistically prohibitive. To mitigate this, we utilized a mathematically robust derivative (inflection point) method, suited for heterogeneous landscapes lacking ground-truth data. Furthermore, we extensively cross-corroborated our satellite-derived metrics with existing Himalayan phenology literature to ensure ecological validity. While this approach is robust for regional-scale assessments, future research should integrate localized phenocam networks to bridge the gap between satellite-derived land surface phenology and species-specific ground observations. The findings emphasize the need for elevation and PFT specific phenological monitoring, integrating both temperature and precipitation metrics to improve predictive models under changing climate regimes. Ultimately, long-term satellite-based monitoring, complemented by in situ observations, will be critical for anticipating shifts in forest productivity, biodiversity, and ecosystem resilience in the Himalaya.

Declarations

Competing interests

On behalf of all the authors, we confirm that this manuscript has not been submitted elsewhere simultaneously, and the submitted work is original and has not been published in any form or language. The manuscript presents a detailed analysis of vegetation phenology and its climatic drivers of the Great Himalayan National Park Conservation Area (GHNPCA) using high-resolution satellite data and climate datasets. This work demonstrates the integration of remote sensing and climatic analysis to improve the understanding of seasonal vegetation dynamics in complex mountainous ecosystems. We declare that there are no financial interests associated with the publication of this manuscript. The results are clearly presented, and all individuals who contributed directly or indirectly to the work have been duly acknowledged.

Authors' contributions

Sanjo Jose V (Corresponding Author) - Conceptualization, data collection and processing, code development (GEE), analysis, results interpretation and manuscript writing. **Aditi Ahlawat** – Code development, result interpretation and manuscript review. **Dr. Tara Chand** - Overall research conceptualization, methodology design, results validation, and manuscript review. **Dr. Arijit Roy** -Workflow design, methodological refinement, technical inputs and manuscript review.

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