PHENOLOGICAL ANALYSIS OF THE WESTERN HIMALAYAN FOREST USING TEMPORAL REMOTE SENSING DATA

P. Singh [1] *, S. K. Ghosh [2], S. Khare [3]

[1] Department of Civil Engineering, Indian Institute of Technology, Roorkee, Uttarakhand 247667, India - prashant.mce@iitr.ac.in (Orcid: 0000-0001-9719-5411)

[2] Department of Civil Engineering, Indian Institute of Technology, Roorkee, Uttarakhand 247667, India - sanjay.ghosh@ce.iitr.ac.in (Orcid: 0000-0001-7849-9313)

[3] Department of Civil Engineering, Indian Institute of Technology, Roorkee, Uttarakhand 247667, India - siddhartha.khare@ce.iitr.ac.in (Orcid: 0000-0002-6996-4583)

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ABSTRACT:

The Himalayan range is considered to include the highest mountains on earth, with a widely recognized assortment of flora and fauna. The Indian Himalayan range spread over 10 states, of which being Uttarakhand, has the largest forest cover of 48.5% of the total area forest. In Doon Valley, the phenological behavior and variations of several forest types have been studied using the Normalized Difference Vegetation Index (NDVI) and Temporal Normalized Phenology Index (TNPI) along with elevation, surface temperature, slope, and aspect data into consideration. A two-scale method has been employed to study forest phenology, using Sentinel-2 data at 10 m spatial resolution for local-scale studies and MODIS NDVI data at 250 m spatial resolution to find large-scale phenological patterns. The framework used in this study is based on Google Earth Engine (GEE) which has potential applications at various spatial and temporal scales. Multiple phenological phases and phenological metrics have been identified and examined within the duration from December 2018 to May 2023. The investigation concluded that phenological behaviors were considerably affected by environmental and topographic variables such as elevation, surface temperature, slope, and aspect. Significant changes in phenology were recorded at low altitudes; however, less fluctuation was reported at medium to higher elevations due to remoteness at greater elevations. Using NDVI from open-source MODIS and Sentinel-2 datasets, TNPI has been successfully tested for this forest region. The findings showed that this study opens new opportunities for trend analysis of forest health and productivity.

1. INTRODUCTION

The Himalayan range, as the world's highest mountain range, has been thought to encompass a diverse range of flora and fauna (Myers, 1990). According to a report submitted by the FSI, 41.5% of the geographical area of the Indian Himalayan range is forest covered, which is distributed across ten states, one of which is Uttarakhand. Rapid urbanization and a rise in tourism have led to a loss of forest cover, which affects changes in the climate, such as those related to temperature and rainfall (Mandal and Joshi, 2014). The presence of invasive plant species, for example, as well as man-made and natural factors have a detrimental effect on the ecosystem. As a result, our study has concentrated on the Doon Valley ecosystem's variety.

Phenology is the study of the time of recurrent biological phases, the cause of their timing with respect to biotic and abiotic influences, and the inter-relationship between phases of the same and distinct species, according to Lieth, (1974). Three methods; in-situ observation, remote sensing monitoring, and model simulation can be used to identify vegetation phenology, according to earlier researches. With respect to the idea that everything in nature is distinct and has a different characteristic in emitting, reflecting, and absorbing electromagnetic radiations, remote sensing monitoring was used to track the phenology of the vegetation. Researchers employ these raw satellite records in a mathematical procedure to produce Vegetation Indices (Lambert et al., 2013). As plant canopy changes from early spring through the late season till these plants reach maturity, they also change their reflectance characteristics. The phenology of the plants has been investigated as a sign of how an ecosystem would adapt to climate change. The employment of satellite remote sensing techniques allows for the capture of changes in the greenness of the vegetation and is a useful indicator of the phenology of the vegetation. The influence of various environmental factors such as sunlight radiation, temperature, precipitation, etc. on phenological cycles results in variation in vegetation, which is sensitive to even small changes in climate conditions (Menzel et al., 2006). Changes in ecosystem composition, structure, and function also affect the exchange of water, heat, and CO2 between soil, vegetation, and the atmosphere (Richardson and Rejmánek, 2011). To describe vegetation dynamics and land surface processes, vegetation phenology has therefore become an essential element (Wang et al., 2010). Because of how plants respond to a warming environment, where leaf emerging occurs earlier and leaf fall occurs later owing to milder winters, phenology monitoring is especially crucial (De Beurs and Henebry, 2010). Where these phenological investigations are carried out by observing how the ecosystem responds to changes in the environment and climate (Joshi et al., 2006; Melaas et al., 2013; Soudani et al., 2008; White et al., 2009). Now that satellite imagery data is available, it is feasible to make use of the potential for time series study of ecology. According to Lambert et al., (2013), vegetation indices (VIs) produced from multispectral data have been extensively utilised

* Corresponding author

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for vegetation categorization, phenological monitoring, spotting ecological changes, and deriving forest biophysical and structural features.

Furthermore, earlier research revealed mathematical correlations between precipitation and temperature data at coarse spatial resolutions and the NDVI (Ji and Peters, 2010; Nordberg and Evertson, 2005; Wang et al., 2010). MODIS-derived NDVI data are commonly utilised to either build regional multiple regression analyses of topography-related vegetation phenology patterns or establish relationships with precipitation and temperature data (Gao et al., 2011; Hwang et al., 2011; Li et al., 2015). In conclusion, environmental factors and topographical variables on forest phenology may have both positive or negative implications on various ecosystems and geographical locations. The Temporal Normalised Phenology Index (TNPI), which was suggested as a better alternative for examining the temporal phenology cycle between two time stages of the maximum and lowest plant growth phase, was created to deal with this quantitative constraint of NDVI (Khare et al., 2017). Additionally, using time series Landsat-8 data, the sensitivity of varying NDVI to specific topography factors derived from remote sensing and land surface temperature was successfully tested using TNPI (Khare et al., 2017).

Even though there have been several studies in this field, the effectiveness of remote sensing has not been proven to be sufficient to evaluate the impacts of environmental elements, such as topographic differences and LST variation, on the phenology of plants at high spatial resolutions, such as 10 m. An early examination revealed that relatively few studies had been conducted for the Western Himalaya region utilising data sets with coarser geographical resolution; as a result, this research region requires in-depth phenology-based analysis at finer spatial resolution. Therefore, the main objective of this study is to evaluate how remote sensing data are used to produce spatiotemporal phenological maps of this difficult terrain. The Normalised Difference Vegetation Index (NDVI) and Temporal Normalised Phenology Index (TNPI), taken together with elevation, surface temperature, slope, and aspect data, have been used to study the phenological behaviour and variations of different kinds of forests in Doon Valley. Sentinel-2 data with a 10 m spatial resolution were used for local-scale research, while MODIS NDVI data with a 250 m spatial resolution were used to uncover large-scale phenological trends in the study of forest phenology. Google Earth Engine (GEE), which has potential applications at many spatial and temporal scales, functioned as the base for the framework employed in this study. It provides an environment where users may use an Integrated Development Environment (IDE) code editor to explore the satellite imagery that is currently accessible without downloading the whole set of imagery. In the foothills of the western Himalayas forest region of doon valley, several phenological phases and phenological metrics have been identified and investigated from December 2018 to May 2023.

2. MATERIAL AND METHODS

2.1 Study Area and Datasets

The western Himalayan region of the Doon Valley in Uttarakhand (India), between latitudes 29° 55' and 30° 30' N and longitudes 77° 35' and 78° 24' E, was chosen as the research area for the phenological study. These areas are located at an altitude of around 300 to 900 meters above mean sea level (MSL). The study area includes the Doon valley's Beribara, Khanpur, Motichur, and Kans Rao forest ranges, among many others. Doon Valley typically has a wide, long shape and is enclosed by the Shivalik Hills; thus, it is surrounded by mountains on all sides. It features a variety of forest kinds, although Sal trees predominate. The region experiences temperatures ranging from 16°C to 36°C and between 5.2°C and 23.4°C during the winters, with an average annual rainfall of 2025mm with a peak quantity of precipitation occurring from June to September. The key factors influencing vegetation type are soil type, temperature, elevation, slope, aspect and rainfall. The research sites contain a variety of forest types, including scrub and degraded forests, North Indian tropical wet Sal Forest, North Indian tropical dry deciduous forest, riverine and forest dominated by Khair and Sissoo, and so on (Champion and Seth, 1968).

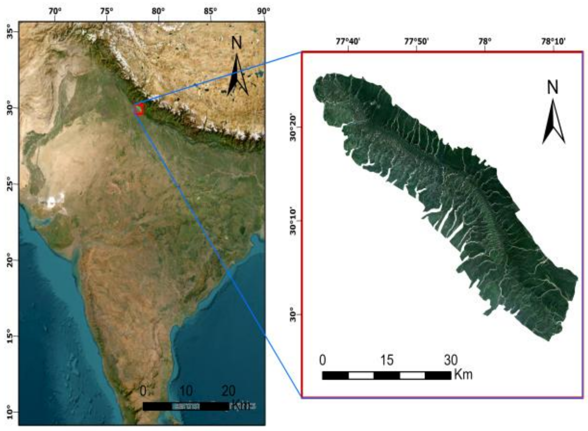

Figure 1. Study area.

Higher temporal and spatial resolutions are necessary for satellite-based vegetation phenology monitoring. Sentinel-2 data with a 10 m geographical resolution were used for local-scale research, while MODIS NDVI data with a 250 m spatial resolution were used to uncover large-scale phenological trends in the study of forest phenology. The Google Earth Engine (GEE) platform is used for MODIS and SENTINEL-2 datasets collection between December 2018 and May 2023. GEE has potential uses at several temporal and spatial resolutions. It provides a setting where users may use an Integrated Development Environment (IDE) code editor to examine the satellite imagery that is currently accessible without downloading the whole set of imagery (Sharma and Ghosh, 2023). We obtained time-series data of the NASA LP DAAC's which is Google Earth Engine (GEE) platform-archived 250 m Terra MODIS Vegetation Indices (MOD13Q1, version 6.1) NDVI. We used GEE's Sentinel-2 Level-2A surface reflectance product to compute the NDVI. This resembled a processed dataset that the European Space Agency (ESA) released to be accessible on the GEE cloud platform. Landsat-8 Collection 2 level-2 band 10 data from the United States Geological Survey (USGS) is used, and a scale factor of 0.000341802 + 149 is also used to convert temperature data from Kelvin and a deduction of 273.15 to change the unit in degree Celsius. to degrees Celsius. Global SRTM 90m Database for the DEM model generation from the CGIAR-CSI that is archived on the GEE platform, version 4 is selected, and which was orthorectified and preprocessed by the data provider. We extracted Slope and Aspect data using the DEM dataset for the study area. The Land Surface Temperature maps, DEM, Slope, and Aspect maps of the study area are developed using ArcGIS pro software.

2.2 Statistics and Methodology

2.2.1 NDVI and Time Series Curve Fitting: Although there are other vegetation indices available, the Normalised Difference Vegetation Index (NDVI) is one of the most often used ones (Ding et al., 2014; Sharma and Ghosh, 2022). NDVI value ranges between +1.0 and -1.0. An extremely low NDVI value, such as 0.1 or below, is typical with areas like bare rock, sand, or snow, whereas areas with sparse vegetation, such as shrubs and grasses, display intermediate NDVI values, such as 0.2 to 0.5. High NDVI values (between 0.6 and 0.9) are associated with thick or dense vegetation, such as that found in temperate and tropical woods or on farmlands when crops are at their peak development stage. As shown below in the equation, the Normalised Difference Vegetation Index (NDVI) is calculated using the NIR and red bands.

$$NDVI=((NIR-RED))/((NIR+RED)) \qquad (1)$$

where Red and NIR are the spectral reflectance values for MODIS Band 1 (620–670 nm) and Band 2 (841–871 nm), respectively. In addition to Vegetation Index data and the pixel reliability layer, which is required for quality assurance, MOD13Q1 is produced from atmospherically adjusted bi-directional surface reflectance imagery (LP DAAC, 2015). SENTINEL-2 also has the necessary bands with NIR (Band 8) and Red (Band 4) sensors.

Using MODIS and SENTINEL-2 datasets, we estimated NDVI mean composite values for the chosen area using the JavaScript code editor in the GEE platform from December 2018 to May 2023. For the chosen region, we derived mean NDVI values time series curve. Time series MODIS NDVI and SENTINEL-2 NDVI were fitted with an 8-order and 6-order polynomial function respectively. The Start of the Season (SOS) and End of the Season (EOS) of the phenological cycle are identified using these time series phenological curves. The investigation of the correlations between NDVI curves and observed pheno-phases is based on these curves.
Here's an 8th-order polynomial equation:

$$f(x) = a_8x^8 + a_7x^7 + a_6x^6 + a_5x^5 + a_4x^4 + a_3x^3 + a_2x^2 + a_1x + a_0 \qquad (2)$$

And here's a 6th-order polynomial equation:

$$g(x) = b_6x^6 + b_5x^5 + b_4x^4 + b_3x^3 + b_2x^2 + b_1x + b_0 \qquad (3)$$

The coefficients (a8, a7,..., a0) and (b6, b5,..., b0) in both equations stand in for the relevant coefficients for each term in the polynomial.

R-Square and Adj. R-Square values for the MODIS NDVI derived polynomial fitting of the time series curve were 0.823 and 0.792 respectively. Similarly, the results for R-Square and Adj. R-Square for the SENTINEL-2 NDVI derived polynomial fitting of the time series curve were 0.705 and 0.696, respectively.

2.2.2 Concept of Temporal Normalized Phenology Index (TNPI): The shift between two phenological phases may be quantified using the Temporal Normalised Phenology Index (TNPI), a temporal index (Khare et al., 2017, 2021). It measures the growth between the beginning and peak of a plant's growth when applied to those two points of measurement. In contrast to other phenological indices, the TNPI only needs two-time steps to quantify change instead of the complete temporal sequence, which reduces the quantity of time series data that must be analysed. This is how the TNPI may be calculated:

$$TNPI=((NDVI_{Max}-NDVI_{Min}))/((NDVI_{Max}+NDVI_{Min})) \qquad (4)$$

where $NDVI_{Min}$ = Minimum NDVI value obtained at the start of leaf flush, $NDVI_{Max}$= Maximum NDVI value obtained at the end of the leaf flush activities. TNPI value ranges between +1.0 and -1.

2.2.3 Methodology: The selected methodology's flow chart is shown in Figure 2. The approach involves the collection and preparation of satellite data as well as the multitemporal NDVI's derivation from two separate datasets that have different spatial resolutions.

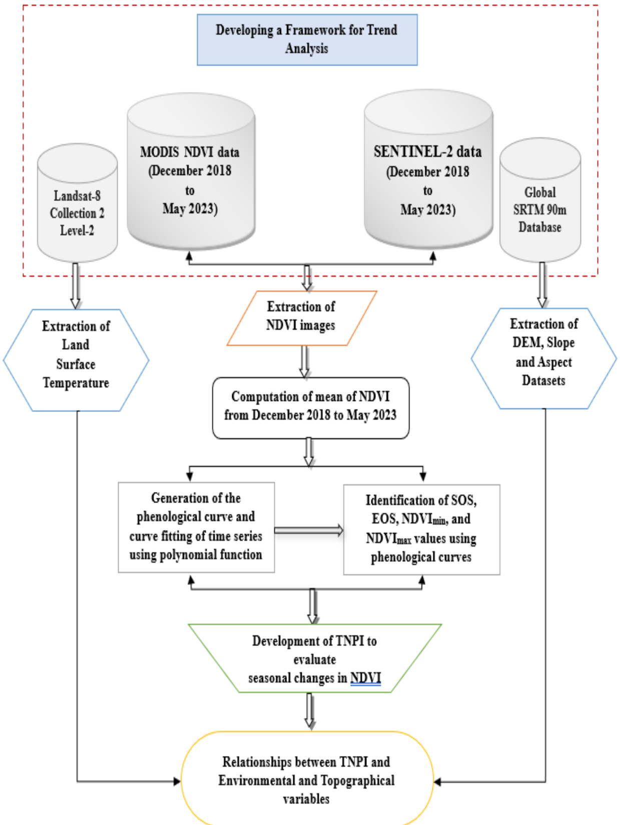

Figure 2. Flowchart of methodology.

For both datasets, NDVI values and time series curves are extracted using the GEE platform, and time series curve fitting is performed using a polynomial function. Based on the five years of time series data, we retrieved phenology characteristics such as Start of the Season (SOS), End of the Season (EOS), NDVImax, and NDVI min. The difference between SOS and EOS was used to calculate the Length of the Growing Season (LOS) (Khare et al., 2019). Using the random point sampling tool in ArcGIS Pro, we randomly selected 500 sample points and then retrieved raster data values of MODIS-based TNPI and

SENTINEL-2-based TNPI, elevation, LST, Slope, and Aspect to model the relationship between TNPI trends in the research area with several environmental and topographical factors.

3. RESULTS AND DISCUSSION

3.1 NDVI-derived Phenology Time Series

Figures 3 and 4 depict the actual NDVI time series curve using MODIS and SENTINEL-2 datasets, respectively. The NDVI derived from MODIS and SENTINEL-2 both followed a trend pattern, with a rapid increase followed by a decrease after a period of time. Even though the MODIS-derived time series trend demonstrates a smooth shift in the growth of NDVI values, but at the time of decrease, there is a tiny variation in the curvature of the curve with each phenology cycle. This fluctuation is seen during the phenological cycle's post-monsoon and winter seasons.

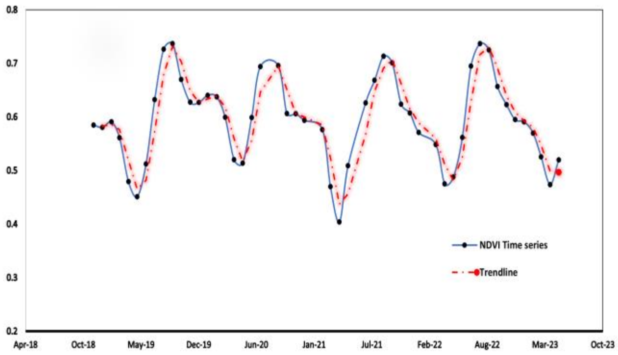

Figure 3. MODIS NDVI derived actual time series.

The NDVI time series curve from Sentinel-2 reveals that while the trend in the phenology trend is nearly identical for the years 2019, 2020, and 2021, there is a significant change in the amplitude of the curve for the year 2022. The cause of this drop in NDVI values is unclear, however it may be critically examined individually in further investigations.

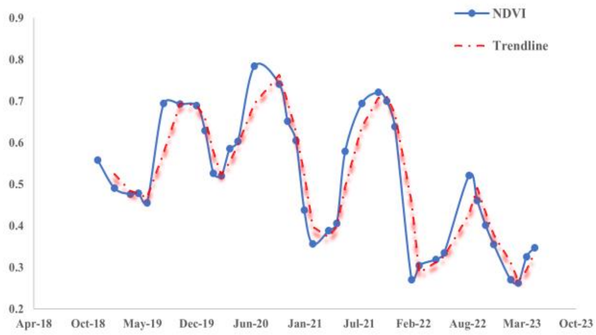

Figure 4. SENTINEL-2 NDVI derived actual time series.

Further, a sudden increase in the phenological curve was seen from April to September because the forest types in the study area continues to grow new leaves during the leaf flush phenophase. Similarly, forest types in the research region with leaf fall activity from December to February, phenological curve rapidly decreased. In the phenological curve, the months of September to December correspond to the mature leaf duration and were associated with higher NDVI values.

3.2 Curve Fitting of Time Series and Phenological Parameters

All the NDVI mean values are utilised for the development of the NDVI time series trend curve from December 2018 to May 2023, and a polynomial fitting of the time series datasets is employed. Figures 5 and 6 demonstrate the polynomial fitting of time series from the study region produced from MODIS and SENTINEL-2 NDVI data, and interpolation of NDVI values are recovered throughout the year using this data. According to the MODIS-derived phenology trend, the minimum NDVI value was 0.473 at Day of Year (DOY) 130.49 and the maximum NDVI value was 0.706 at DOY 256.11. In a similar manner, Start of the Season (SOS) April and May, Peak of the Season (POS) was August-September and End of the Season (EOS) was comprehended between March-April. According to the SENTINEL-2 derived phenology trend, the minimum NDVI value was 0.367 at DOY 117.5 and maximum NDVI value was 0.677 at DOY 293.67. Similarly, SOS occurred in April and May, POS appeared in September and October, and EOS was identified in March and April. It is obvious that the peak of the season has been shifted to the month of October. This shift may be the result of a lack of dataset during the months of July and August, which is a consequence of cloud restrictions.

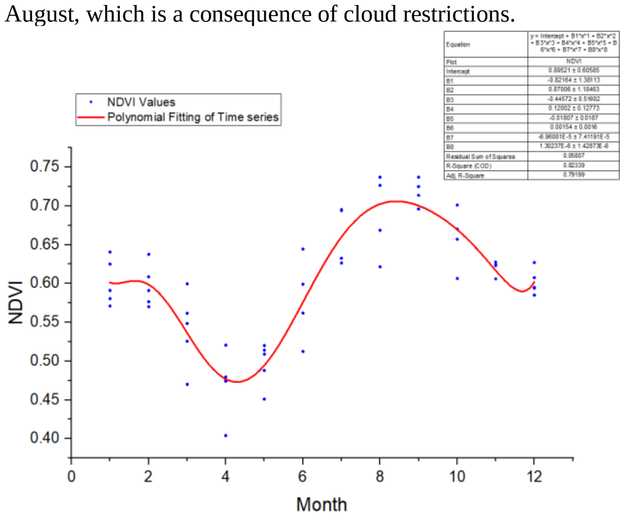

Figure 5. MODIS NDVI derived polynomial fitting of time series.

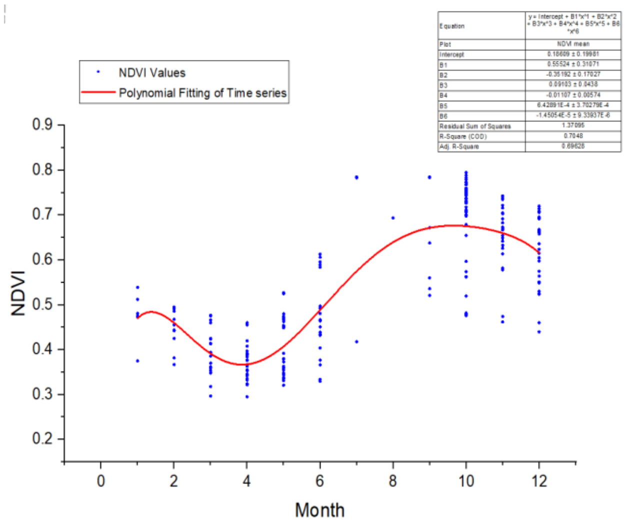

Figure 6. SENTINEL-2 NDVI derived polynomial fitting of time series.

The overall findings can be supported by prior research on the same types of forests and geographical areas, which has demonstrated that the period of leaf-flushing activity is between March and May, and that of leaf-falling activity is between January and April, according to most available literature on the subject of this research (Boojh and Ramakrishnan, 1983; Jeganathan et al., 2010; Kikim and Yadava, 2001; Upadhyay et al., 2013).

3.3 TNPI and Environmental Factors

Figure 7 shows the TNPI, ΔLST, DEM, Slope and Aspect maps of the study site. The suggested TNPI, which uses the normalised ratio of the maximum and minimum NDVI values, was then generated to assess the change dynamics in the NDVI between two time stages of the time series curve using Equation 4. The slope and aspect maps of the region of interest were extracted using DEM data. Slope values lies between 0 to 70.556 and TNPI values lies between -1 to +1. The research area's maximum and minimum temperature variations day of the year were used to create Land Surface Temperature (LST) maps using LANDSAT-8 data at 30m spatial resolution. The change in LST (ΔLST) was computed substracting the maximum and minimum temperature data during the one season phenology. Elevation map values lies between 290 to 915 meters and ΔLST lies between 15.31 to 32.21 degree celcius.

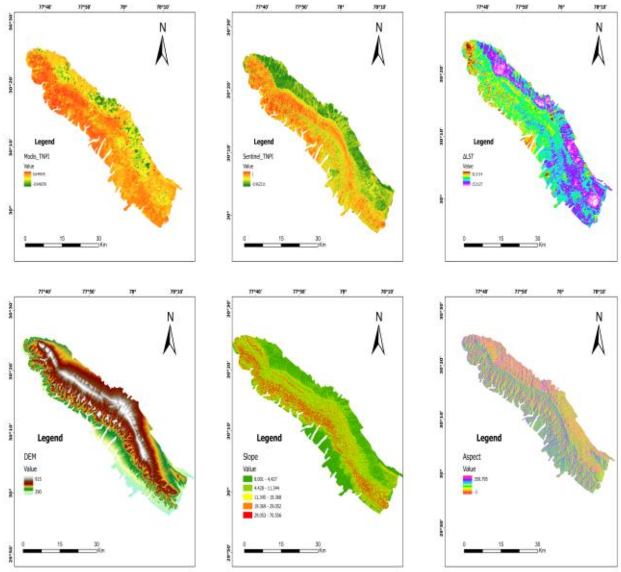

Figure 7. TNPI and Environmental Variables maps.

On TNPI maps of both the datasets, lower TNPI values represent less variety in vegetation greenness, whereas higher TNPI values represent more variation. Rapid phenological variations were also noted at low elevations, but due to the remoteness at higher elevations, less variability was seen at mid to high elevations. Lower-elevation locations often have a more sensitive distribution of the forest cover to climatic factors like rainfall and LST during both the increase and decrease vegetation greenness in the phenology. Therefore, it is evident from the TNPI maps of both datasets that the top half of the ridge has less variance and, consequently, greater values of TNPI than the lower region of the ridge due to higher altitude and less variation in LST. On the other hand, it is evident that the ΔLST map's surface temperature data variance was smaller in the upper section of the ridge line compared to the lower part of the ridge line.

3.4 Relationship between TNPI and Environmental Variables

In order to model the relationship between TNPI trends in the study area and various environmental and topographical factors, we randomly selected 500 sample points using the random point sampling tool in ArcGIS Pro and then retrieved raster data values of MODIS-based TNPI and SENTINEL-2-based TNPI, elevation, ΔLST, Slope, and Aspect for 500 locations as shown in Figure 8 and 9. According to MODIS derived TNPI, the correlation between TNPI and ΔLST, Slope, and Aspect is positive, indicating that the variable values are moving in the same direction, Hence, the places with the higher ΔLST, Slope, and Aspect also had the higher variation in vegetation greenness i.e. higher values of TNPI. However, the TNPI calculated from MODIS shows a negative association with Elevation, suggesting that the variable values are moving in the opposite direction. As such, the areas with more elevation observed less variation in vegetation greenness, or lower TNPI values. Variable maps (Figure 7) were also demonstrated that vegetation greenness changes less rapidly at higher elevations.

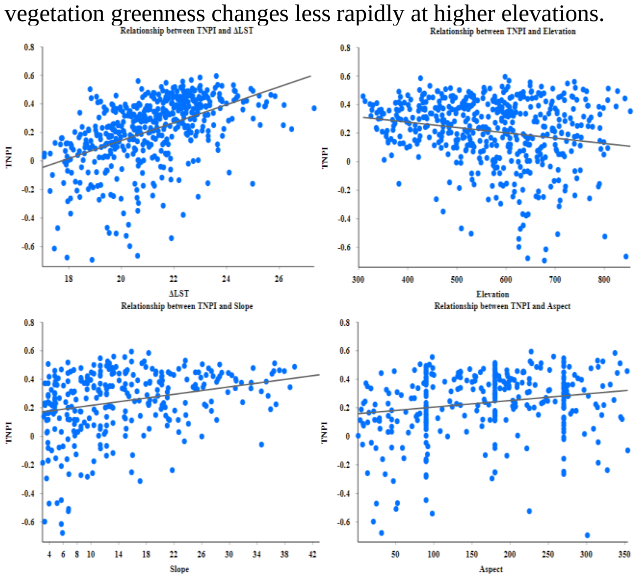

Figure 8. Univariate statistics for 500 random points of raster data highlighting the estimated relationship of MODIS derived TNPI with environmental factors.

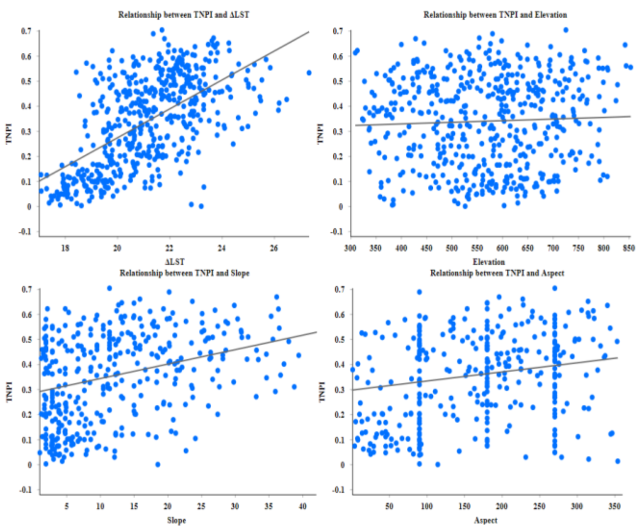

Figure 9. Univariate statistics for 500 random points of raster data highlighting the estimated relationship of SENTINEL-2 derived TNPI with environmental factors.

Similarly, the correlation between TNPI and ΔLST, Slope, and Aspect is positive, indicating that the variable values are moving in the same direction as the derived TNPI from SENTINEL-2. As a result, the locations with higher ΔLST, Slope, and Aspect also had higher variations in vegetation greenness, i.e. higher values of TNPI. However, the TNPI derived from SENTINEL-2 does not clearly demonstrate a connection with Elevation, indicating that there was no discernible direction of movement for the variable values. Additionally, it was found that the TNPI data from MODIS had a better linear function fit than the TNPI data from SENTINEL-2.

4. CONCLUSION

According to the findings and responses of this work, MODIS and Sentinel-2 TNPI data provide new opportunities for trend analysis of the productivity and health of forest regions at two different spatial scales. The study found that topographic and environmental factors such elevation, surface temperature, slope, and aspect had a significant impact on phenological behaviours and phenophases such as SOS, POS and EOS. Overall conclusions showed that the TNPI had a positive relationship with changes in LST, slope, and aspect in the study region and a negative correlation with elevation data. Phenology changed significantly at low elevations, but because higher elevations are more isolated, there was less volatility at those altitudes. Visual examination of maps and numerical data makes it abundantly obvious that there were certain similarities and variations between the phenology results from MODIS and Sentinel-2 datasets. These variations may be primarily caused by the platform and sensor combinations are different in orbital, spatial, and spectral configurations, this also depends on the availability of datasets i.e., same date of imagery in both satellites. The main drawbacks of the work were the inability to conduct a thorough ground assessment as it would require properly resourced techniques. In the above study of phenology, high temporal resolution datasets are needed, which was not always possible due to clouds, haze, moisture in the atmosphere, or other atmospheric flaws that cause the occurrence of anomalous or outlying phenological values in some of the imagery.

The findings showed that two-time stages (the highest and lowest NDVI values) in the phenological cycle could potentially be used to analyse the temporal variations in phenology, negating the need for an extensive collection of data for time-series evaluation. TNPI has been successfully evaluated for this forest region using NDVI from open-source MODIS and Sentinel-2 datasets at the two points of peak and lowest growth in the vegetation phenology phase. As consequently, future study on forests of similar kind may utilise our findings as a basis for further investigation. Sentinal-2 and other higher resolution datasets can be used in future studies to do more precise time series analysis and can be modelled with more climate change variables. The effectiveness of TNPI can also be tested for various other forest areas or farmlands where phenology-related studies are able to be carried out using various spatial and temporal resolution datasets. Furthermore, this type of remote sensing-based studies can be conducted on large areas with a mixture of plants and trees that could provide a diversified result and better understandings.

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