

Article

Spatiotemporal Vegetation Dynamics, Forest Loss, and Recovery: Multidecadal Analysis of the U.S. Triple Crown National Scenic Trail Network

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Abstract: The U.S. National Scenic Trail system, encompassing over 12,000 km of hiking trails along the Appalachian Trail (AT), Continental Divide Trail (CDT), and Pacific Crest Trail (PCT), provides critical vegetation corridors that protect diverse forest, savannah, and grassland ecosystems. These ecosystems represent essential habitats facing increasing environmental pressures. This study offers a landscape-scale analysis of the vegetation dynamics across a 2 km wide conservation corridor (20,556 km²), utilizing multidecadal Landsat and MODIS satellite data via Google Earth Engine API to assess the vegetation health, forest disturbance recovery, and phenological shifts. The results reveal that forest loss, primarily driven by wildfire, impacted 1248 km² of land (9.5% in the AT, 39% in the CDT, and 51% in the PCT) from 2001 to 2023. Moderate and severe wildfires in the PCT (713 km² burn area) and CDT (350 km² burn area) corridors exacerbated the vegetation stress and facilitated the transition from forest to grassland. LandTrendr analysis at 15 sample sites revealed slow, multi-year vegetation recovery in the CDT and PCT corridors based on the temporal segmentation and vegetation spectral indices (NBR, NDVI, NDWI, Tasseled Cap). The post-disturbance NBR values remained significantly reduced, averaging 0.31 at five years post-event compared to 0.6 prior to the disturbance. Variations in the vegetation phenology were documented, with no significant trends in the seasonal advancement or delay. This study establishes a robust baseline for vegetation change across the trail system, highlighting the need for further research to explore localized trends. Given the accelerating impacts of climate change and wildfire frequency, the findings underscore the necessity of adaptive conservation strategies to guide vegetation management and ensure the long-term stability and sustainability of vegetation cover in these vital conservation areas.

Keywords: vegetation; MODIS; Landsat; wildfire; LandTrendr; phenology; Pacific Crest Trail; Continental Divide Trail; Appalachian Trail



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1. Introduction

The U.S. National Scenic Trail system serves numerous ecological, conservation, and cultural purposes. Designated by the U.S. Congress in the National Trails System Act of 1968 [1], the network of conserved hiking trails located throughout the country is intended to demonstrate the landscape's rich natural and cultural heritage. The wilderness trails are designed to connect the public with their protected lands through recreation and citizen stewardship [2,3]. However, the environmental stability along these conservation

corridors is threatened by the shifting climate [4], spread of invasive species [5–7], and wildfire-induced vegetation loss [8] along three of the longest National Scenic Trails: the Appalachian Trail (AT), the Pacific Crest Trail (PCT), and the Continental Divide Trail (CDT), collectively referred to as the Triple Crown.

The Triple Crown trail system includes more than 12,674 km of hiking trails. It is protected through a patchwork of conservation lands, including National Forests, National Parks, Bureau of Land Management public lands, and Wildlife Refuges [9]. The majority of lands surrounding the Triple Crown are owned publicly and include dozens of wilderness areas managed by numerous local, state, and federal government agencies, including the Bureau of Land Management (BLM), the United States Forest Service (USFS), and the National Park Service (NPS) [10]. In addition, tribal nations and non-profit entities play a key role in land management [11].

To monitor the environmental health of the trail system, scientific studies of trail environmental phenomena include the examination of the species distribution [9,12], water quality [13], invasive species [14], landslide and geomorphology analysis [15], and geologic mapping [16]. Research into ecosystem processes and environmental health guides comprehensive plans and informs land management decisions [17,18]. Some trail sections, such as the Appalachian Trail, have benefitted from thorough multi-year vegetation mapping efforts, informed through extensive ecological field work and geographic spatial analysis [12]. However, the massive size of the Triple Crown system inhibits continuous ground-based assessment due to the insufficient number of personnel and financial limitations. While in situ monitoring remains vital for scientific research and data collection, remote sensing provides an additional tool to monitor broad landscape patterns and identify trends across the entire trail system over long periods [11,19,20]. Large-scale conservation efforts require consideration of the complex spatial and temporal scales involved in managing huge land areas [21]. Synthesis of various datasets and diverse expertise is also essential to holistically identify trends across the landscape [3,22].

Remote sensing is an essential tool for comprehensive vegetation analysis at various temporal scales, as outlined by Darabi et al. in 2025 [23]. The changes captured in multidecadal satellite imagery include gradual shifts caused by factors such as vegetation growth [24,25], land degradation [26], invasive species [27], and shifting climate [23]. Research into seasonal vegetation dynamics includes phenological shifts [28], while investigation of abrupt changes considers natural hazard impacts and rapid land cover modification [29]. Case studies of vegetation health often consider multiple temporal scales and are frequently conducted using a combination of remote sensing methods, including image classification for change detection [30], implementation of numerous spectral algorithms [31], advanced trend analysis [32], and assessment of recovery metrics [33,34]. For example, Tian et al. utilized MODIS, Landsat, Sentinel-2, GF-1, GF-4, and Planet imagery to investigate the vegetation dynamics and wildfire impacts in Liangshan Prefecture, Sichuan Province, China [35]. Beale et al. [36] investigated the vegetation cover dynamics along Himalayan rivers using a combination of Landsat spectral indices, land cover modeling, and seasonal and inter-annual approaches. Li et al. investigated the vegetation greenness using MODIS data while incorporating consideration of climate data and anthropogenic impacts within the Tibetan plateau [37]. Fang et al. utilized land cover, MODIS imagery, and LandTrendr modeling to examine the vegetation dynamics in Quebec, Canada [38].

Forest health is of vital importance in trail corridors. While the hiking paths were created as a space for recreational activities, the trails also serve as an important conservation corridor for plant and animal species [22]. The PCT connects seven national parks, the AT transverses six national parks, and the CDT intersects three national parks, including Rocky Mountain, Grand Teton, and Yellowstone. As the trails are located along mountain

ridges, the corridors act as a climate refuge for numerous species due to the diversity of the habitat in mountainous terrains [10]. The extensive size of this complex trail system limits continuous ground-based vegetation monitoring and benefits from broad, comparative landscape-scale remote sensing analysis. Landsat and MODIS satellite imagery are crucial resources to study comprehensive vegetation health and assist in forest productivity assessment [39,40]. Remote sensing is a powerful tool for understanding forest loss and has been applied along segments of the Triple Crown trail system through the use of satellite systems, aerial imagery, and LiDAR [19,22,26,41]. Satellite imagery can also be used to estimate forest productivity, a critical metric for carbon cycling and forest health [42].

Wildfire regimes play a significant role in vegetation and have been examined in numerous locations along the PCT and CDT [43–45]. Wildfires are recognized as a natural landscape process in regions of the Triple Crown such as the mid-elevation xeric interior forests of the Rocky Mountains along the CDT and the Sierra Nevada Mountains of California along the PCT [8,46,47]. As these fires remove low-growing brush and rejuvenate the soil, tree species such as lodgepole pine (*Pinus contorta*) are fire-adapted for rapid recovery [8]. However, the intensity and frequency of wildfires have changed due to human influences such as anthropogenic climate change, drought, and intentional acts of arson [48]. In addition, in some locations, forest management practices suppressed fires, preventing low-intensity burns and causing an accumulation of underbrush [49,50]. Wildfires have caused numerous closures of the trail system due to the dangerous conditions. These wildfire events pose a significant threat to the U.S. National Scenic Trail system as vegetation recovery after intense burns is often slow and hindered by prolonged drought conditions [8,51]. Optical imagery such as Landsat Thematic Mapper/Operational Land Imager and Moderate Resolution Imaging Spectroradiometer (MODIS) are available to monitor the long-term change associated with wildfire events over several decades and compute spectral indices such as the normalized burn ratio (NBR) and normalized differenced vegetation index (NDVI) [52,53]. The long-term impact following vegetation disturbance can also be monitored through analysis of various spectral indices and temporal segmentation to identify recovery rates [54].

Phenological patterns are shifting throughout the world as the onset of spring, peak summer vegetation growth, and fall senescence dates are altered by global climate change [55]. The altered annual temperature cycle may modify species ranges and pose a particular risk for endemic species dependent on environmental conditions in a specific location. Changes to the timing of vegetation processes also pose a threat due to the phenological mismatch between flowering plants and pollinators [56]. To collect ground-based phenology data, large citizen science efforts are being implemented at specific sites, such as the Walking with Wildflowers effort in Yosemite National Park on the PCT [57]. Citizen science phenology data are also collected in the Great Smoky Mountain National Park along the AT [58] and at Lily Lake in Rocky Mountain National Park on the CDT [59]. These ground-based observations are consolidated in databases such as iNaturalist. In addition, phenology data are collected through a network of PhenoCams, in situ digital cameras that collect imagery at a high temporal frequency [60]. Additional monitoring of phenological shifts using remote sensing techniques can help managers assess system-wide trends.

A landscape-scale vegetation assessment of the Triple Crown and a broad-perspective multidecadal analysis of the vegetation patterns provide a valuable comparative framework to analyze the trail network. Threats from the changing climate, the shifting wildfire regimes, and the spread of invasive species warrant holistic monitoring of the Triple Crown National Scenic Trail system. To better understand the environmental trends along each trail corridor, our objectives for this research are to (1) assess the vegetation health in terms of the land cover change and vegetation productivity; (2) evaluate the forest loss

and recovery rates after significant disturbance events such as wildfires; and (3) assess the phenological change across the trail system to better understand the impacts of shifting climate regimes.

2. Methods

This study utilized Google Earth Engine’s JavaScript API to analyze massive quantities of remote sensing data across large study areas (Figure 1) [61]. Input data were collected from a variety of sources to examine the trends in the vegetation dynamics over several decades (Table 1). As the data were aggregated across the study site to examine the minimum, median, and maximum values, the variable spatial resolutions of the input data did not prohibit trend analysis. The LandTrendr temporal segmentation algorithm [62] was implemented to examine the recovery after disturbance events along the trail network. Phenological analyses were conducted in R v.2024.09.1 +394, while geographic information system (GIS) processing and cartographic visualization were implemented in ArcGIS Pro v3.4.

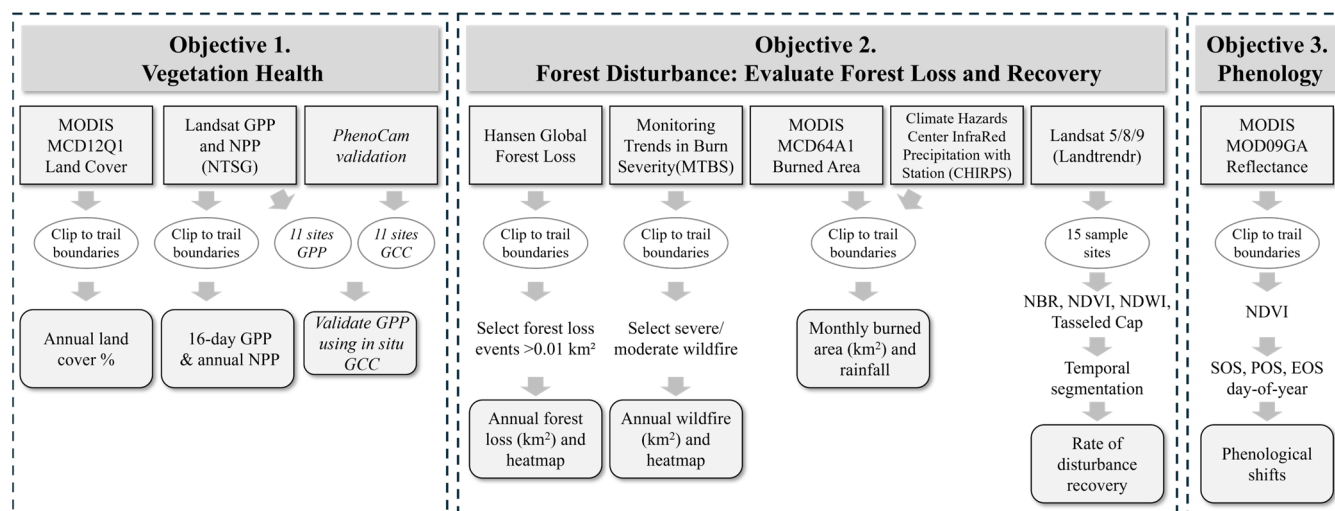


Figure 1. Technical flowchart outlining the process steps.

Table 1. Data sources used in this study.

Data Source	Dates	Temporal Resolution	Spatial Resolution	Units	Data Accessed
MODIS Land Cover Type MCD12Q1 v6.1 [63]	2001–2023	Annual	500 m	Thematic (land cover)	Google Earth Engine (GEE) https://earthengine.google.com (accessed on 19 January 2025)
Landsat Gross/Net Primary Production Numerical Terradynamic Simulation Group (NTSG) [64]	1986–2021	GPP 16-day, NPP annual	30 m	kg*C/m ²	GEE https://earthengine.google.com (accessed on 11 January 2025)

Table 1. Cont.

Data Source	Dates	Temporal Resolution	Spatial Resolution	Units	Data Accessed
PhenoCam v2.0 [65]	Variable	Daily	--	Green chromatic coordinate (GCC)	ORNL DAAC https://daac.ornl.gov/VEGETATION/guides/PhenoCam_V2.html (accessed on 24 January 2025)
Hansen Global Forest Change v1.11 [66]	2001–2023	Annual	30 m	Date (disturbance)	GEE https://earthengine.google.com (accessed on 11 January 2025)
Monitoring Trends in Burn Severity (MTBS) [67]	2001–2024	Annual	30 m	Thematic (low to high severity)	GEE https://earthengine.google.com (accessed on 8 January 2025)
MODIS MCD64A1 v6.1 Burned Area [68]	2001–2023	Daily	500 m	Date (burn occurrence)	GEE https://earthengine.google.com (accessed on 8 January 2025)
Climate Hazards Center InfraRed Precipitation with Station (CHIRPS) [69]	2001–2023	Pentad	5566 m	mm/pentad	GEE https://earthengine.google.com (accessed on 8 January 2025)
LandTrendr Landsat 5/7/8 [62]	1984–2024	16-day	30 m	Digital number (DN)	GEE https://earthengine.google.com (accessed on 21 January 2025)
National Agriculture Imagery Program (NAIP)	22 June 2009 7 June 2010	Variable	1 m	Digital number (DN)	USGS Earth Explorer https://earthexplorer.usgs.gov (accessed on 22 January 2025)
MODIS MOD09GA v6.1 Surface Reflectance [70]	2001–2024	Daily	500 m	Digital number (DN)	GEE https://earthengine.google.com (accessed on 20 January 2025)
MODIS MOD10A1 v6.1 Terra Snow Cover [71]	2001–2023	Daily	500 m	% snow cover	GEE https://earthengine.google.com (accessed on 10 January 2025)

2.1. Study Site

The Triple Crown trail polyline vector data were acquired from the National Park Service, National Forest Service, Continental Divide Trail Coalition, and Pacific Crest Trail Association. ArcGIS Pro was utilized to buffer the polylines with a distance of 1 km on either side of the linear trail path to create a 2 km wide corridor (Figure 2). The 2 km corridor was selected based on prior research examining the ecological function of trail networks as linked conservation corridors [10]. In addition, the 2 km wide corridor allowed for analysis of broad landscape patterns across large protected areas using moderate spatial resolution imagery such as 500 m MODIS data products [72].

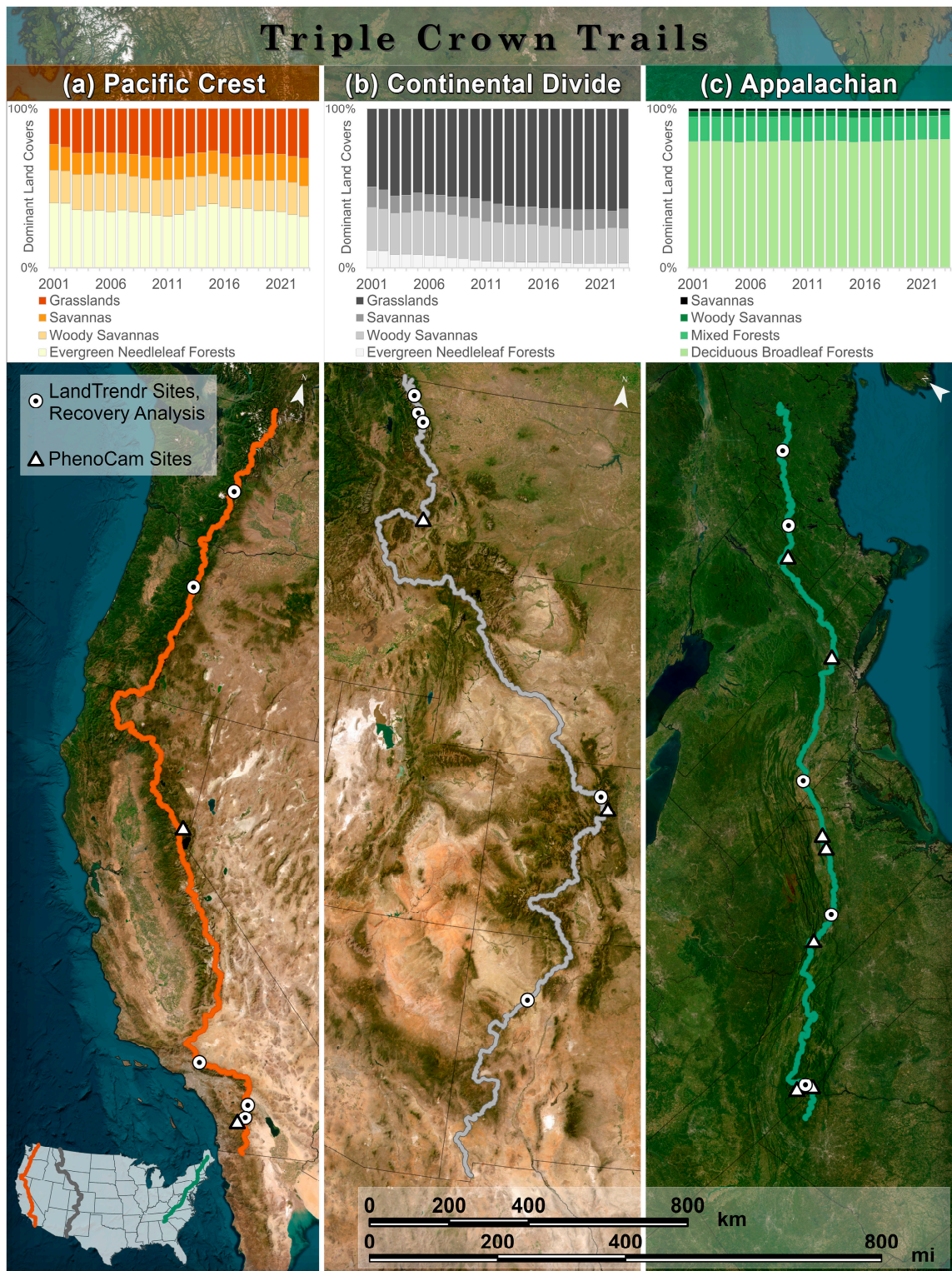


Figure 2. Corridors of the (a) Pacific Crest, (b) Continental Divide, and (c) Appalachian National Scenic Trails with the locations of sites for LandTrendr recovery analysis and the distribution of PhenoCam sites for validation. The MODIS Land Cover Type MCD12Q1 trends are presented for each trail, showing an increase in grasslands and a decrease in evergreen needleleaf forests along the PCT and CDT from 2001 to 2023.

The 20,556 km² study area includes variable habitat with 24 different Level III ecoregions [73]. The ecoregions along the PCT transition from the arid Sonoran Desert in the south to more mountainous environments, including the Sierra Nevada, Klamath Moun-

tains, and Cascade Range in the north. The CDT follows a similar pattern, beginning with the Chihuahuan desert on the trail's southern terminus and moving northward through the Rocky Mountains. Along the AT, the ecoregions include the temperate forests of the southern Blue Ridge, Ridge and Valley, and the northern Appalachian Mountains. Each trail contains a variety of micro-climates and habitats as a result of the extreme elevation change in mountainous environments. The elevations range from near sea level to over 4 km on the PCT, 1.2 to 4.35 km on the CDT, and 0.04 to over 2 km along the AT.

2.2. Vegetation Health

The multidecadal land cover trends across the trail system were quantified using the MODIS Land Cover Type MCD12Q1 v6.1 global data product [63]. Using supervised classification, the 500 m spatial resolution MCD12Q1 data are generated by the United States Geological Survey (USGS) from MODIS Terra and Aqua sensors. The MCD12Q1 data were analyzed annually to identify the dominant land cover classifications along each trail corridor for the years 2001–2023.

The terrestrial primary production was analyzed to quantify the vegetation contributions to the ecosystem energy budget within the Triple Crown network. The terrestrial gross primary production (GPP) includes all the energy captured by plants in the form of biomass, while the net primary production (NPP) also accounts for energy lost through respiration [74]. The long-term trends in the GPP and NPP from 1986 to 2021 were estimated using the Landsat GPP and NPP CONUS data products from the University of Montana Numerical Terradynamic Simulation Group (NTSG) [64]. Compared to 1 km and 500 m MODIS MOD17 GPP/NPP data, the improved 30 m spatial resolution of the Landsat GPP/NPP products is useful for estimating terrestrial production in environments with high spatial variability, such as mountainous terrain.

PhenoCam data from eleven sites were obtained from the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center Phenom Dataset v2.0 [65]. The PhenoCam data include conventional visible-wavelength automated digital camera imagery (red, green, and blue reflectance) collected in situ at high spatial and temporal resolution from stationary ground-based cameras. The images capture the seasonal dynamics and can be used to characterize the phenological patterns of the observed vegetation [75]. Seven PhenoCam sites were located along the AT, two sites along the PCT, and two sites along the CDT. The PhenoCam observations were used as in situ validation data to confirm the Landsat GPP estimates [76,77]. The ORNL PhenoCam data (acquired Jan 2025) provide estimates of the green chromatic coordinate (GCC), where:

$$\text{GCC} = \text{Green} / (\text{Red} + \text{Blue} + \text{Green}) \quad (1)$$

The GCC vegetation index estimates the amount of foliage in the plant canopy and ranges from 0 to 1, with higher values representing a higher degree of greenness [78]. The r^2 between the smoothed ground-based GCC and satellite-derived Landsat GPP time series was used to validate the accuracy of the remote sensing estimates, with maximum r^2 values indicating stronger accuracy.

2.3. Forest Loss Severity and Recovery

Hansen Global Forest Change v1.11 Forest Loss data (hereafter referred to as Hansen Forest Loss) were used to identify forest loss events between 2001 and 2023 [66]. These data define trees as vegetation taller than 5 m in height and forest loss as stand-replacement disturbance or change to a non-forest state. Forest loss within the Triple Crown network may occur due to wildfire, logging, land cover change, and natural hazards such as landslides and flooding. As many disturbances were small in surface area ($<0.01 \text{ km}^2$

in size), events greater than 0.01 km² were selected to identify larger events for further examination. The centroids of the forest loss polygons were used to generate a heatmap (weighted by surface area) showing locations with a high density of tree loss events across the Triple Crown network.

To evaluate the annual occurrence of moderate and severe wildfires, 30 m Monitoring Trends in Burn Severity (MTBS) data provided annual estimates of the wildfire severity for 2001–2024 [67]. The MTBS data were processed to identify the locations and surface extent of moderate to severe wildfires [79]. In addition, 500 m MODIS MCD64A1 v6.1 Burned Area data [68] were examined to investigate the seasonal timing of wildfires and the relationship with the Climate Hazards Center InfraRed Precipitation with Station (CHIRPS) rainfall estimates for 2001–2023 [69].

Vegetation recovery was assessed by selecting high-disturbance forest loss events and examining the length of time taken for the vegetation index values to rebound to pre-disturbance levels based on Landsat 5/7/8 spectral data. Using the Hansen Forest Loss boundaries, fifteen of the largest forest loss locations were selected (five sites on each trail), and sample point locations were digitized directly along trail paths with a buffer of 1000 m. Each of the fifteen sample sites was examined with the LandTrendr model [62] to interpret rapid versus gradual vegetation recovery based on the Landsat Surface Reflectance Tier 1 datasets [80]. Landsat Tier 1 data are atmospherically corrected by the USGS and are masked to reduce the influence of cloud, shadow, water and snow [81]. For the LandTrendr temporal segmentation, seven spectral indices were examined to identify vegetation recovery and interannual trends using the Google Earth Engine LandTrendr model: NDVI, NBR, normalized difference moisture index (NDMI), and Tasseled-Cap Brightness, Greenness, Wetness, and Angle (TCB, TCG, TCW, and TCA) [82–84] (Table 2). These algorithms employ the near-infrared (NIR) and shortwave-infrared (SWIR) bands due to vegetation’s strong reflectance in these wavelengths [85]. An abrupt decline in the index values over time indicates disturbance, while the subsequent increase in the index values reflects regrowth or recovery. A decrease in the index typically occurs when vegetation is lost and soil exposure increases [82,83]. Therefore, a sharp drop in the index indicates a rapid and substantial loss of vegetation cover.

Table 2. Spectral indices assessed for the LandTrendr temporal segmentation.

Spectral Index	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$(\text{NIR} - \text{R})/(\text{NIR} + \text{R})$	Tucker (1979) [86]
Normalized Burn Ratio (NBR)	$(\text{NIR} - \text{SWIR2})/(\text{NIR} + \text{SWIR2})$	Key and Benson (2005) [87]
Normalized Difference Moisture Index (NDMI)	$(\text{NIR} - \text{SWIR1})/(\text{NIR} + \text{SWIR1})$	Wilson and Sader (2002) [88]
Tasseled Cap Brightness (TCB)	$0.2043 \times \text{Blue} + 0.4158 \times \text{Green} + 0.5524 \times \text{Red} + 0.5741 \times \text{NIR} + 0.3124 \times \text{SWIR1} + 0.2303 \times \text{SWIR2}$	Crist (1985) [89]
Tasseled Cap Greenness (TCG)	$-0.1603 \times \text{Blue} - 0.2819 \times \text{Green} - 0.4934 \times \text{Red} + 0.7940 \times \text{NIR} - 0.0002 \times \text{SWIR1} - 0.1446 \times \text{SWIR2}$	Crist (1985) [89]
Tasseled Cap Wetness (TCW)	$0.0315 \times \text{Blue} + 0.2021 \times \text{Green} + 0.3102 \times \text{Red} + 0.1594 \times \text{NIR} - 0.6806 \times \text{SWIR1} - 0.6109 \times \text{SWIR2}$	Crist (1985) [89]
Tasseled Cap Angle (TCA)	$\text{Arctan}(\text{TCG}/\text{TCB})$	Powell et al. (2010) [90]

The medoid image compositing approach was implemented with a date range of 10 June–20 August for each year to maintain consistent seasonality and reduce the influence of snow cover. The LandTrendr fitting parameters were not independently calibrated but were accepted a priori based on the performance of the model in the 15 high-disturbance landscapes identified for analysis (max segments: 7; spike threshold 0.9; vertex count overshoot: 3; prevent one-year recovery: true; recovery threshold: 0.25; *p*-value threshold: 0.05; best model proportion: 0.75; min observations needed: 7).

2.4. Phenology

The NDVI values were calculated from MODIS MOD09GA v6.1 imagery [70]. This dataset represents the ground-level surface spectral reflectance. To mask low-quality data, pixels were removed using a bitmask filter based on the MODIS QA values to remove the influence of cloud, cloud shadow, snow, and ice. In addition, water pixels were removed using the MOD44W.005 MODIS/Terra Land Water Mask derived from MODIS and SRTM L3 [91]. As such, the NDVI values were produced with a low amount of influence from atmospheric conditions such as cloud cover. The MODIS Surface Reflectance (MOD09GA) data were processed in Google Earth Engine (GEE) to estimate the NDVI for each trail for the 24-year period from 2001 to 2024. Based on the temporal resolution of the satellite sensors and missing observation dates, the MODIS reflectance values have some temporal gaps [92]. A variety of smoothing methods can be used to convert the raw NDVI and GPP values into a daily time series to allow for the interpretation of seasonal patterns, such as the Savitzky–Golay (SG), spline smoothing, and Gaussian approaches; however, there is no agreement on the optimal method in all locations [93]. The spline smoothing method was used here based on successful implementation in phenological studies and broad application across habitats [94–96]. Temporal smoothing and gap-filling using splines were conducted in R with the *greenbrown* phenology package (<https://greenbrown.r-forge.r-project.org> (accessed on 20 January 2025)) [97]. The phenological metrics were generated based on White et al. [98] to calculate the annual phenology metrics: start of season (SOS), end of season (EOS), length of season (LOS), mean spring value (MSP), mean autumn value (MAU), rate of spring green-up (RSP), rate of autumn senescence (RAU), position of peak (POP), position of trough (POT), and mean growing season (MGS). To examine the seasonal shifts in terms of the snow cover, the MOD10A1.061 Terra Snow Cover Daily Global 500 m data product [71] was analyzed to identify the first day of no snow on each trail for the years 2001–2023.

3. Results

3.1. Vegetation Health

3.1.1. Forest Productivity

Based on the year 2023 MODIS MCD12Q1 v6.1 land cover data, 95% of the AT study area is vegetated, with 93% deciduous broadleaf and mixed forest and 1.9% grassland (Figure 2). In contrast, the PCT and CDT include fewer forests. The PCT is 29.2% evergreen needleleaf forest, 34.9% grassland, and 33.1% savanna. The CDT corridor includes only 2.8% evergreen needleleaf forest, 64.3% grassland, and 32% savanna. Over the 23-year period, the MODIS MCD12Q1 land cover data indicate the generalized land cover classes were stable along the AT corridor, with consistent dominance of deciduous broadleaf forest for all years (Figure 1). In contrast, the PCT and CDT land covers transitioned over time. Along the PCT corridor, grasslands increased from 20.4% of the study area in 2001 to 28.1% in 2023. During the same period, evergreen needleleaf forest along the PCT decreased from 37.2% to 29.1%. For the CDT corridor, grasslands increased from 46.3% to 59.3%, while evergreen needleleaf forest declined from 10.3% to 2.8%.

To quantify the change in vegetation productivity, 16-day GPP and annual NPP time series were generated for each trail over 35 years (Figure 3). The NTSG Landsat-derived GPP and NPP data indicate the highest productivity within the Appalachian Trail, followed by the PCT and CDT corridors. The PCT shows the greatest variability in the GPP values across the trail, with a wider interquartile range as the trail transverses desert to forested environments. There is less variability in the GPP values across the AT corridor as the study area is more consistently forested and receives higher precipitation within the eastern U.S. climate. Despite the forest loss events and the transition from evergreen needleleaf forest

to grassland along the western trails, all three trails showed an increase in NPP over the 35 years.

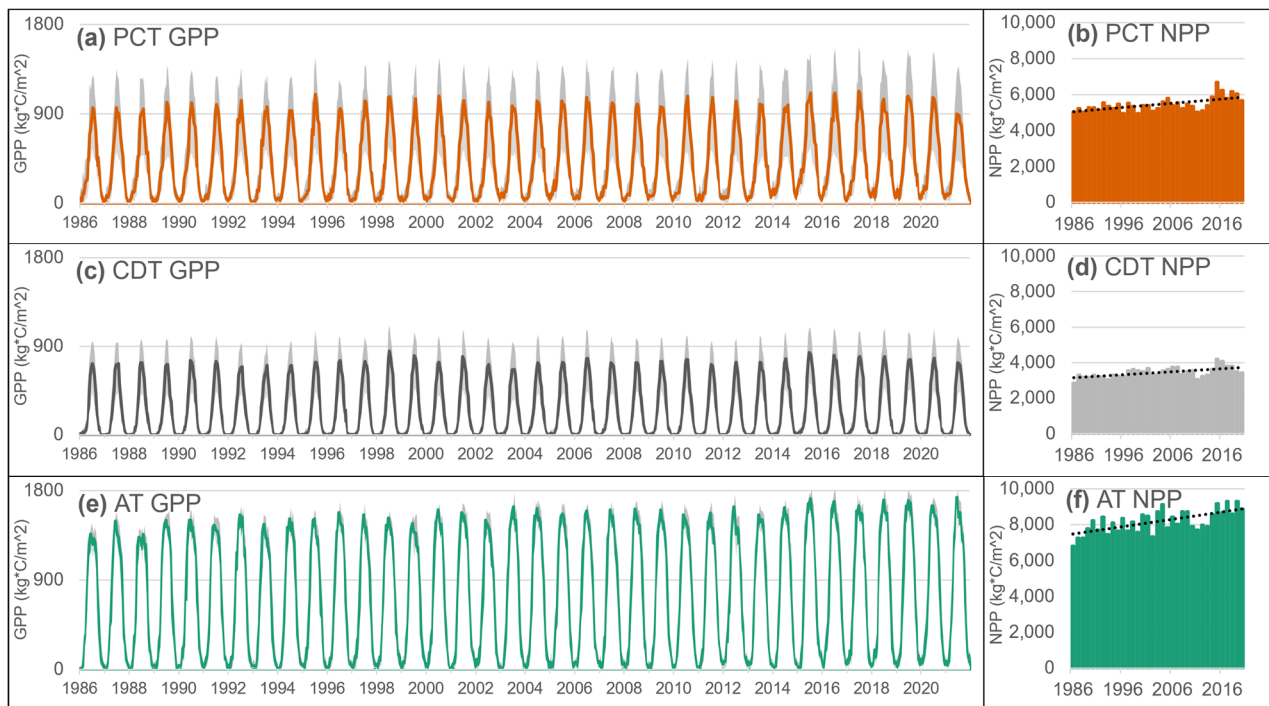


Figure 3. Landsat-derived 16-day GPP and annual NPP time series for the (a,b) PCT, (c,d) CDT, and (e,f) AT. Gray areas indicate first and third quartile values, while the colored line indicates the median GPP.

3.1.2. PhenoCam Validation

A correlation between the Landsat-derived GPP and the PhenoCam GCC was found at ten of the eleven sites. For the AT sites, the average $r^2 = 0.81$, CDT average $r^2 = 0.81$, and PCT average $r^2 = 0.47$, with all the correlations exceeding the 99% confidence level. There was variation in the GPP and GCC fit between specific PhenoCam sites, with forested eastern locations such as the AT NEON D02.SERC.DP1.00033 PhenoCam site having a stronger correlation ($r^2 = 0.872$) and western sites such as the PCT Sagehen PhenoCam site having a weaker correlation ($r^2 = 0.5$) (Figure 4). Sites within the Eastern Temperate Forest and Northern Forest ecoregions had a better fit, while the Californian Mediterranean and Northwestern Mountainous Forest ecoregions did not perform as strongly [73].

3.2. Forest Loss Severity and Recovery

3.2.1. Forest Loss

Over the 2001–2023 study period, the Hansen Forest Loss data indicate events larger than 0.01 km^2 in size were frequent and occurred every year on every trail. Across all three Triple Crown corridors, a total land area of 1248 km^2 experienced forest loss (6% of the study area). The AT corridor totaled 119 km^2 in forest loss during the study period (2.1% of the AT). Most events occurred along the PCT (641 km^2 , 9.9% of the PCT corridor) and CDT (488 km^2 , 5.8% of the CDT corridor). Based on the spatial intersection of the Hansen Forest Loss and MBTS burn area vector polygons, 59% of the Hansen Forest Loss was caused by wildfire.

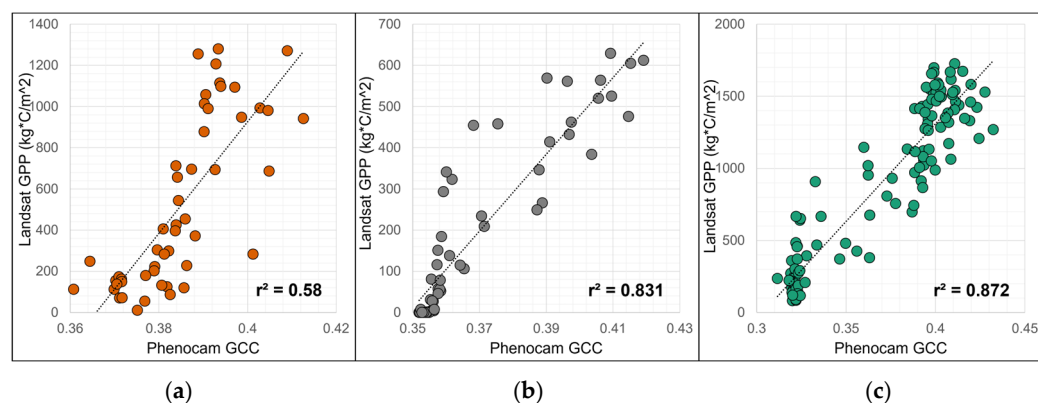


Figure 4. Scatterplots comparing the PhenoCam GCC estimates and the Landsat-derived GPP for (a) PCT Sagehen PhenoCam site (39.431°, −120.239°), (b) CDT Butte PhenoCam site (45.95°, −112.479°), and (c) AT NEON D02.SERC.DP1.00033 PhenoCam site (38.89°, −76.560°).

The monthly time series show variable quantities of forest loss along the PCT corridor each year, with the maximum forest loss occurring in 2021 (Figure 5a). PCT forest loss is often associated with wildfire events, such as the devastating 2021 wildfire season (Figure 5b). Analysis of the CDT forest loss data indicates a concentration of forest loss in the northern portion of the trail along the Canadian Rockies, with additional hotspots in the Southern Rockies and Arizona/New Mexico Mountains (Figure 5c). The AT tree loss is concentrated in the Northern Appalachian and Atlantic Maritime Highlands in the far northern portion of the trail within the state of Maine (Figure 5c). Deforestation in this region is not caused by wildfire but is instead driven by logging [26], such as the timber harvesting near East Carry Pond.

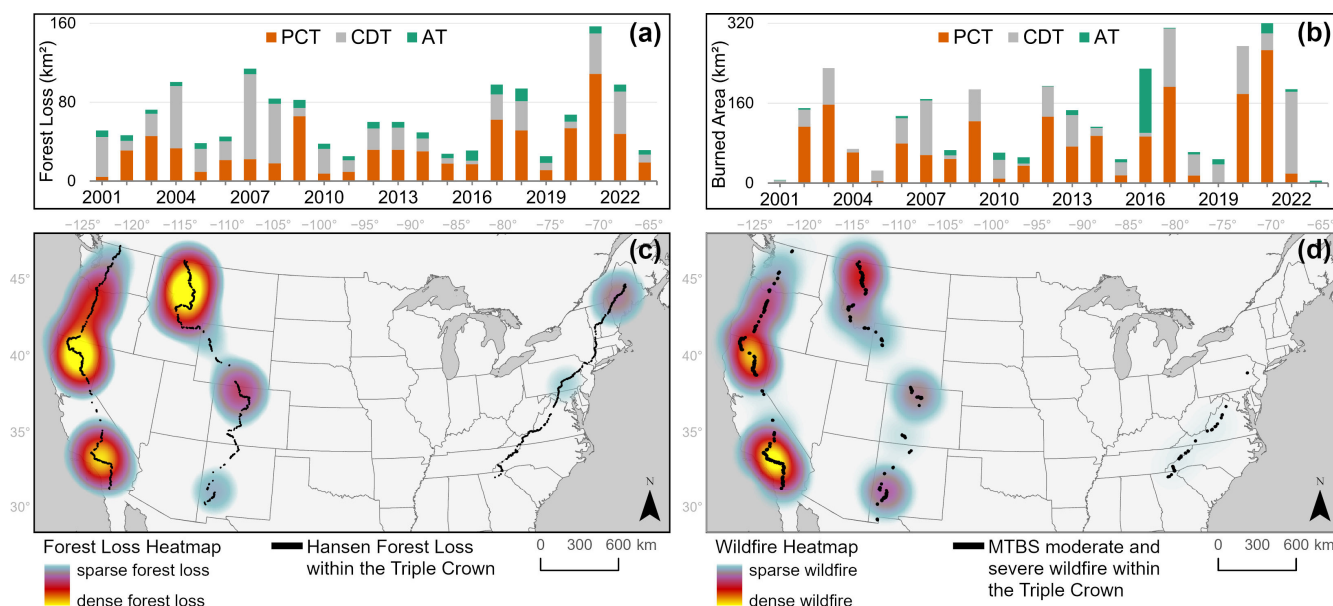


Figure 5. Time series (a,b) and heatmaps showing the density of the (c) Hansen Forest Loss events and (d) MTBS moderate and high severity burns 2001–2023.

3.2.2. Wildfire

The MTBS wildfire data indicate a total of 1073 km² burned at moderate or high intensity (levels 3 and 4) during the study period. While the Hansen Forest Loss data include many burn area boundaries, 330 km² of additional wildfire locations were not

captured in the annual Hansen Forest Loss dataset. This includes fires on unforested lands, such as grassland, and wildfires within landscapes with rapid recovery.

Most of the moderate and high-intensity wildfire burn areas occurred within the PCT corridor (66% of the fire area), with 33% within the CDT and less than 1% of burned areas within the AT. The annual wildfire burn area is significantly correlated with the annual forest loss along the PCT ($r^2 = 0.68$), with the correlation exceeding the 99% confidence level. However, the relationship between the burn area and the forest loss is less significant along the CDT and AT (Figure 6). The drier conditions in the western U.S. and the seasonal occurrence of winter precipitation create a strong seasonal cycle of wildfire occurrence during the summer months on the PCT and CDT (Figure 7). Along the southern portion of the PCT, the Station Fire burn in 2009 occurred in the Southern and Baja California Pine-Oak Mountains near Los Angeles, CA, USA [99]. Additional significant wildfire hotspots on the PCT center on the 2020 and 2021 wildfires in California's Sierra Nevada mountain range (e.g., 2020 Claremont fire, 2020 Lionshead fire). The 2021 Dixie fire burned over 100 trail miles of the PCT [100]. The PCT wildfire hotspots then extend northward into the Klamath Mountains of northern California and up through the Cascades of Oregon and Washington, which experienced severe burns in 2017 [101].

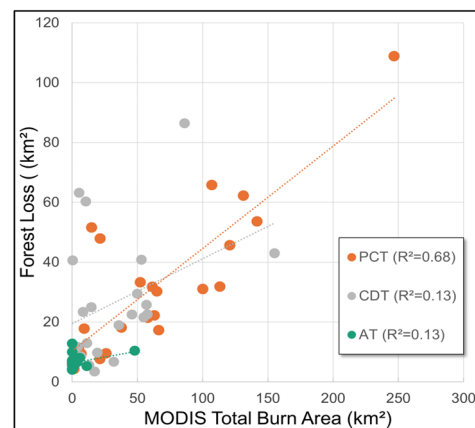


Figure 6. Scatterplot comparing the annual Hansen Forest Loss (km^2) and MODIS-derived burned area (km^2). The annual wildfire burn area is correlated with the forest loss area along the PCT ($R^2 = 0.68$) but the relationship is less significant along the CDT ($R^2 = 0.13$) and AT ($R^2 = 0.13$).

The MTBS and MODIS burn area data along the CDT indicate major wildfire events in the northern portion of the trail along the Canadian Rockies of Montana in multiple years, including the 2006 Red Eagle fire in Glacier National Park, the Fool Creek Wildfire of 2007 [43], and the Meyers Wildfire of 2017 (Figure 5c). The Idaho Batholith ecoregion was also prone to persistent wildfires, with burn events occurring repeatedly in the past four years. A third hotspot of CDT wildfire activity is in the Southern Rockies near Rocky Mountain National Park, Colorado. The wildfires in this area include the 2020 East Troublesome Fire, Colorado's second-largest wildfire on record [44]. Finally, in the southern portion of the CDT, the 2022 Black Fire in New Mexico was the largest in the state's history and directly burned more than 45 miles of the trail path [49].

While the AT experienced relatively few wildfires directly along its 2 km corridor, a significant event occurred in late 2016 within the Great Smoky Mountain National Park in the southern Appalachians [45] and is visible on the MODIS burned area time series (Figure 5c) and map (Figure 5d).

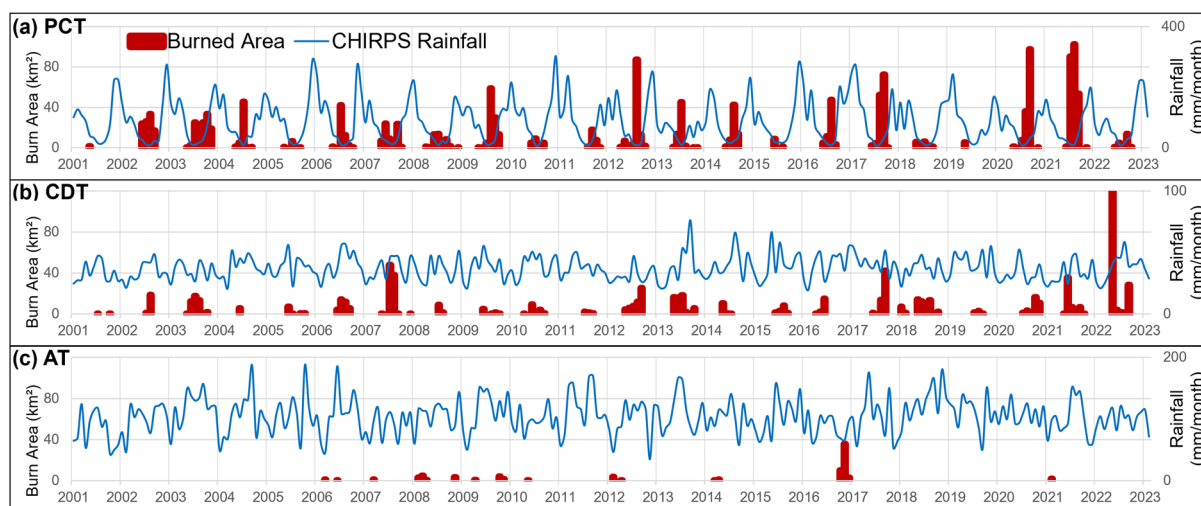


Figure 7. Dual-axis time series showing the relationship between the monthly MODIS burned area and CHIRPS average monthly rainfall for (a) the PCT, (b) the CDT, and (c) the AT. Note the different y-axis values for rainfall on each trail. Wildfires along the PCT are frequent and highly seasonal, occurring during dry summer months.

3.2.3. Recovery

Of the fifteen high-disturbance sample sites selected for the vegetation recovery analysis, eleven of the locations were confirmed as wildfire sites based on the MTBS fire severity and MODIS burn area data. Of the seven spectral indices tested using the LandTrendr model (NBR, NDVI, NDMI, TCB, TCG, TCB, and TCA), the NBR performed best on temporal segmentation fitting with lower RMSE values. The 15 sites showed variable rates of NBR recovery following forest loss events (Figure 8). The NBR values remained lowered for many years after disturbance, with an average NBR of 0.6 pre-event, -0.04 immediately following the event, and 0.31 five years later. For the six sites that fully recovered the pre-disturbance NBR values, the average time until total recovery was 10.8 years, as some locations rapidly improved (e.g., Figure 8k,o) and other locations took 15–20 years to recover the NBR values (e.g., Figure 8a,c).

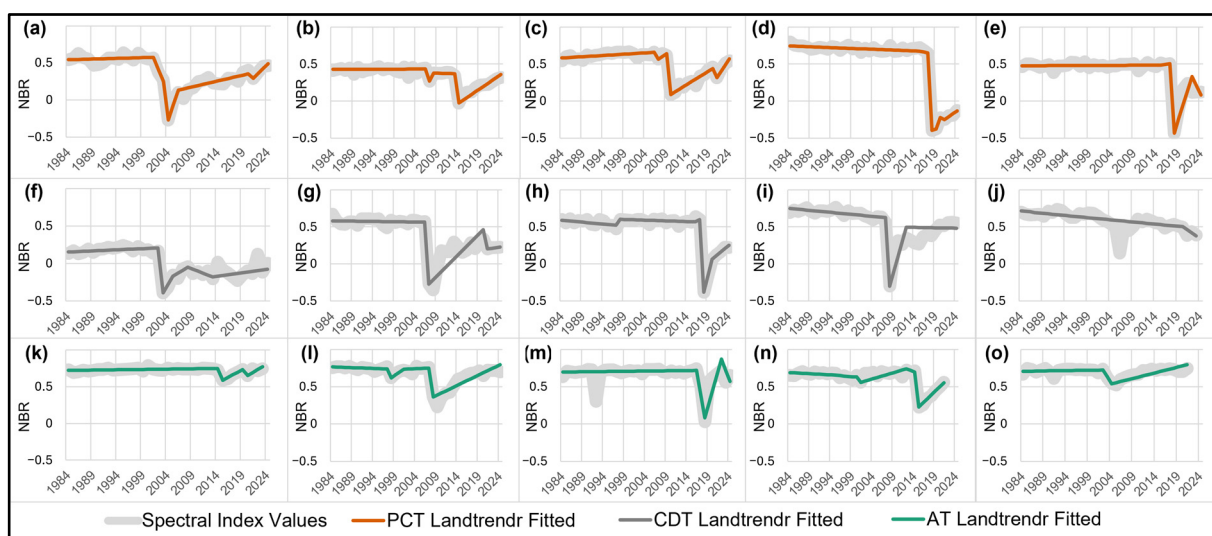


Figure 8. Forest loss impact and recovery for selected disturbance sites on the PCT (a–e), CDT (f–j), and AT (k–o) based on the Landsat-derived NBR spectral index values and LandTrendr temporal segmentation, where higher NBR values indicate more vegetation. The average NBR values decreased from 0.6 pre-event to 0.31 five years later.

The more arid western PCT and CDT trails exhibited slower recovery and more frequent changes in land cover after forest loss. Notably, four of the CDT sites (Figure 8f,g,i,j) had not fully recovered the pre-disturbance spectral index values more than 15 years after the disturbance event. The sites that changed vegetation more permanently include the PCT sample site (Figure 8c), which burned in the August 2009 Station Fire in the Southern and Baja California Pine-Oak Mountains of California (Figure 9). Analysis of the MODIS MCD12Q1 data at this location demonstrates the transition from a dominance of evergreen needleleaf forests before 2009 to grasslands and subsequent savanna-dominated systems after the wildfire and continuing through 2023 (Figure 9a). The National Agriculture Imagery Program (NAIP) high-spatial-resolution 1 m aerial imagery from 2009 and 2010 show the fire impact on the PCT trail and surrounding vegetation (Figure 9b,c). Comparison of the spectral index performance and the LandTrendr temporal segmentation shows the slow vegetation recovery captured by most spectral indices (Figure 9d). The TCB index did not effectively capture the impact of the Station Fire event and the TCB failed at 12 of the other sample sites, as well. While the NDVI was able to capture the Station Fire, the NDVI did not capture forest disturbance at four of the sample sites.

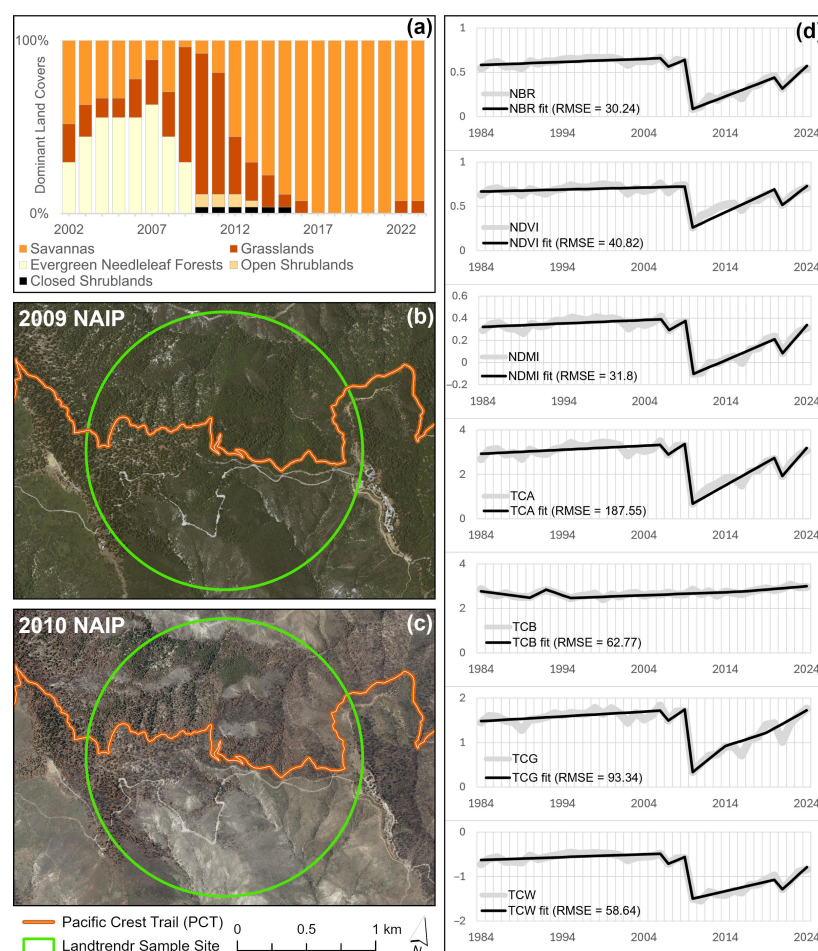


Figure 9. Vegetation recovery analysis at PCT trail site C (34.379, −118.164) following the 2009 Station Fire. The MODIS MCD12Q1 land cover analysis for the study site (a) shows a transition from abundant evergreen needleleaf forest (2002–2008) to grassland (2009–2011) and savanna (2012–2023). The NAIP aerial imagery from (b) 22 June 2009 and (c) 7 June 2010 shows the loss of vegetation resulting from wildfires. The LandTrendr temporal segmentation with various spectral indices (d) reveals the impact of wildfire on the study site and the gradual revegetation over time.

3.3. Phenology

Seasonal metrics derived from the MODIS NDVI values indicate gradual variations in the vegetative phenology throughout the 2001–2024 study period (Figure 10). However, none of the trails indicate a statistically significant trend toward advancement or delay in either the start-of-season, end-of-season, or peak productivity metrics at the broad scale of this analysis. Temporal analysis of the annual snowmelt conditions indicates snow is melting around 0.65 days earlier per year on the PCT and around 0.72 days earlier per year on the AT.

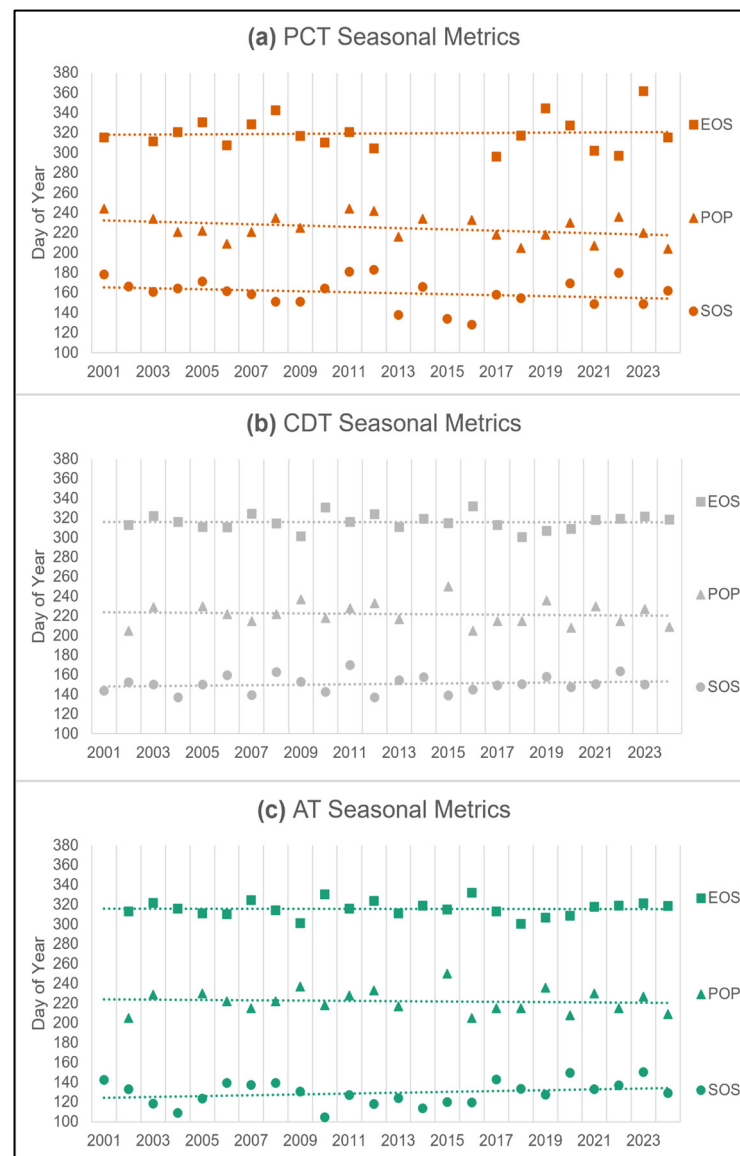


Figure 10. MODIS NDVI time series plots showing the start of season (SOS), peak of season (POS), and end of season (EOS) for the (a) PCT, (b) CDT, and (c) AT.

The MODIS NDVI boxplots show strong seasonal signatures across all three trails, with increased NDVI values during summer months (Figure 11). The AT shows the highest NDVI values, with the summer median NDVI often exceeding 0.7. In contrast, the PCT is located in a much drier climate and the seasonal growth shows less of a pronounced effect. The CDT includes vast expanses of desert and the median NDVI values are much lower in comparison.

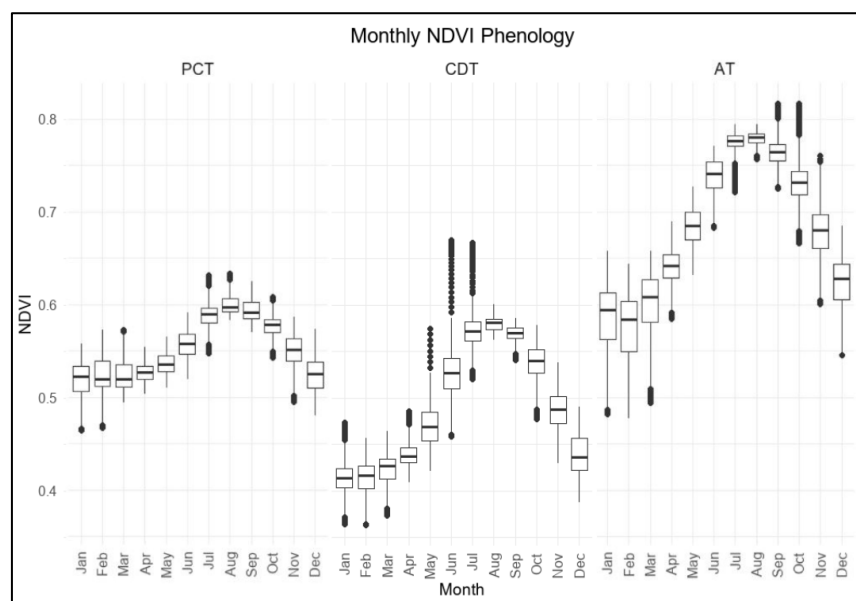


Figure 11. Boxplots and whisker plots showing the monthly NDVI for the PCT, CDT, and AT.

4. Discussion

The broad, comparative analysis of the vegetation dynamics across the Triple Crown trail system revealed changing dominant land covers, hotspots of deforestation, and significant impacts of wildfire. The land cover change and the transition from needleleaf forests to grasslands along the western PCT and CDT likely resulted from a combination of wildfires, dry climatic conditions, and invasive species [41]. Prior studies indicate wildfire occurrence and transition to shrub and herbaceous land cover increased more significantly in warmer areas with temperatures above 17.5 °C [102]. As the climate continues to warm, the land cover shift away from forested habitats will likely continue along these trails.

The tree cover loss documented in southern regions such as the Southern and Baja California Pine-Oak Mountains in this study may also result from the impact of invasive species. Invasive species such as the Western Pine Beetle and Spruce Beetle cause widespread die-off of Ponderosa pine forests along the PCT and disturb ecological dynamics [6]. The full impact of these invasive species may not be captured using MODIS or Landsat imagery as the shortcomings of optical spectral indices in identifying invasive species using satellites are documented [5]. In the Appalachian Mountains, acid rain and Hemlock decline from the invasive Woolly Adelgid have significantly transformed the forest structure [3], but these impacts are best identified with high-resolution imagery and often require manual digitization and ground-truthing to quantify the understory dynamics [7].

Seasonality highly influenced terrestrial productivity across the Triple Crown network throughout the 35 years of analysis. On the AT, the highest median GPP values occurred in recent years, potentially a result of warmer temperatures and increased atmospheric carbon levels from anthropogenic climate change [103]. The PCT showed a slight dip in GPP after 2017, likely related to wildfire events. Even after ecosystem conditions improve to the initial state, there is often a delay in vegetation biomass recovery [104]. In the state of California, the large fire burn area and increased fire severity in recent years have decreased the carbon uptake in affected areas [105]. The increase in the annual NPP over the 35-year time period across all three trails is consistent with warmer temperatures and longer growing seasons associated with climate change [106]. While this analysis is intentionally broad in scale, it must be noted that ecosystem productivity is highly dependent on microclimate and environmental variables and may differ greatly across the study area based on local factors and elevation [107].

The lower correlation between the PhenoCam GCC and Landsat-derived GPP at some sites is likely explained by the different vegetation covers in arid environments. The GCC data for the PhenoCam locations in the Southern and Baja California Pine-Oak Mountains section of the PCT showed significantly lower accuracy than other sites, potentially due to the drought and wildfire conditions in the region. Some ecoregions within the Triple Crown network are better suited for vegetation monitoring with remote sensing, as was indicated by the weaker correlation between the PhenoCam data and Landsat GPP in Northwestern Mountainous Forest [73]. There are also possible discrepancies between the PhenoCam GCC and Landsat GPP due to the large spatial resolution accompanying Landsat products. In addition, ground-based PhenoCam estimates are unavailable across most of the trail system and the eleven PhenoCam stations used here are not representative of all the ecosystems. Vegetated areas such as the PCT Klamath Mountains and Eastern Cascades Slopes and Foothills and the CDT Canadian Rockies and Idaho Batholith do not have nearby PhenoCam data within 15 km of the study site. In addition, more arid areas, such as the CDT Chihuahuan Desert, Arizona/New Mexico Mountains and Plateau, Wyoming Basin, and the PCT Mojave Basin and Range, are also missing PhenoCam validation data. While the MODIS NDVI estimates were not validated with PhenoCam data in this study, in Thapa et al.'s [77] study various sensing methods for forest phenology were tested and correlation ($r > 0.93$) was found between the in situ PhenoCam data and MODIS estimates. To support the more accurate assessment of vegetation dynamics, funding and installation of additional PhenoCams within a variety of ecosystems is required. As technology advances and infrared spectrometry becomes more widely implemented at PhenoCam sites, using in situ NDVI estimates could improve the validation accuracy.

The Hansen Forest Loss analysis revealed that forest loss events were heavily driven by wildfire, particularly along the western trails. This study documented the prevalence of wildfire on the PCT and the increased frequency and severity of these events over the past few decades [108]. The loss of tree cover due to the increased occurrence of wildfires is well documented in California [102]. Wildfire also devastated portions of the CDT during the study period. For example, the Calf Canyon/Hermits Peak Fire in 2022 was the largest and most destructive wildfire in New Mexico's history and impacted land cover as well as air quality [49]. PCT and CDT ecoregions such as the mid-elevation Southern Cascades and the Northern Sierra Nevada have a long history of recurring wildfires [46,109]. After low to moderate burn events, robust growth of understory species can lead to increased biodiversity. However, the increased severity of recent fires coupled with warmer and drier climate conditions can slow ecosystem recovery and may require habitat restoration efforts [110].

The LandTrendr recovery analysis demonstrated the lasting impact of forest disturbance. While some locations recovered quickly, the multiple years being required to reach stability after severe forest disturbance is consistent with the analyses by Cohen et al. [83] and Hughes et al. [111]. While multiple spectral indices performed strongly for the temporal segmentation, the NDVI was unable to capture forest disturbance at four sites and the TCB failed at thirteen sites. While the NDVI is a standard index of vegetation "greenness" with broad applicability, spectral indices using the SWIR band have shown increased sensitivity in leaf-on conifer canopies [112]. Indeed, SWIR-based indices such as the TCW and NBR exhibit stronger performance for forest disturbance detection [113] and exhibited the best fit with lower RMSE values in this study. Locations with faster recovery were associated with smaller disturbances and less severe wildfires [104]. In locations with severe wildfire occurrences, such as the Southern and Baja California Pine-Oak Mountains, a shift to a more herbaceous grassland habitat occurred. Prior research by Oseghae et al. [53] also

indicates that the presence of long-needle timber litter is correlated with the occurrence of high-intensity wildfires in Central California.

While many of the spectral indices performed well, the interpretation of a single vegetation index may pose issues for accurately detecting certain forest disturbance types [114]. In addition, the LandTrendr model was applied using the median reflectance values across a 1000 m study area, which may fail to capture the loss of forest species scattered throughout the canopy, such as the Eastern Hemlock. Another potential limitation of this study is the compositing timestep used by the LandTrendr fitting algorithm, as lower temporal resolutions may miss inter-seasonal variability at shorter time intervals [115,116]. For example, numerous locations experiencing low-severity wildfires (MTBS data) did not appear within the annual Hansen Forest Loss data, potentially due to recovery within less than one year. The site-specific parameterization of the LandTrendr model also influences the fitting algorithm and recovery estimates [116,117]. As consistent model parameterization was implemented in this study, some environments may have more accurate recovery estimates than other locations.

The phenological metric analysis indicated no significant change in the trends of vegetative emergence or senescence at the broad scale used in this study. The variability in the seasonal change across the study zones suggests a high degree of influence from the specific environmental contexts of each trail. A lack of phenological trend has been identified in other large and mountainous study sites, such as the Tibetan Plateau [118]. While general trends of spring advancement and autumnal delay have been identified, the large latitudinal span of each study zone complicates analysis of the entire zone, as previous studies have identified spatial variability in the phenological shifts across latitudes. For instance, along the Appalachian Trail (AT), the phenological shifts analyzed using citizen science datasets revealed variation in the phenological change based on the latitude, with the greatest advancement of trees and understory plants (~ 10 days/ $^{\circ}\text{C}$) occurring in the mid-Atlantic region, while other regions remained phenologically stable [4]. Elevational effects often play an important role in phenological shifts; one study in the Great Smoky Mountains National Park showed that elevation had the greatest effect in spring months [119].

In addition, the variability in the response between vegetation species is an important factor, as different species within an environment advance their phenologies at different rates as a response to climatic changes. For example, studies have found spring-flowering herbs to indicate an earlier emergence than trees [120]. These species-specific responses underscore the importance of considering the vegetation composition when interpreting phenological trends. Identification of shifts in the senescence delay and emergence advancement may also vary based on the index being used; for example, a study in the western U.S. found that the NDVI typically shows a longer spring season and an earlier peak day than the normalized microwave reflection index (NMRI), an index sensitive to the moisture content in vegetation [121]. While this analysis could not determine significant trends for the senescence delay, autumnal phenological metrics are less strongly linked to temperature increases than spring phenological metrics [122]. Precipitation and soil moisture are significant drivers of senescence timing, but with such large variability in these drivers across each study zone, their impact is less clear.

The MODIS NDVI boxplot analysis revealed distinct seasonal signatures in each trail, showcasing their unique environmental contexts. The AT produced the highest NDVI values, indicating the dense and productive vegetation in the temperate and moisture-rich climate [123]. The PCT is characterized by a drier and more varied climate, passing through many more ecoregions, ranging from arid desert to alpine environments. The CDT, however, exhibits the lowest median NDVI values, consistent with the trail's expansive desert

and steppe regions, where sparse vegetation and limited moisture constrains vegetative productivity.

The annual analysis of each trail's first "no snow" dates showed a significant trend toward earlier snowmelt on the PCT and AT. The shortened snowmelt periods and the associated earlier spring onset along the PCT may be linked to a trend of lengthened vernal windows, as described by Contosta et al. [124]. Analysis of the CDT showed a less variable snowmelt trend, with no signs of advancement, possibly owing to its higher elevation zones providing a buffering effect against year-to-year variability.

A limitation of this study is the sampling bias and irregularity of the satellite observations across large study areas and diverse climates. This lack of consistent satellite observations creates uncertainty when interpreting vegetation trends across space, as environments with consistent cloud cover have fewer observations [23]. Additionally, the increase in observations over time may skew the interpretation of long-term multidecadal vegetation trends [125]. Recommendations for future research include the use of high-temporal-resolution nanosatellites to analyze the daily patterns in plant senescence at higher spatial resolutions across the trail system (e.g., Planet, MAXAR). In addition, a comparative analysis of the local phenological shifts within isolated environments throughout the trail system is required. As savannas and grasslands may be misclassified at the boundaries of their environmental ranges, implementation of high-resolution land cover classification would help land managers track the decline in forested land cover [126].

5. Conclusions

The results of this study reveal significant vegetation changes along the 12,674 km Triple Crown National Scenic Trail system due to shifting land covers, frequent wildfire events, and slow recovery after disturbances. The vegetation within the 20,556 km² conservation corridor transitioned over the past two decades, with an increase in grasslands and a decrease in woody vegetation along the PCT and CDT. Between 2001 and 2023, wildfires affected 1248 km² of the study area (9.5% within the AT, 39% within the CDT, and 51% within the PCT). As the frequency and severity of wildfires is projected to increase in the future [127], these vegetation transitions are likely to continue.

In the analysis of the vegetation recovery, the 15 sample sites demonstrated an average recovery period of 10.8 years to the pre-disturbance normalized burn ratio (NBR) spectral reflectance values. The results indicate that all the trails exhibit a highly seasonal growth pattern, with the AT exhibiting the most extensive forest cover and highest productivity, followed by the PCT and CDT. The shifts in vegetation health, as indicated by the increased net primary productivity (NPP) and earlier snowmelt, suggest potential impacts of climate change. However, shifts in the start-of-season and end-of-season phenology could not be conclusively identified at the broad spatial scale of this study.

To advance the science, future studies should investigate more localized land cover and phenological shifts within the Triple Crown, as vegetation responses vary across species and ecoregions. In addition, installation of additional PhenoCam sites would support more localized validation approaches compared to the analysis performed here.

This study underscores the utility of remote sensing in conducting comprehensive, landscape-level analyses over large geographic areas. The findings offer trail managers and citizen participants essential data to identify vulnerable vegetation along the trail system, which may require additional conservation efforts. By contributing to trail management and conservation initiatives, this work emphasizes the importance of ongoing monitoring of the vegetation dynamics within these protected corridors of the Triple Crown National Scenic Trail system.

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Conflicts of Interest: Author Dylan F. Ricke was employed by the company Jacobs Engineering but this company does not have any direct financial interest in the monitoring or management of the National Scenic Trail conservation lands considered in this research project. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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