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RESEARCH

Monitoring the operational changes in surface reflectances after logging, based on popular indices over Sentinel-2, Landsat-8, and ASTER imageries

Çiğdem Özer Genç · Arif Oğuz Altunel

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Abstract Revealing the status of forests is important for sustainable forest management. The basis of the concept lies in meeting the needs of future generations and today's generations in the management of forests. The use of remote-sensing (RS) technologies and geographic information systems (GIS) techniques in revealing the current forest structure and in long-term planning of forest areas with multipurpose planning techniques is increasing day by day. Significant technological advances are in allowing programmers to modernize how they manage data. Sentinel-2, which is a relatively new addition to Earth observing satellites, is a new-generation satellite that has enabled classification and monitoring of land cover change with high precision at ease. Visible R, G, B, and near-infrared (NIR) bands have offered exceptional 10-m spatial reasolution, making them suitable for vegetation monitoring along with the additional 20-m bands to spare especially in chlorophyll content analyses. On the contrary, Landsat-8 and ASTER which have been longer lasting in Earth observation were rougher results especially in forestry studies. In this study, Landsat-8 and ASTER satellite images were compared against the Sentinel-2 images as a reference in conjunction with GIS techniques to monitor and assess the impact of various logging procedures, including selective logging and regeneration silviculture. The investigation employed a range of plant vegetation indices, including NDVI, GNDVI, and SAVI, to evaluate the efficacy of image resolution in detecting forest cover changes in the Kastamonu region, where the timber production is the hightest in Turkey. For selective and regeneration activities, satellite images were taken pre-harvesting and immediately post-harvesting, and index maps were produced. NDVI, GNDVI, and SAVI indices were the most accurate indicators of green vegetation change in the Sentinel-2A imagery. Similarly, for the Landsat-8 imagery, the SAVI, NDVI, and GNDVI indices were found to be satisfactory indicators. As for ASTER imagery, the success sequance was like SAVI, GNDVI, and NDVI. Based on the findings of this study, it has been noted that the ASTER imagery closeness to Sentinel-2A was more remarkable in detecting changes in green vegetation in forested areas. The data derived from ASTER imageries demonstrated superior efficacy compared to Landsat-8 in generating forest cover maps, owing to their proximity to those produced by Sentinel-2. The findings also indicated that ASTER imagery, with suitable spatial and spectral resolution, could still be utilized as efficienly as Landsats to generate forest cover density maps and monitor long-term forest conservation practices, particularly in professionally managed forests. Thus, this methodology demonstrated the capacity for efficient worldwide forest management.

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Introduction

Forest-based ecosystems are at the forefront of sustainable development processes. Forests that are the basic building blocks of those are the leading renewable natural resources, which provide commodity and ecosystem services for the well-being of societies (Maier et al., 2021). Just like the other revenue generating ones, forests need to be managed, rationally and productively (Tolunay, 1999). While providing for the people, forests are seriously affected by human-induced development attempts and changes. Rapid population boom experienced all across the Earth during the past quarter century put pressure on forests (Buras et al., 2021; Maja & Ayano, 2021; Rudel, 2023). The rise in population has inadvertently forced the rural population, predominantly residing in proximity to forested regions, to rely more on the forest resources. Consequently, this has contributed to the occurrence of illicit activities within forest areas (Cesur & Bulut 2023; Tolunay, 1999). Furthermore, the influence of social and economic factors on forests, the competence of forest management professionals, the capacity of state agencies to regulate forests, silvicultural processes, and their execution have all exerted a significant impact on forests (Ashton & Kelty, 2018; Ellis et al., 2019).

Silvicultural interventions and natural disturbances are the primary elements influencing forest dynamics in natural forestry management. Forest clearance can typically be quantified as the percentage of forest area represented by the vertical projection of tree canopies (Čater et al., 2014). Common forest management practices such as natural/artificial regeneration, tending, and selective cutting should prioritize the preservation of the natural structure and balance. The utilization of forest ecosystems is primarily regulated by the harvesting activities and utilization of other functions offered by the ecosystem. Therefore, by employing resolute and well-executed logging methods, it becomes feasible to minimize forest degradation, mitigate the occurrence of insect and fungal damages, and enhance the habitat, thereby promoting sustainable forest management (Ozer Genc & Aricak, 2022; Hu et al., 2022). It is crucial to monitor forest cover changes at global, regional, and local levels in order to inform future decision-making and planning related to sustainable forest management. Thus, ensuring the sustainable management of Türkiye's forest ecosystem, renowned for its abundant biodiversity, is crucial at both local and global levels. However, to achieve success in forest resource planning, it is imperative to have current and trustworthy information and knowhow (Saglam & Sakici, 2024; Kangas et al., 2006; Schreuder et al., 1993). Remote-sensing technologies here provide the most reliable, efficient, and accurate means to determine and monitor the abovementioned circumstances in large forest regions.

Optical satellite images formed with various spectral bands are frequently employed to detect changes in forest areas (Lambert et al., 2015; Borrelli et al., 2014). Since the early 1970s, first the USA, then French, and Japan have extensively employed modern technology to develop and utilize medium resolution satellite images, such as Landsat, Sentinel, ASTER, Spot, and Modis, for various purposes. Although limited in the beginning, these images possessed abundant spectral bands and have particularly been valuable in detecting temporal and spatial variations, as well as creating comprehensive thematic maps for national forest inventories (Dees et al., 1998; Akay et al., 2017; Puliti et al., 2021; Pi et al., 2021). By employing these means and capabilities, it becomes feasible to identify deforestations and yearly alterations in vegetation coverage particularly in coniferous forests. Using Landsat™ images, methodologies employing pixel-oriented techniques have generated nationwide annual forest cover change distributions (Zhang et al., 2023; Jawak et al., 2015). Sequential Landsat images could be configured to detect the degree of logging/forest harvesting interventions. Likewise, dual Sentinel-2 imagery (A and B), thanks to their 13 spectral bands, especially with the ones having 10 m ground resolution, has facilitated the detection of vegetation condition variations (Soffianian et al., 2023). Therefore, more research is still up for grabs to determine the additional practicality of Sentinel-2's band combinations on forest cover variations. Similarly, ASTER imagery, which has long been used for change (French et al., 2008; Hariyanto et al., 2023), surface temperature (Boori et al., 2015; Jimenez-Munoz & Sobrino, 2009), and mineral deposit (Oliver & Van der Wielen, 2006) detection, has also been a tried and tested program to see if it would also be able to detect production-related changes in forest stands.

Landsat data has offered one of the most significant datasets for observing the Earth's surface during the past 50 + years (Topaloğlu et al., 2016). The Sentinel-2 program, on the other hand, has been acquiring data since 2015 and possesses superior spatial, spectral, and temporal capabilities (Immitzer et al., 2016; Lefebvre et al., 2016; Paul et al., 2016). Consequently, evaluating the performance of various satellite image datasets can render data analysis as dependable as that derived from field observations. In instances where imageries are unavailable for download or access is restricted, alternative sensor-generated products may be utilized alternately. Numerous research exist on this subject within the literature. Various sensors interact by assessing which sensor can be substituted with another within a specific detectable band (Korhonen et al., 2017). The absence of access results from restrictions enforced on certain nations or adverse weather conditions that hinder satellite picture acquisition. In this instance, other measurement procedures may be employed. Zhang et al. (2018) examined the impact of atmospheric correction on spectral indices derived from Sentinel-2 and Landsat-8 imageries. This study's findings indicated that the normalized vegetation index (NDVI) derived from Sentinel-2 and Landsat-8 data exhibit no statistically significant differences. Thus, the NDVI values from one can be utilized in place of the other as required. Feng et al. (2021) indicated in a separate investigation that Sentinel-2 images shown superior performance in the extraction of built-up regions. The superiority became more apparent when spectral indices were employed in the classification procedures (Xie et al., 2020).

Large regions have provided enough extent for assessing vegetation cover changes (Xiao & Moody, 2005), and many researchers have employed satellite-based indices to do so (Jiang et al., 2008; Kallel et al., 2007). Numerous vegetation characteristics, including leaf area, biomass, diameter at breast height (DBH), canopy cover %, age class, height, basal area, and tree volume, were assessed using these indices (Baret & Guyot, 1991; Verrelst et al., 2008). Utilizing vegetation indices is crucial for improving the efficiency of sustainable forest management and for understanding the world's forest cover dynamics. In order to examine the relationship between forest parameters, the normalized difference vegetation index (NDVI), green normalized difference vegetable index (GNDVI), and soil-adjusted vegetable index (SAVI) have been investigated in a large number of research papers and are extensively used in forest research. For example, SAVI reduces the background effect by accounting for the soil's changing optical characteristics. It is utilized in place of NDVI in regions where the plant still acts as cover because the latter is unable to produce reliable data due to the influence of the soil. According to Basso et al. (2013), it can be used to forecast the biophysical characteristics of the plant.This study used Landsat-8, Sentinel-2, and ASTER satellite imagery together with GIS approaches to monitor several logging procedures (selective logging and regeneration silviculture), using various plant vegetation indices (NDVI, GNDVI, SAVI) to see if image resolution would be enough to detect subtle land cover changes. Consequently, this investigation would further test their long list of established accomplishments with the addition of logging pattern detection.

Material and methodology

This study was carried out at Karadere Planning Unit within Kastamonu Regional Directorate of Forestry in stands where regeneration and selective logging activities were implemented in 2021–2022 period. The study area is dominated *Pinus nigra* L. stands, and the selective logging and regeneration silviculture respectively cover an area of approximately 328 ha and 70 ha (Fig. 1).

Remote-sensing data

Two different sites were identified where 10-m Sentinel-2 images were used as reference data. Besides, the corresponding frames of Landsat and ASTER imageries were obtained from pre-operation and post-operation dates (USGS Earth explorer portal). A total of 12 satellite images were acquired from the designated logging sites where two distinct silvicultural interventions were implemented, capturing imagery both prior to and following the interventions (2 distinct silvicultural prescription areas × 3 different satellite sensors × 2 temporal acquisitions, before and after). Pre- and post-operation images coinciding with the dry period, May through October, were selected from 2020 and 2022, respectively. The rationale for utilizing photographs from these months was the reduced cloud and snow cover on the vegetation. Dry period was when the bulk of Turkish harvesting operation have continued.

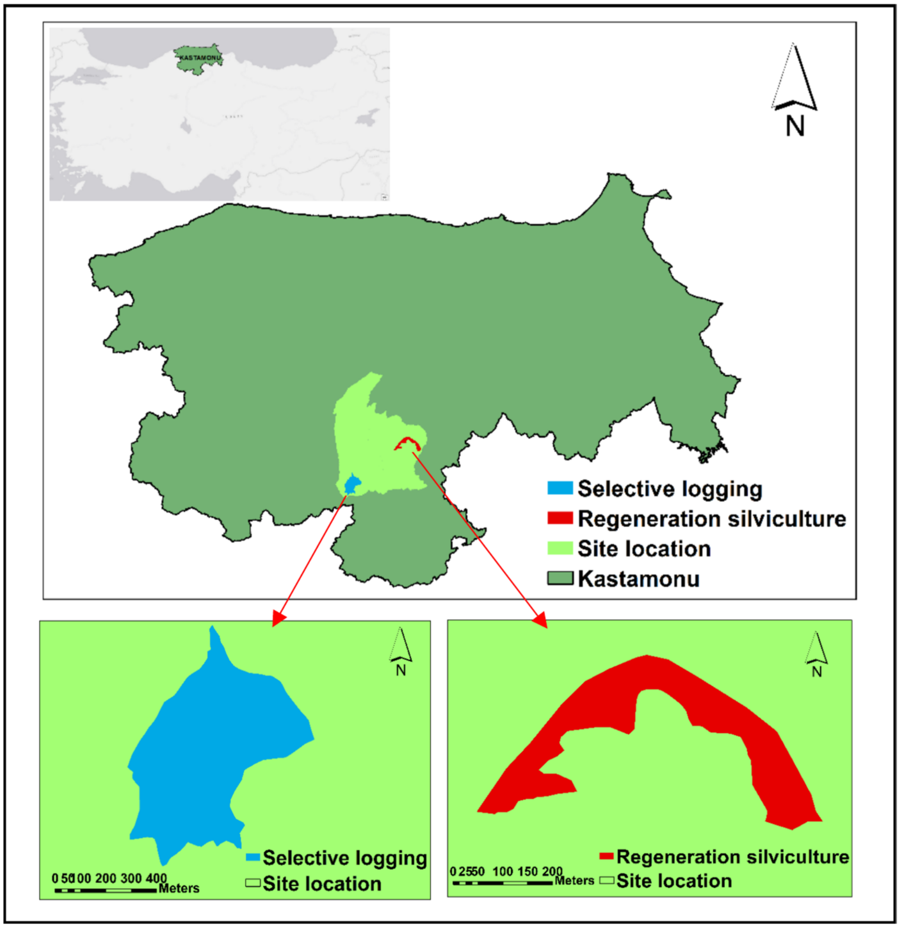

Fig. 1 The study sites location

Methodology

Remote sensing plays a crucial role in detecting and evaluating forest cover, making it a vital tool in natural resource management and decision-making processes. Within this framework, studies were conducted to investigate the vegetation indices and evaluate the land cover changes of various fields using imageries from Sentinel-2, Landsat-8, and ASTER satellites. The objective of this study if land cover change resulting from forest harvesting operations could be satisfactorily detected. Vegetation indices that rely on slope calculations involve the merging of data from the red band and near-infrared band and are extensively utilized (Schmidt & Karnieli, 2001; Silleos et al., 2006). Distance-based vegetation indices, on the other hand, incorporate soil line parameters and/or correction factors in conjunction with the red band and near-infrared band. The ground line depicts the linear correlation between the near-infrared band and the red band of the satellite image. Pixels in close proximity to the soil line are designated as soil, and pixels located further away are designated as vegetation (Baret et al., 1993). The purpose of the soil line correction factor (L) is to mitigate the impact of soil on vegetation measurement. For high-density vegetation, the value should either be 0 or 0.25, whereas for low-density vegetation, the value chosen is 1. The adjustment factor for vegetation with average density is 0.5. The value of L in this study was set to 0.5. The study utilized two slope-based vegetation indexes, namely the normalized difference vegetation index (NDVI) and the green vegetation index (GNDVI), as well as one distance-based vegetation index, known as the soil-adjusted vegetation index (SAVI) (Table 2).

Instead of producing common remote-sensing accuracy assessment metrics, e.g., user, producer, overall accuracies, and Kappa values, we opted to go with areal comparisons because the study's logic did not allow us employ a point-based validation scheme. The sites that were tested for the study were "selective logging applied" vs. "regeneration." Both prescriptions were uniformly applied by the forest service within the stands so not to speculate any wrong doing as might be the case in illegal operations. Assurance for selecting this kind of approach was repeated in several studies (Akturk et al., 2020: Altunel et al., 2020; Akturk et al. 2023; Altunel & Celik, 2024).

Producing vegetation indices from Sentinel-2, Landsat-8, and ASTER satellite images was carried out with the help of raster calculater in ArcGIS 10.5 software. The performances of satellite images in forestry harvesting studies were evaluated by performing plant index analyses with satellite images without and post silvicultural activities for regeneration silviculture and selective logging stands. The study necessitated the use of NIR and red bands. With respect to Sentinel-2's 10-m NIR band, Landsat-8 and ASTER had a 30 m and a 15 m ones, respectively.

NDVI (normalized difference vegetation index)

NDVI is calculated by measuring the discrepancy in reflectance between the red area (caused by pigment absorption) and the highest reflectance in the near-infrared region (caused by cellular structure). The index mentioned, as stated by Aguilar et al. (2012), is extensively utilized in the field of remote sensing (Rouse et al., 1973). NDVI (Li et al., 2021), a very effective measure of vegetation and greenness, is utilized for evaluating the ecological environment (Cai et al., 2015), capturing vegetation phenology (Hmimina et al., 2013; Vrieling et al., 2018), and determining land cover. It is extensively employed for monitoring the land cover dynamics (Baeza & Paruelo, 2020; Huang et al., 2018). Hence, NDVI is thought to be a suitable index for our investigation and may be computed using the equation provided in Table 1 (Zhang & Ye, 2020).

NDVI relates to the rate of radiation absorbed by the process of photosynthesis and evaluates the amount and strength of vegetation on the ground. The NDVI level is directly correlated with the magnitude of the photosynthetic activity in the plants being studied. Typically, higher NDVI values correspond to increased vegetation strength and quantity. NDVI quantifies the extent of green vegetation in a certain area on Earth, serving as an indicator of its coverage (Das et al., 2023).

GNDVI (green normalize difference vegetation index)

GNDVI is an enhanced iteration of the NDVI algorithm that integrates green and NIR light to more accurately represent the fluctuation of chlorophyll levels in plants. Contrary to NDVI, it quantifies the green wavelength range from 0.54 to 0.57 μ as opposed to the red wavelength range (Venegas-Quiñones, 2022). This serves as a measure of the photosynthetic activity of plants. It is commonly employed to assess the moisture level and nitrogen concentration in plant leaves using multispectral data that lacks an excessive red band reflectance variability (Table 1).

SAVI (soil-adjusted vegetation index)

The leaf area index (Broge & Mortensen, 2002) shows a strong association with spectral vegetation indices that rely on red and near-infrared reflectances. Conversely, in regions characterized by limited plant cover, the level of reflection from the ground, namely soil and sand, is significantly greater. SAVI is, thus, employed to rectify the NDVI by accounting for the impact of soil reflectance in regions with limited vegetation coverage (Rondeaux et al., 1996). SAVI, which is derived from the land surface reflectance, is computed by taking the ratio of the R and NIR values. The soil brightness correction factor (L) is set at 0.5 to accommodate a wide range of land cover types. Its calculation closely resembles that of the NDVI. Formulas used to calculate the indices were given in Table 1.

The vegetation values range from -1 to $+1$, while the values for barren and wetlands range from -1 to 0 (Aquino & Oliveria, 2012; Crippen, 1990). The study conducted analyses to evaluate vegetation density, which was classified into three categories: low, medium, and high (Table 2).

Table 1 Formulas used to calculate the indices

Vegetation index	Abbreviation	Equations
Normalized difference vegetation index	NDVI (Rouse et al., 1973)	$NDVI = \frac{NIR-RED}{NIR+RED}$
Green difference vegetation index	GNDVI (Gitelson et al., 1996)	$GNDVI = \frac{NIR-(540:570)}{NIR+(540:570)}$
Soil-adjusted vegetation index	SAVI (Huete, 1988)	$SAVI = \frac{NIR-R}{NIR+R+L} \times (1+L)$

Table 2 Vegetation classess and values (Aquino and Oliveria, 2012)

Vegetation classes	Class definitions	Value
1	Bare soil, water, or very low vegetation density	≤ 0.2
2	Low or moderately low density	$0.2 < * \leq 0.6$
3	Modarately high or high density	$0.6 < * \leq 1$

Results

Forestry activities, including both natural and artificial regeneration efforts, tending operations and selective activities, the construction of forest roads, and natural disasters or illicit exploitations, lead to alterations in the forest ecosystems. Differences in reflection values recorded by the satellite sensors in the forests are caused by several factors such as tree species, crown structure, branch and leaf compositions, and vegetation phase. To accurately characterize vegetation and identify any variations, it is crucial to understand the specific spectral reflectance values exhibited by various species of vegetation throughout the distinct bands in the satellite sensors. The comparison focused on the selective logging and regeneration silviculture activities from production studies, and the evaluation of changes in forest areas was based on the obtained results (Table 3, Table 4).

The investigation revealed that the entire area had a canopy class of 3, as assessed by the NDVI analysis conducted using Sentinel-2 imagery prior to the implementation of silvicultural interventions in the selected stands. Post the selective logging, the three rated canopy class sustained significant alterations, and the stand structure shifted towards the 1st and 2nd canopy grading classes. Based on the GNDVI study, it was established that the area was classified as a closed area of the 3rd class prior to the selective logging. Following the operation, the crown closure shifted towards the 1st and 2nd classes. Following the SAVI analysis, the area exhibited class 3 closure prior to the implementation of the operation. Following the selective logging, it was found that the level of crown closure for the 3rd class reduced to 31%, while the 1st and 2nd classes experienced an increase in the amounts of 67% and 2%, respectively (Fig. 2).

Table 3 Classification values to identify areas pre and post the harvesting operations; Landsat-8, Sentinel-2A and ASTER imageries, respectively

	Sentinel-2				Landsat-8				ASTER			
	Preselective logging		Postselective logging		Preselective logging		Post-selective logging		Pre-selective logging		Post-selective logging	
	Class	Area (%)	Class	Area (%)	Class	Area (%)	Class	Area (%)	Class	Area (%)	Class	Area (%)
NDVI	**3**	100	**1**	9	**1**	94	**1**	100	**1**	4	**1**	13
			2	91	**2**	4			**2**	96	**2**	87
GNDVI	**3**	100	**1**	6	**1**	100	**1**	100	**1**	22	**1**	100
			2	94					**2**	78		
SAVI	**3**	100	**1**	2	**1**	83	**1**	92	**1**	1	**1**	3
			2	67	**2**	17	**2**	8	**2**	96	**2**	96
			3	31					**3**	3	**3**	1

Table 4 Classification values of Landsat-8, Sentinel-2A, and ASTER imageries to detect reflectance changes between pre- and post-harvesting operations

	Sentinel-2				Landsat-8				ASTER			
	Pre-regeneration silviculture		Post-regeneration silviculture		Pre-regeneration silviculture		Post-regeneration silviculture		Pre-regeneration silviculture		Postregeneration silviculture	
	Class	Area (%)	Class	Area (%)	Class	Area (%)	Class	Area (%)	Class	Area (%)	Class	Area (%)
NDVI	**3**	100	1	9	**1**	97	**1**	100	**2**	100	**1**	24
			2	91	**2**	3					**2**	76
GNDVI	**3**	100	1	6	**1**	100	**1**	100	**1**	23	**1**	100
			2	94					**2**	77		
SAVI	**3**	100	3	100	**1**	60	**1**	88	**2**	7	**1**	7
					2	40	**2**	12			**2**	72
									3	93	**3**	21

The NDVI analysis conducted using Landsat-8 satellite imagery revealed that in the selected stands, 94% of the land exhibited a 1st-class canopy, while 4% exhibited a 2nd-class canopy, prior to the selective logging operation. However, post the selective logging, it was concluded that the second-class rating was entirely broken and shifted towards the first class. Based on the GNDVI study, it was concluded that there was no alteration in the canopy of the stand pre and post the selection application. The SAVI analysis of the stand revealed that prior to the selective logging, 83% of the stand had a class stand structure of 1, while 17% had a class stand structure of 2. However, post the operation, the percentage of the second class decreased to 8%, while the percentage of 1st class increased to 92% (Fig. 3).

Prior to the operation, NDVI produced with ASTER imagery showed a stand cover structure of 4% in the 1st class and 96% in the second class. However, post the field procure, the cover in the second class reduced to 87%, while the cover in the 1st class increased to 13%. GNDVI wise, utilizing again the ASTER imagery pre the operation, 22% and 78% of the stand were classified within the first- and second-class stand structures, respectively. However, following the operation, the second-class canopy was completely vanished, and a tendency towards a class canopy of 1 was materialized. The SAVI analyses revealed that prior to the selective logging, the stand exhibited canopy percentages of 1%, 96%, and 3% in the 1st, 2nd, and 3rd classes, respectively. However, following the operation, the canopy percentage of the 3rd class declined to 1%, while the canopy percentage of the 2nd class stayed at 96%. Further, it was also found that the closure rating for class 1 increased to 3% (Fig. 4).

Based on the NDVI analysis results conducted prior to the harvesting operations within the regeneration stands, it was concluded that the canopy closure was classified as 100% and designated in the 3rd class when Sentinel-2 imagery was concerned. Following the analysis of regeneration prescripts, it was concluded that the uniformity experienced in the 3rd class was entirely compromised, exhibiting an inclination towards the 1st and 2nd classes, registering 91% and 9%, respectively. Based on the GNDVI analysis conducted prior to the regeneration prescriptions, it was concluded that the entire stand structure had a canopy classification of class 3. Post the operations, all of the third class gravitated towards the first and second classes, according to the regeneration prescriptions. The results showed that second-class confinement amassed at 94%, while first class stayed around 6% (Fig. 5).

The Landsat-8 NDVI analysis revealed that the pre-regeneration area was categorized into classes 1 and 2. Following the regeneration, it was concluded that the second-class enclosure exhibited a clear shift towards first-class quality. The GNDVI value was found to be consistently high pre and post the stand intervention, indicating a state of optimal closure. Prior to the regeneration works, the Landsat-8 SAVI value indicated that the canopy coverage was predominantly in the 1st and 2nd classes. However, following the intervention, the proportion of canopy in the 2nd class reduced to 12%, while the rest shifted to the 1st

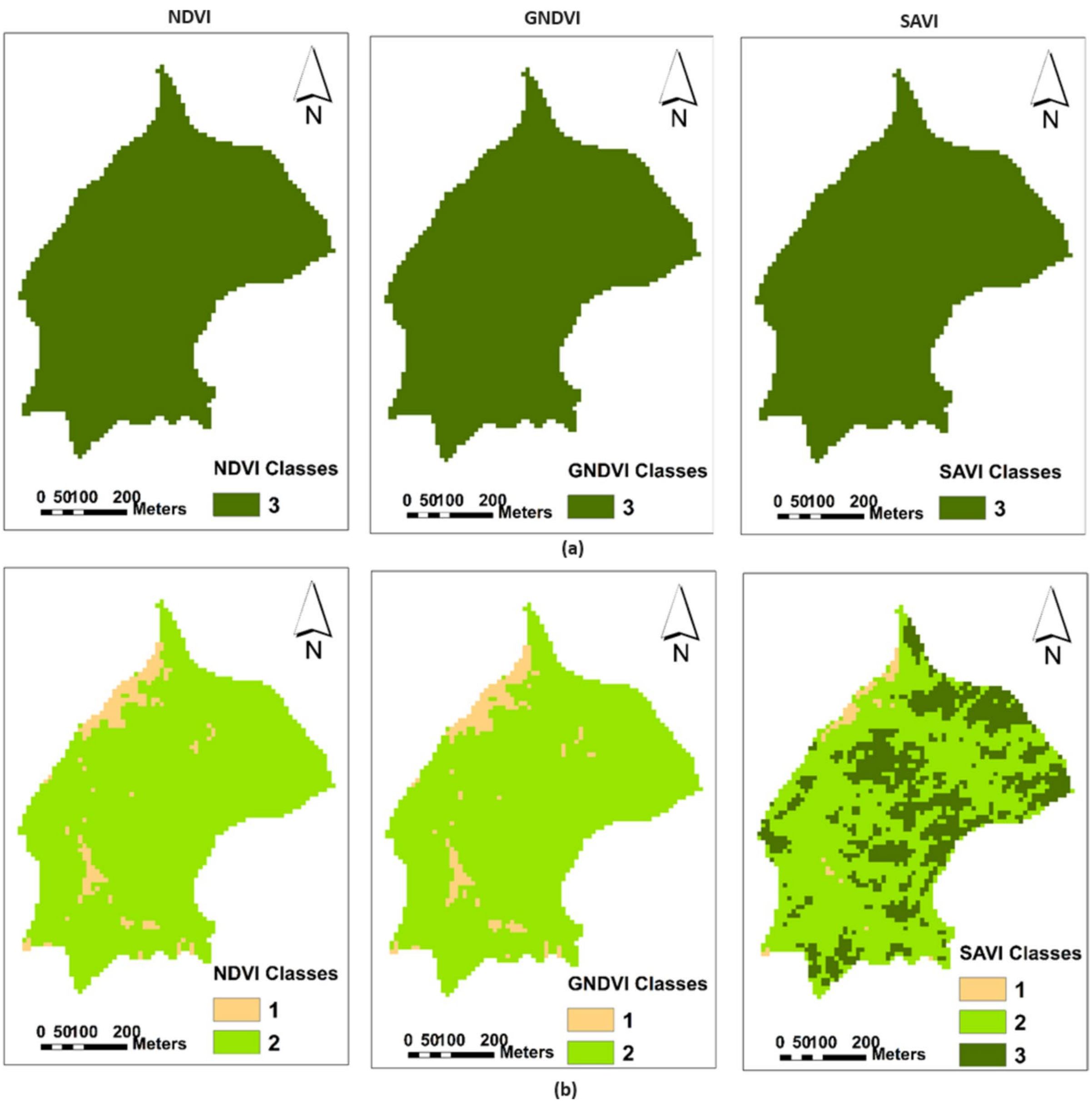

Fig. 2 Maps of the NDVI, GNDVI, and SAVI indices of the Sentinel-2 satellite image pre (**a**) and post (**b**) selective logging

class grew to 88% (Fig. 6). Landsat-8 imagery (30 m) is too coarse to map small-scale forest disturbances in forests, such as those resulting from logging studies.

Pre the application of regeneration, it was found that the Aster NDVI depended acreage was entirely within the 2nd class. Following the application, the coverage of the 2nd class reduced to 76%, while the coverage of the 1st class climbed to 24%. The Aster GNDVI value-dependent acreage was found to be 23% and 77% for the 1st and 2nd classes, respectively, prior to the regeneration. Following the application, it was seen that the 2nd-class coverage was entirely disrupted and exhibited a propensity towards the 1st class. The SAVI calculated acreage was found to be in the 2nd and 3rd classes prior to regeneration works. The 3rd-class closure amounted to 93% of the

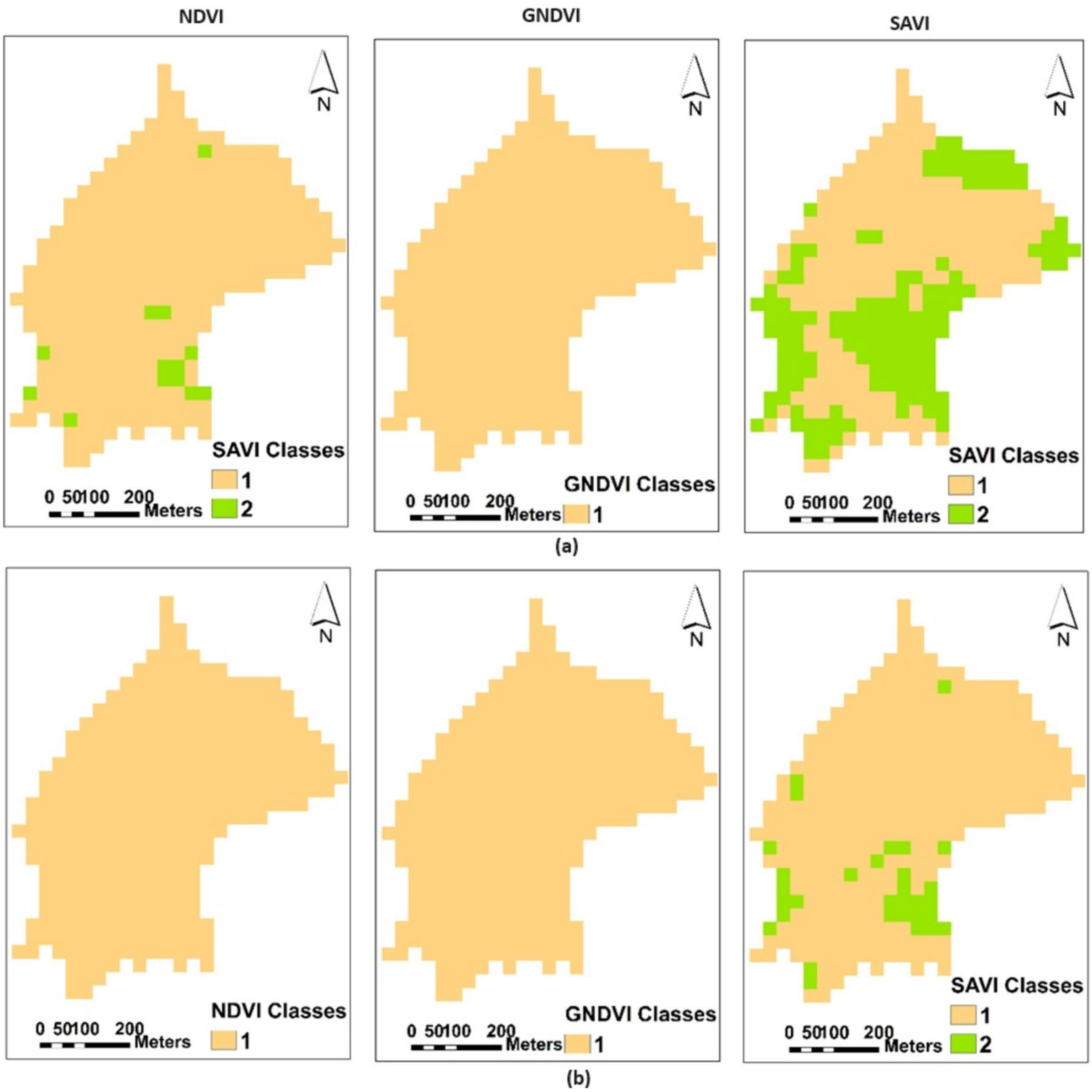

Fig. 3 Maps of NDVI, GNDVI, and SAVI indices of Landsat-8 satellite image pre (**a**) and post (**b**) selective logging

area, while the 2nd-class closure stayed at a meager 7% of the area. Following the regeneration application, the SAVI-dependent acreage reduced to 21% in class 3. The study found that the proportion of class 1 designated coverage climbed to 7%, while class 2 coverage increased to 72% (Fig. 7).

As can be seen from the graph (Fig. 8), within the scope of the study, ASTER and Landsat-8 were compared according to Sentinel-2, and it was determined that Landsat-8 produced coarser values than other satellite images. However, ASTER is closer to Sentinel-2 and has similar data.

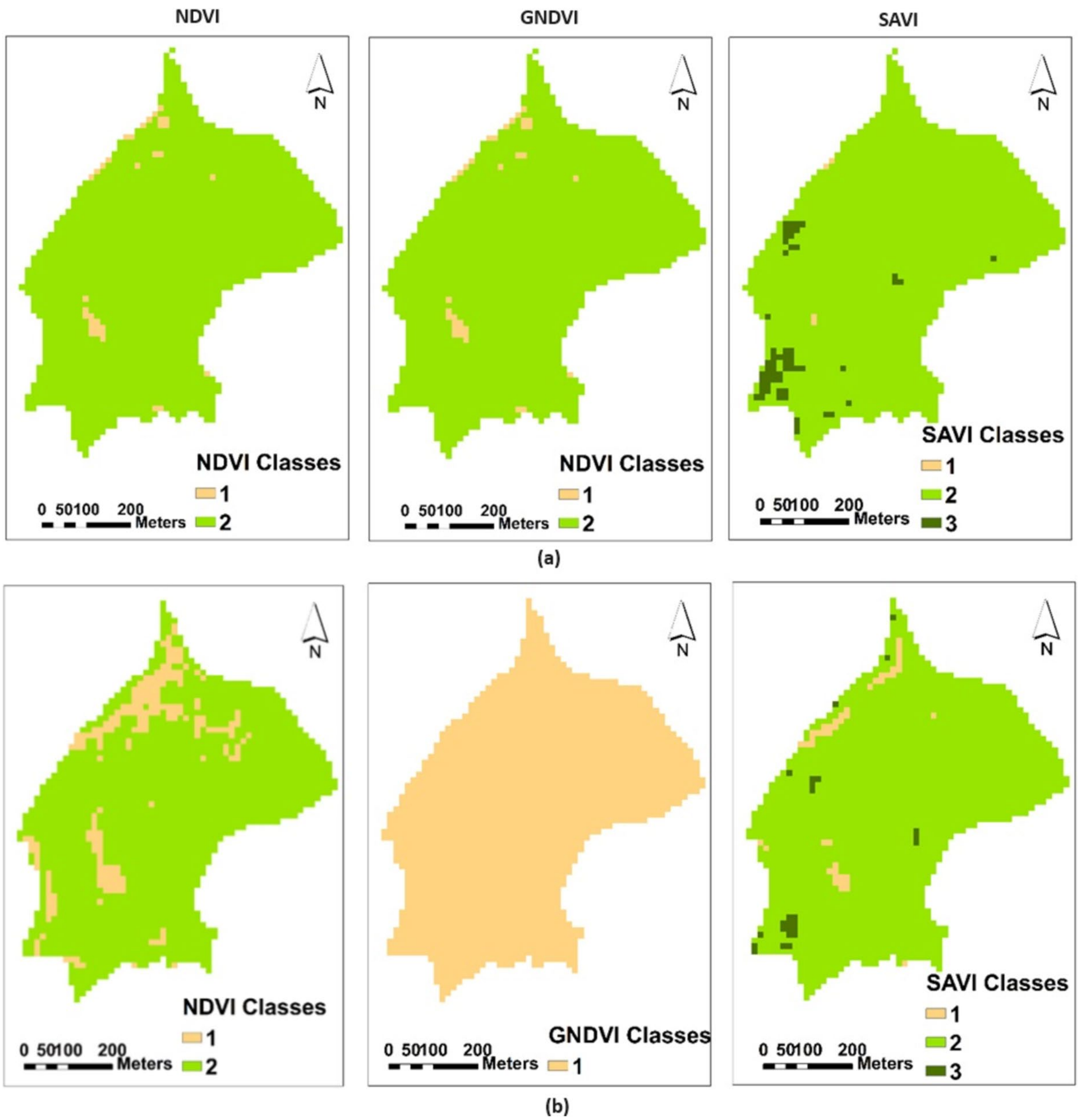

Fig. 4 Maps of NDVI, GNDVI, and SAVI indices of ASTER satellite image pre (**a**) and post (**b**) selective logging

Discussion

Currently, remote sensing is being utilized proficiently in many aspects of forests and forestry activities. Vegetation index algorithms are commonly used in vegetation-related research due to their ease of practicality and effectiveness. Although different algorithms were utilized, Wang and Xu (2010) showed in a hurricane-ravaged forest that vegetation indices were perfectly suitable in determining the disturbed forest patches. No matter how different is the intervention approach, hurricane vs. intentional forestry practice, when stable forest cover is somehow broken, indices such as NDVI, GNDVI, and SAVI have produced rather sensitive results to changing crown structure (Nath & Acharjee, 2013; Palas & Zawadzki, 2020).

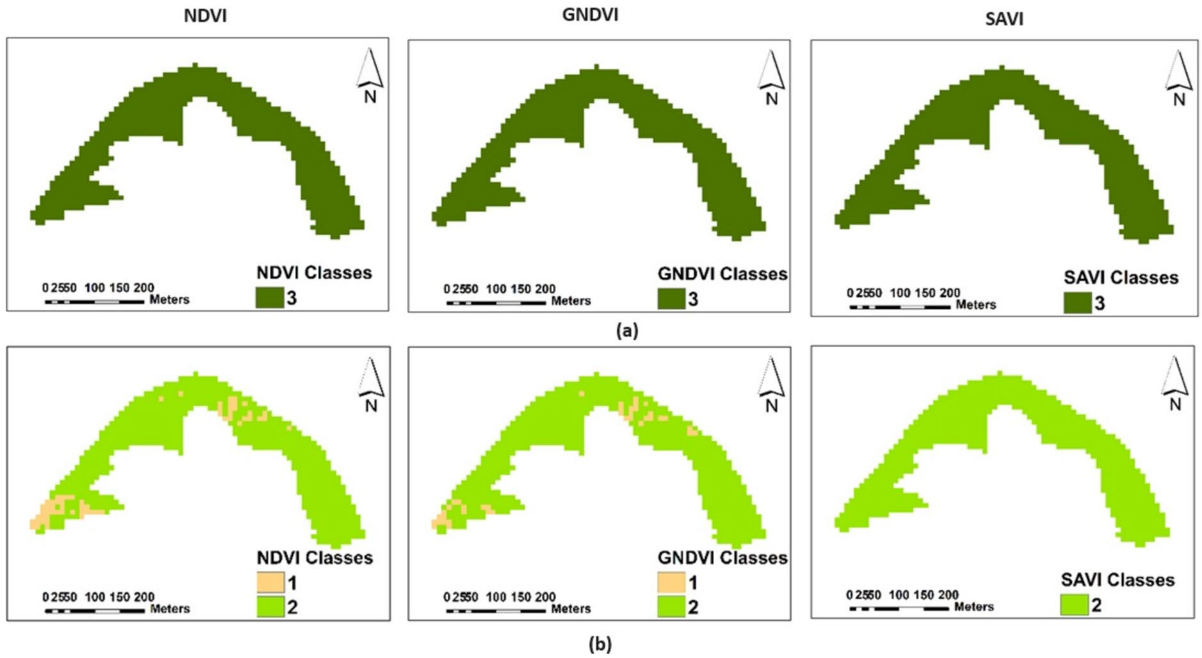

Fig. 5 Maps of NDVI, GNDVI, and SAVI indices of Sentinel-2 satellite image pre (**a**) and post (**b**) regeneration silviculture

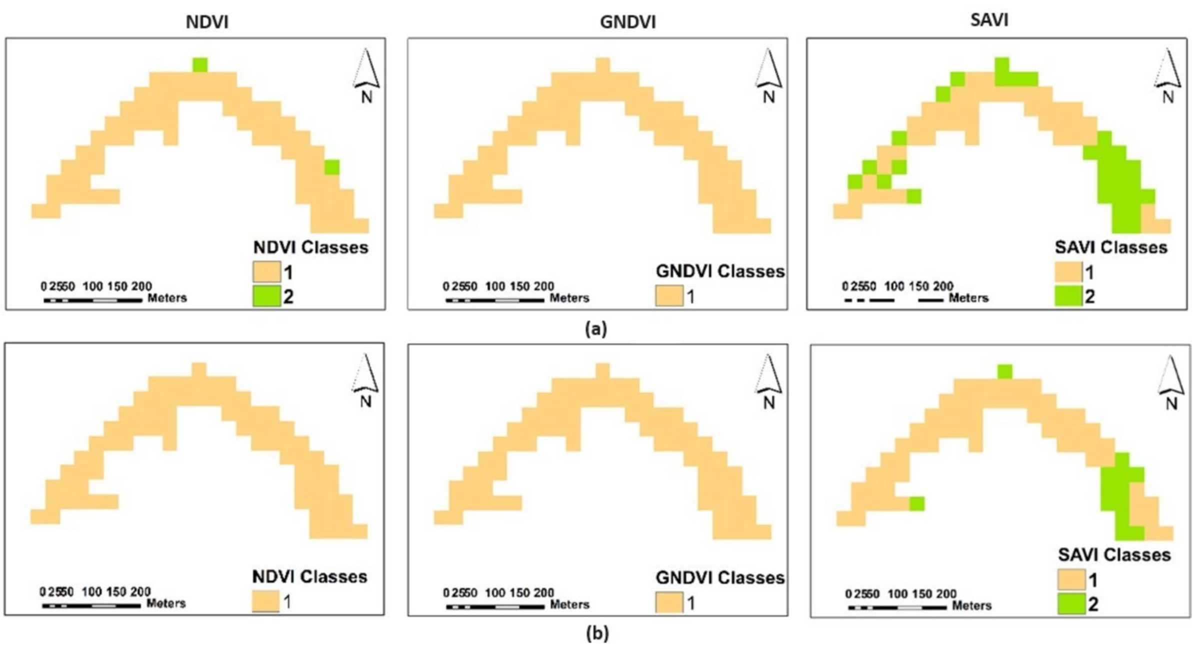

Fig. 6 Maps of NDVI, GNDVI, and SAVI indices of Landsat-8 satellite image pre (**a**) and post (**b**) regeneration silviculture

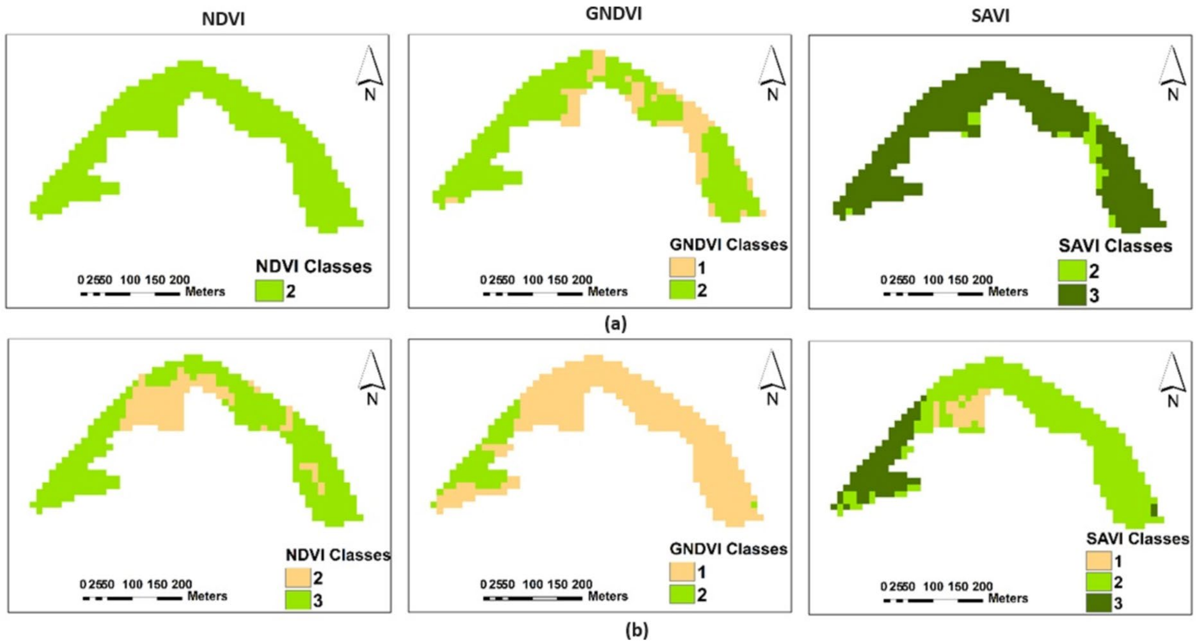

Fig. 7 Maps of NDVI, GNDVI, and SAVI indices of ASTER satellite image pre (**a**) and post (**b**) regeneration silviculture

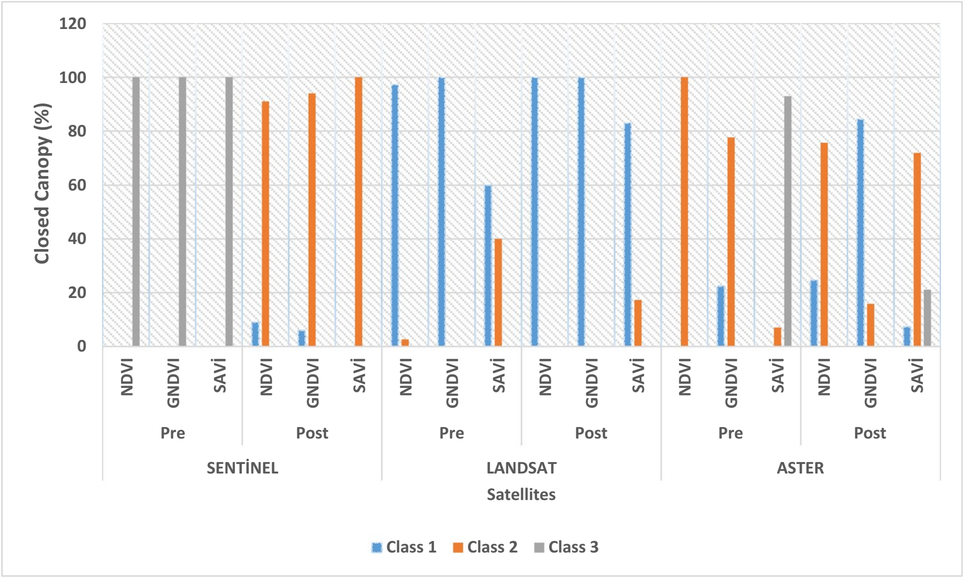

Fig. 8 Graphical representation of closed canopy values of Sentinel-2, Landsat-8, and ASTER satellite images according to vegetation indices

Other than an unexpected natural disturbance, forests are professionally managed during their accepted rotation periods, so from time to time, the stands are tended with the specie or composition dictating managerial interventions. The amount and distribution of these interventions inside the stands are critical for the remaining stands final yields, so continuous monitoring is essential to detect any wrong doing down the road and to remediate, if possible, as soon as possible. Remote sensing and the constantly evolving engineering and know-how alongside are therefore so indispensable in forestry that forests without remote sensing watch are vulnerable to many unforeseen phenomenon. Models constructed using indices from Sentinel-2 shown enhanced performance relative to those produced using Landsat-8 data (Pertille et al., 2020). Khan et al. (2020) asserted in their research that the high spatial resolution (10 m) and spectral bands of Sentinel-2 imageries enabled vegetation indices to predict deforestation, biomass, and carbon stock with superior accuracy relative to other sensors. Sothe et al. (2017) examined the effectiveness of Sentinel-2 and Landsat-8 data in assessing long-term alterations in forest cover and concluded that the examination of Sentinel-2 data with vegetation indices revealed superior performance compared to Landsat-8-based ones. Lima et al. (2019) defined that it was important to analyze the consequences of moving from the Landsat-8 moderate spatial resolution to the finer spatial scale of Sentinel-2 data. In previous studies, it was determined that the accuracy of Sentinel-2 images was higher compared to Landsat-8 satellite images abouting forest cover change (Tritsch et al., 2016). Asner et al. (2005) pointed out that Sentinel-2 has a better capability for detecting selective logging features (43.2%) compared to Landsat-8 (35.5%), which can most likely be attributed to its finer spatial resolution. The detectability over all types of logging features was similar to values. Similar values were obtained by Grecchi et al. (2017), Souza et al. (2013), and Verhegghen et al. (2015). Schultz et al. (2016) favored that the use of wetness-dependent vegetation indices in Landsat-8 imagery is better than greenness-based indices, so our choice of SAVI alongside the others gave the study a firm edge in explaining the results. Barakat et al. (2018) sought to monitor and analyze the geographical and temporal dynamics of forest cover with Aster and Sentinel-2 imagery. The study demonstrated that both satellites delivered high-quality data; nevertheless, they were inferior to the results obtained from what Sentinel-2 produced.

Conclusion

Forests are crucial components of the sustainable ecosystem cycle, making a substantial contribution to the civilization. Hence, it is crucial to oversee forests, monitor their alterations, and adopt conservatory measures for their future existances. To achieve these objectives, employing procedures and methodologies that yield prompt, dependable, and precise outcomes enhances the efficacy of the intended targets. This study attempted to assess the impact of two different harvesting operations (selection and regeneration) on forest areas in the Kastamonu region. The effects were determined using vegetation indices (NDVI, GNDVI, SAVI) derived from Sentinel-2A, Landsat-8, and ASTER satellite imagery. For this study, we compared the vegetation indices of Landsat-8 and Aster satellite images with the field verification held, interpreting Sentinel-2 imagery. The Sentinel-2A image offered a more realistic, detailed, and highly resolved image compared to other satellite images, thanks to its spatial resolution of 10 m.

This study aimed to evaluate the production activities in the Kastamonu Karadere Forest Management Directorate by utilizing three distinct vegetation indices derived from satellite imageries captured by Sentinel-2A, Landsat-8, and Aster. The performance of these vegetation indices was subsequently assessed.

The study found that the NDVI, GNDVI, and SAVI indices were the most accurate indicators of green vegetation change in the Sentinel-2A satellite imagery. Similarly, for the Landsat-8 satellite imagery, the SAVI, NDVI, and GNDVI indices were found to be the most reliable indicators. As for the Aster satellite imagery, the trend was towards SAVI, GNDVI, and NDVI. Based on the findings of this study, which were gathered from pre- and post-production studies conducted in the study area, it has been noted that the ASTER imagery closest to Sentinel-2A was more effective in detecting changes in green vegetation in forested areas resulting from production activities in the study area. This was evident from the changes in plant biomass and the models developed using vegetation indices, which served as key indicators of leaf area indices.

The vegetation indices obtained for Karadere Forest Planning Unit could be applicable to the forest ecosystems that shared similar characteristics with the research area. Furthermore, these findings were crucial for determining the potential changes happening in forest vegetations. The findings can potentially be extrapolated to research utilizing ASTER data in conjunction with Sentinel-2 on regional or larger extents. Employing high-resolution optical data to evaluate deforestation and degradation can further enhance the intended targets.

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Author contribution Çiğdem ÖZER GENÇ and Arif Oğuz ALTUNEL designed the study, wrote the manuscript and analyzed the data.

Data availability No datasets were generated or analysed during the current study.

Declarations

Ethics approval All authors have read, understood, and confounded with the statement on "Ethical Responsibilities of Authors" as found in the "Instructions for Authors."

Conflict of interest The authors declare no competing interests.

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