INTERNATIONAL SCIENTIFIC JOURNAL
GEOGRAPHICA PANNONICA
Volume 28, Issue 4, 238–249 (December 2024)
Journal homepage: http://www.dgt.uns.ac.rs/en/homepage/pannonica/

Phenology Analysis for Detection of Vegetation Changes Based on Landsat 8 Images in Nature Park Kopački rit, Croatia

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KEYWORDS

- vegetation activity
- “npphen” package
- management zones
- phenology analysis
- normalized difference vegetation index (NDVI)
- k-means classification

ABSTRACT

This study proposed a method for detecting vegetation changes and establishing geospatial management zones based on the 10-year phenology analysis using normalized difference vegetation index (NDVI) long-term trends from Landsat 8 multispectral imagery in Nature Park Kopački rit. The main components of the proposed method include phenology analysis and NDVI anomaly detection supported by unsupervised k-means classification of vegetation management zones. The reference monthly NDVI values (2013–2019) with three test years (2020–2022) strongly indicated very high heterogeneity in vegetation activity. A 100 m spatial resolution and a monthly temporal resolution were used. The results of unsupervised k-means classification in five vegetation activity classes indicated that three of these classes have considerably high negative NDVI anomalies, covering 64.1% of the study area. While the proposed method ensures the detection of vegetation changes and vegetation activity zones, a comprehensive field observation is required to determine the potential environmental and/or anthropogenic causes. However, the proposed approach significantly reduces the need for extensive fieldwork, allowing biologists to focus their efforts on areas with detected abnormal vegetation activity.

Introduction

Detecting changes in vegetation within protected natural areas is critical for environmental monitoring, conservation, and management (Slingsby et al., 2020). Vegetation is a key indicator of ecosystem health, biodiversity, and environmental change, which is of special importance in managing protected natural areas (Wang et al., 2020). Changes in vegetation patterns can indicate a variety of ecological disturbances, including wildfires, invasive species, or human-caused impacts such as land use change. Conservationists, land managers, and policymakers can use timely and accurate detection of these changes to develop effective mitigation solutions and maintain the biological integrity of protected areas (Elsen et al., 2023). Monitoring vegetation dynamics also provides significant insights into the effects of climate change, as changes in plant composition and phenology are often associated with changing climate pat-

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doi: 10.5937/gp28-50802
Received: May 2, 2024| Revised: September 27, 2024| Accepted: October 22, 2024

terns. The invasive species (ElMasry & Nakauchi, 2016), and human-caused events such as land-use changes (Ntukey et al., 2022) can cause changes in vegetation that can have a major impact on biodiversity and overall ecological balance. The emerging threats can be timely addressed by identifying these changes in real-time using advanced monitoring technologies such as remote sensing (Khanal et al., 2020). This proactive strategy enables the adoption of specific conservation measures, such as habitat restoration, invasive species control, or wildfire management, to reduce the impact of disturbances. In addition, the data provided by vegetation change detection supports evidence-based decision-making for land-use planning and policy-making that promotes the protection of natural areas (Bell et al., 2023).

Remote sensing technologies, especially open data satellite imagery, have greatly improved the ability to detect rapid changes in vegetation over multiple geographic and temporal scales (Radočaj et al., 2020). Such developments allow for early intervention and adaptive management and contribute to the overall sustainable management of protected natural areas, ensuring the survival of various ecosystems and their essential ecological services (Li et al., 2020). This high spatial and spectral resolution enables precise monitoring of plant cover and the detection of small changes that may indicate disturbance (Ustin & Middleton, 2021). In addition, its temporal resolution enables multiple sensing to the same region, allowing the detection of phenological patterns that represent seasonal changes in vegetation over time. Phenology analysis is critical for determining the timing of key life cycle events such as flowering and leaf emergence, which are sensitive markers of environmental change (Dronova & Taddeo, 2022). However, it requires long-term satellite imagery to establish long-term trends in vegetation activities, for which Landsat missions provide stable and historically available data since 1972 (Hemati et al., 2021). Using Landsat multispectral imagery for phenology analysis improves the ability to detect and interpret rapid changes in vegetation, resulting in a more complete understanding of biological changes within protected areas. This knowledge is critical for making informed conservation decisions, as it helps to establish adaptive management methods tailored to the unique biological needs of protected natural areas (Roux et al., 2021).

The use of vegetation indices for ecological studies, including phenological analysis, requires careful evaluation of individual study objectives and environmental factors (Poggi et al., 2021). While indices such as the enhanced vegetation index (EVI), normalized difference red edge vegetation index (NDRE), and soil adjusted vegetation index (SAVI) have distinct advantages, the normalized difference vegetation index (NDVI) remains the preferred option for a phenology analysis due to its standardized [-1,1] value range and well-documented relationship of its values to vegetation health and vigor (Misra et al., 2020; Torgbor et al., 2022). NDVI has proven successful in capturing the many phenological phases of vegetation, such as green-up in spring and senescence in fall (Zeng et al., 2020). Its sensitivity to chlorophyll concentration makes it a reliable indicator of plant photosynthetic activity, and thus an effective proxy for phenological shifts. Moreover, a recent study showed that these indices mutually produce a significant level of multicollinearity, indicating that there are only minor differences in their use for assessing vegetation health (Radočaj et al., 2023). The simplicity and ease of understanding of the NDVI makes it generally relevant across different ecosystems, facilitating comparisons across studies. While previous studies thoroughly evaluated various vegetation indices as a part of phenology analysis (Granero-Belinchon et al., 2020; Hu et al., 2021; Zhou et al., 2020), there has been a research gap in developing the methodology to detect vegetation changes and establish geospatial management zones for effective vegetation monitoring and management.

To address this research gap, the objective of this study is to propose a straightforward and robust method of detecting vegetation changes utilizing Landsat 8 multispectral imagery for phenology analysis during 10 years (2013–2022) for protected Nature Park Kopački rit in eastern Croatia.

Data and methods

The proposed method of detecting vegetation changes utilizing Landsat 8 multispectral imagery for phenology analysisconsists of three major steps: 1) acquiring and preprocessing of Landsat 8 multispectral imagery; 2) phenology analysis and NDVI anomalies detection; and 3) unsupervised classification of vegetation management zones (Figure 1).

Study area

Nature Park Kopački rit covers 177 km^2 of ecologically diverse wetland region situated in eastern Croatia along the Danube River (Figure 2). Dominant vegetation includes forests of white willow in the floodplain, while slightly elevated areas support forests of black poplar and pedunculate oak (Šag et al., 2016). Aquatic vegetation thrives in the park's numerous water bodies, with communities of duckweed, water lilies, and bulrushes prevalent. The park is crucial for preserving the ecological balance of the area, maintaining migrating bird populations, and providing nesting habitats for various species (Bjedov et al., 2023). Identifying changes in vegetation is crucial for monitoring ecosystem health and detecting potential dangers such as

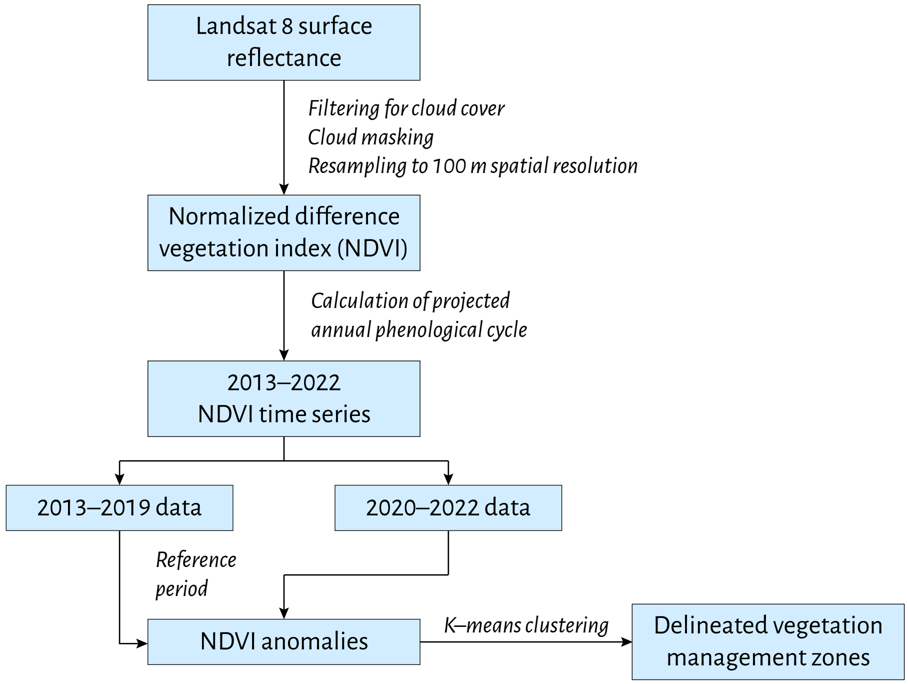

Figure 1. Flowchart of the study

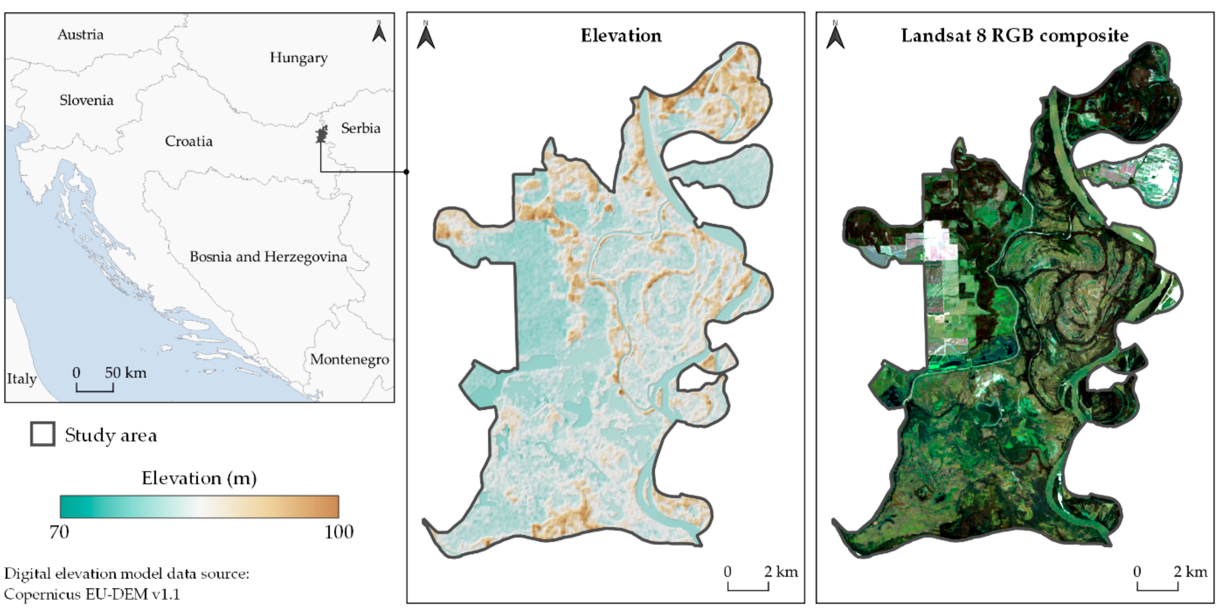

Figure 2. Study area of the Nature Park Kopački rit

invasive species, habitat loss, or water quality deterioration. Early identification of these changes enables timely implementation of adaptive management strategies and interventions to minimize negative effects and preserve the ecological integrity of Nature Park Kopački rit.

Landsat 8 multispectral imagery and preprocessing

The Landsat 8 Surface Reflectance (SR) imagery underwent preprocessing using a cloud masking approach after obtaining the Landsat 8 satellite imagery from Google Earth Engine (Gorelick et al., 2017). The time frame for filtering available imagery was set from 1 January 2013 to 31 December 2022, leaving only satellite scences with less than 75% overall cloud cover. The cloud masking function utilized various masking approaches to filter out unreliable pixels affected by cloud cover or sensor saturation, such as Quality Assessment (QA) and Radiometric Saturation (RADSAT) values (Pereira et al., 2020). The spatial resolution of calibrated Landsat 8 bands was resampled to the 100 m spatial resolution in the Croatian Terrestrial Reference System (HTRS96/TM) prior to the phenology analysis. The NDVI was calculated using red (band 4) and near-infrared (band 5) Landsat 8 bands, using a normalized difference formula (Zeng et al., 2020). It was selected as a vegetation index for phenology analysis, as its formulation increases the sensitivity of the index to changes in chlorophyll content, canopy structure, and overall vegetation vigor using the scale range from -1 to 1 (Eisfelder et al., 2023; Garroutte et al., 2016). In addition, NDVI's widespread use in ecological studies and its compatibility with historical satellite data make it an excellent choice for long-term phenology monitoring, allowing researchers to evaluate vegetation trends and changes over extended periods of time (Granero-Belinchon et al., 2020).

Table 1. provides a comprehensive overview of the number of Landsat 8 images utilized in the study per month and year from 2013 to 2022. The data reveal variations in the number of Landsat 8 images acquired over the study period, reflecting factors such as satellite availability, cloud cover, and operational considerations. Overall, the number of Landsat 8 images used in the study ranges from 25 to 33 per year, with slight fluctuations observed across different years. Months with higher counts of Landsat 8 images, such as July and August, indicate periods of more frequent satellite acquisitions, influenced by favorable weather conditions and lower cloud cover. Conversely,

Table 1. The number of valid preprocessed Landsat 8 images per month during the study period of 2013–2022

Month	Study year									
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
January	0	3	0	1	4	2	2	2	2	4
February	0	1	1	2	2	1	2	3	2	1
March	0	2	4	3	3	1	4	3	2	2
April	1	2	3	2	2	2	2	3	3	3
May	3	2	2	2	3	4	1	3	4	3
June	3	2	4	3	3	3	4	2	4	4
July	5	4	3	4	4	3	3	3	4	3
August	4	4	3	4	4	4	4	4	3	2
September	4	1	3	2	1	2	3	4	2	1
October	3	2	1	0	3	1	3	1	2	3
November	1	2	2	1	1	1	2	2	3	1
December	4	1	3	3	3	1	3	1	2	0
Overall	28	26	29	27	33	25	33	31	33	27

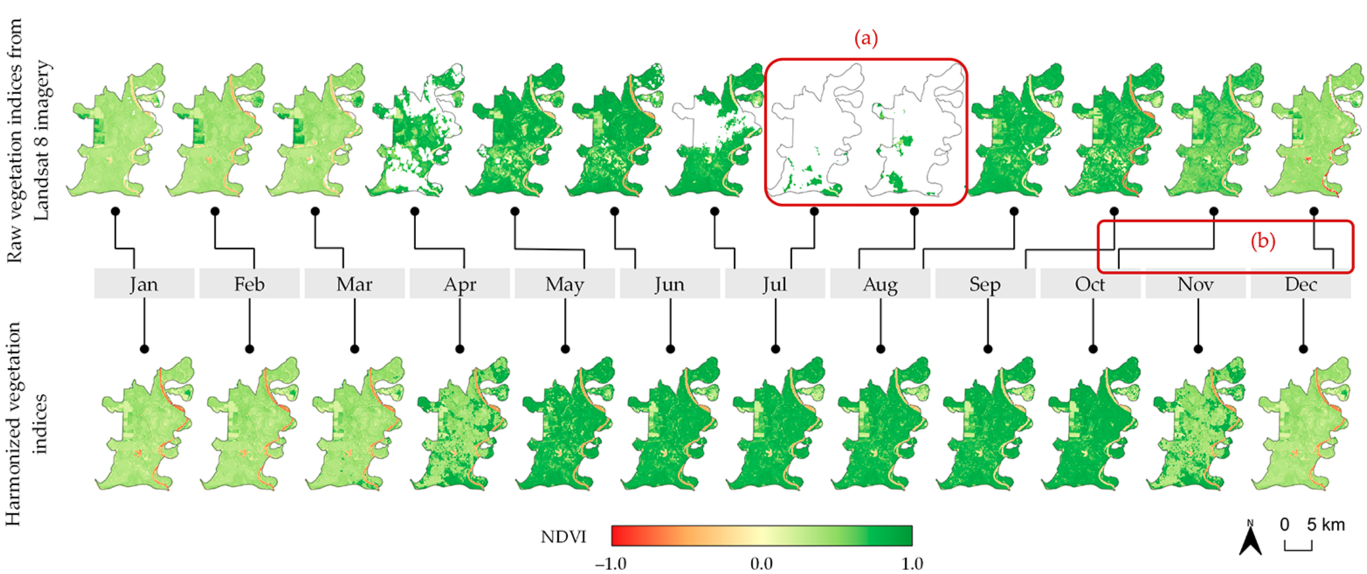

Figure 3. The representation of Landsat 8 images before and after harmonization using "npphen" package, having the issues of: a) dominant cloud cover, and b) missing images with less than 75% overall cloud cover across large intervals. Harmonized vegetation indices displayed on the bottom represent resulting rasters from phenology analysis

months with lower counts, such as January and October, suggest periods of reduced satellite availability or higher cloud cover, limiting the number of usable images.

However, since the availability of cloud-free Landsat 8 images varies across the long-term periods, the phenology analysis for the creation of harmonized monthly NDVI rasters was required (Figure 3). The harmonization process within the "npphen" package involved aligning NDVI values across different images to account for seasonal changes and resampling them to the uniform grid system due to presence of multiple Landsat 8 tile grids.

Phenology analysis and ndvi anomalies detection

The "npphen" R package was used for phenology analysis and detecting anomalies that indicate vegetation changes (Chávez et al., 2023). Designed to maximize the potential of satellite-derived vegetation indices, "npphen" facilitated the extraction of phenological metrics such as season start, season end, and season peak, which are crucial for understanding vegetation dynamics. It also included anomaly detection techniques that allowed finding deviations from predicted phenological patterns from the reference seven-year period that indicate rapid changes in plant activity. However, since it was released very recently, there is very restricted documented research on "npphen" application in research studies. The "npphen" time series analysis capabilities allowed a systematic evaluation of temporal patterns in vegetation indicators, revealing changes in phenological cycles caused by disturbances such as wildfires, disease outbreaks, or anthropogenic impacts (Estay et al., 2023). The ability to detect anomalies using "npphen" enhanced the ability to quickly detect and respond to ecological disturbances, which helps in the development of targeted conservation and management plans for protected natural areas. As a comprehensive and user-friendly tool, "npphen" made a significant contribution to phenology research and monitoring by providing essential insights into ecosystem health and resilience (Chávez et al., 2023). Using Landsat 8 long-term imagery, the approach was based on calculating the projected annual phenological cycle using raster stacks of vegetation indices or time series. The method efficiently captured the distribution of NDVI values over time by utilizing a bivariate kernel density estimator (Wand & Jones, 1994). From the 10-year study period, seven years during 2013–2019 were selected as the reference period for the phenology analysis, providing a basis for the anomaly detection for each year in the remaining three-year test period during 2020–2022.

Unsupervised classification of vegetation management zones

The final delineation of vegetation management zones within the Kopački rit Nature Park was based on the sum of NDVI anomalies between 2020 and 2022, using the R package "terra" (Hijmans et al., 2024). K-means clustering, a data-driven approach that divided the study area into discrete groups based on similarities in NDVI anomaly patterns, was utilized without the requirement for pre-defined training samples. K-means clustering is an effective geospatial approach to identify spatially coherent zones that display similar vegetation dynamics and anomalies based on NDVI anomaly data collected over the long term (Ahmed et al., 2020). This method also distinguished locations that consistently face vegetative stress or are resilient to environmental changes from other sites with unique phenological features (Silveira et al., 2022). The accuracy and dependability of vegetation management zone delineation were improved by adding NDVI anomalies over a multi-year period, which provided a strong foundation for capturing long-term trends and variability in vegetation dynamics.

Results

The boxplots in Figure 4 after outlier removal using the interquartile range approach present that the reference study period produced comparatively lower median NDVI values for the majority of months in comparison to each of the test years. Most notably, NDVI value ranges during January–April 2020 were notably lower than both the reference period and the other two years in the test period. However, it also produced the highest median NDVI values during August–December, which reinforces the necessity of observing multiple years in the phenology analysis, as diverse environmental and anthropogenic effects might affect the long-term trends in vegetation activity.

Figure 5 displays representative NDVI anomalies for each of the test years, indicating diverse vegetation change cases. While their occurrence in the western part of the study area is justified by the presence of arable cropland and the effect of crop rotation systems, there is a necessity for extensive field monitoring to detect the causes of vegetation anomalies without an apparent cause. Moreover, since high anomalies for arable cropland are expected due to crop rotation systems, the cause for vegetation anomalies at those areas is known. All three representative NDVI anomalies also produced distinctively lower NDVI values for most of their respective test years, following a more normalized trend according to the long-term NDVI trend based on the reference period.

Table 2. presents an interpretation of NDVI anomalies across five classes produced by k-means unsupervised

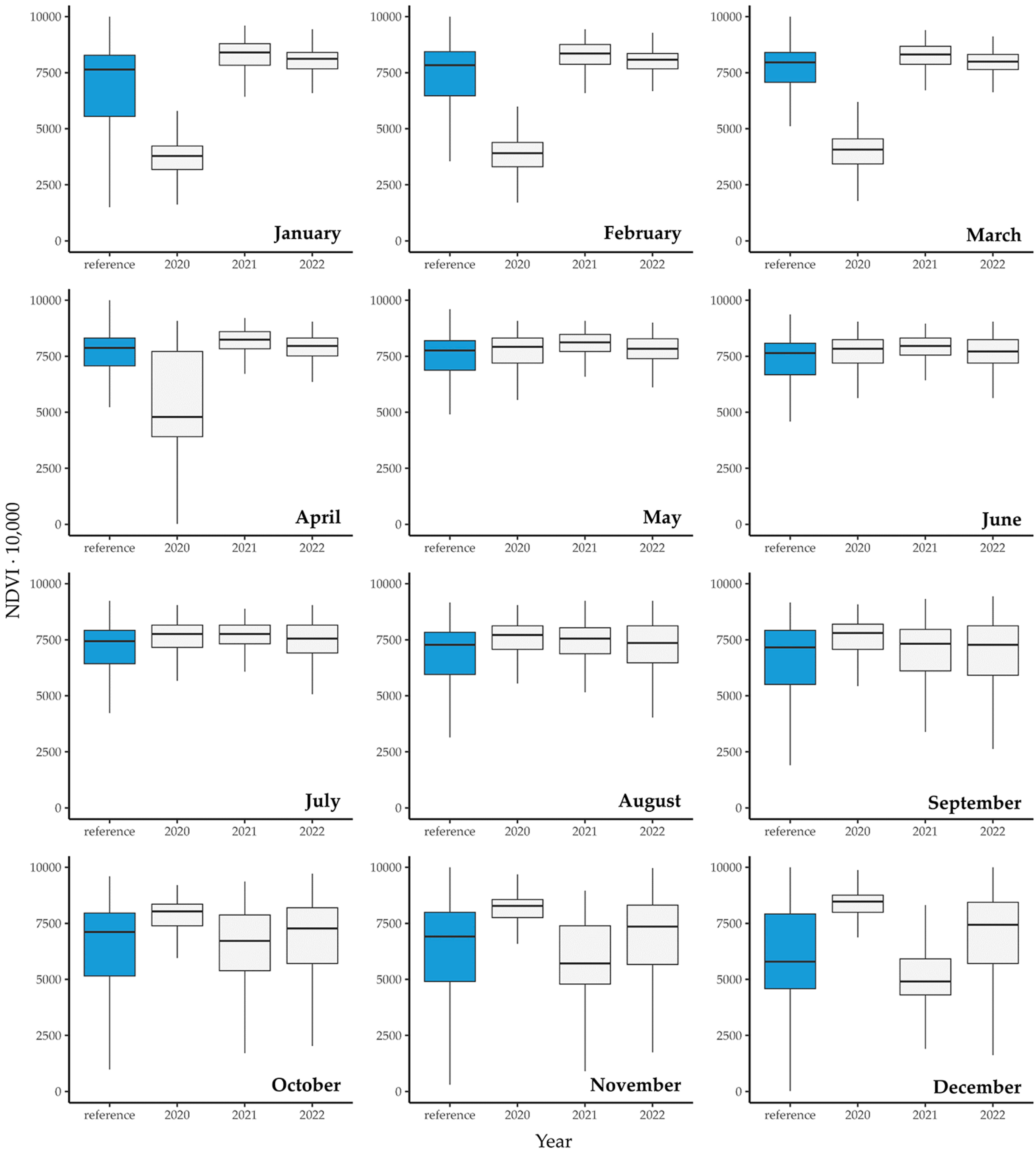

Figure 4. The boxplots of monthly NDVI values for the reference period (2013–2019) and three test years (2020–2022) with removed outliers

classification and their respective areas within the study area over the years 2020, 2021, and 2022, along with their average values. The NDVI anomalies provided in the table represent class centers from k-means classification results from test years. NDVI anomalies were categorized into five classes based on their magnitude: extremely negative, moderately negative, slightly negative, neutral, and positive NDVI anomalies. The negative NDVI anomalies, including extremely, moderately, and slightly negative categories, exhibit decreases in vegetation greenness compared to the reference period, with extremely negative anomalies indicating the most severe declines. Converse-

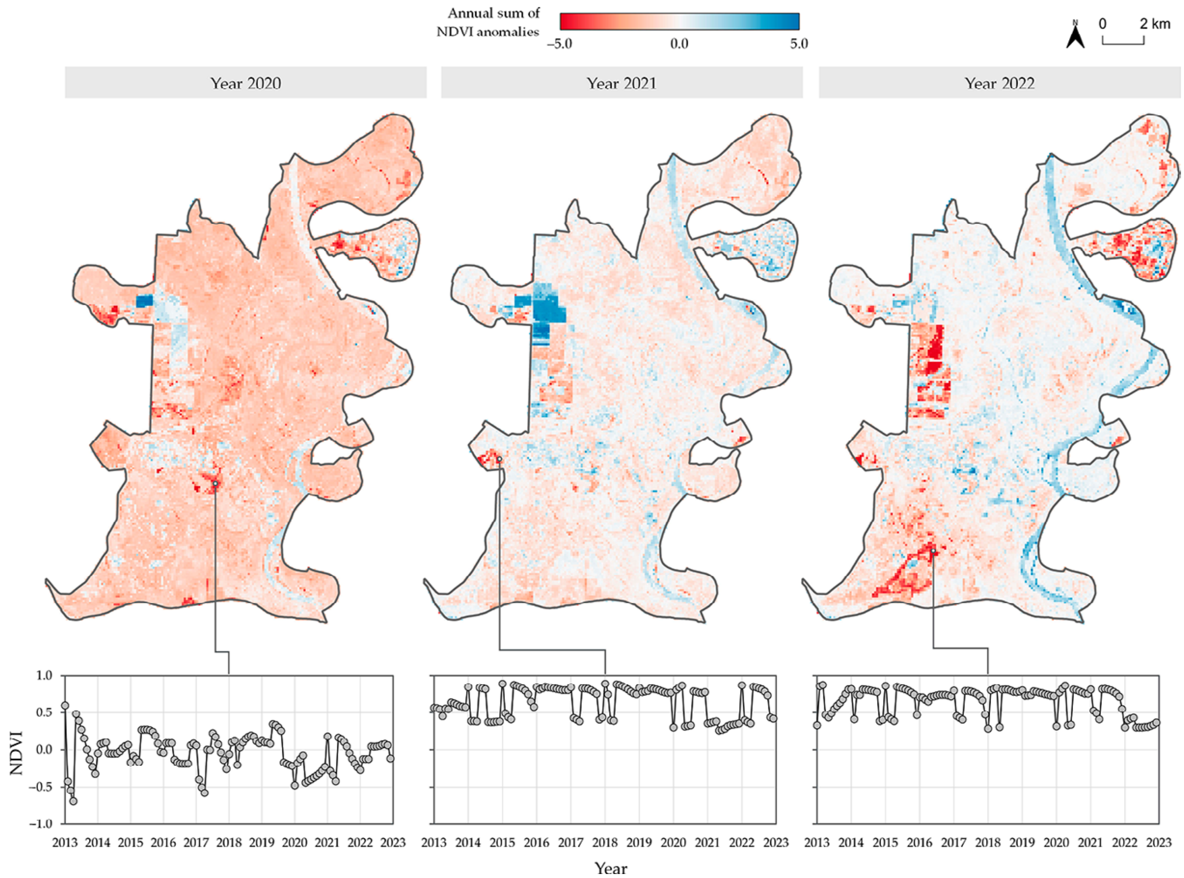

Figure 5. The example NDVI anomalies for each of test years based on their monthly sum, indicating vegetation changes

ly, positive NDVI anomalies denote increases in vegetation greenness and primarily contain arable cropland and water bodies. The table illustrates notable variations in the magnitude and distribution of NDVI anomalies across the study period. For instance, the area affected by extremely negative NDVI anomalies experienced a substantial increase from 2020 to 2022, reaching its peak in 2022. Conversely, moderately negative NDVI anomalies displayed fluctuations over the years, with a significant decrease observed in 2022 compared to the previous two years. Slightly negative NDVI anomalies exhibited a decreasing trend over the study period, with the area affected declining sharply from 2020 to 2021 and almost disappearing in 2022. Neutral NDVI anomalies showed fluctuations over the years, with a notable increase in 2021 compared to 2020 and a subsequent decrease in 2022. Positive NDVI anomalies demonstrated an overall increasing trend, particularly notable in 2021, indicating improvements in vegetation greenness compared to the baseline. The resulting five vegetation activity classes based on the sum of monthly NDVI anomalies during test period are displayed in Figure 6.

Table 2. The results k-means unsupervised classification of NDVI anomalies during test years and corresponding statistics in five vegetation activity classes

Classes	NDVI anomalies				Area (%)
	Annual sum (2020)	Annual sum (2021)	Annual sum (2022)	Average	
Extremely negative NDVI	–13598	–8770	–34921	–19097	4.9%
Moderately negative NDVI	–17768	–7965	–10917	–12217	15.2%
Slightly negative NDVI	–14916	–4606	–77	–6533	44.0%
Neutral NDVI	–8599	1355	–687	–2643	28.3%
Positive NDVI	3273	15527	15908	11569	7.5%

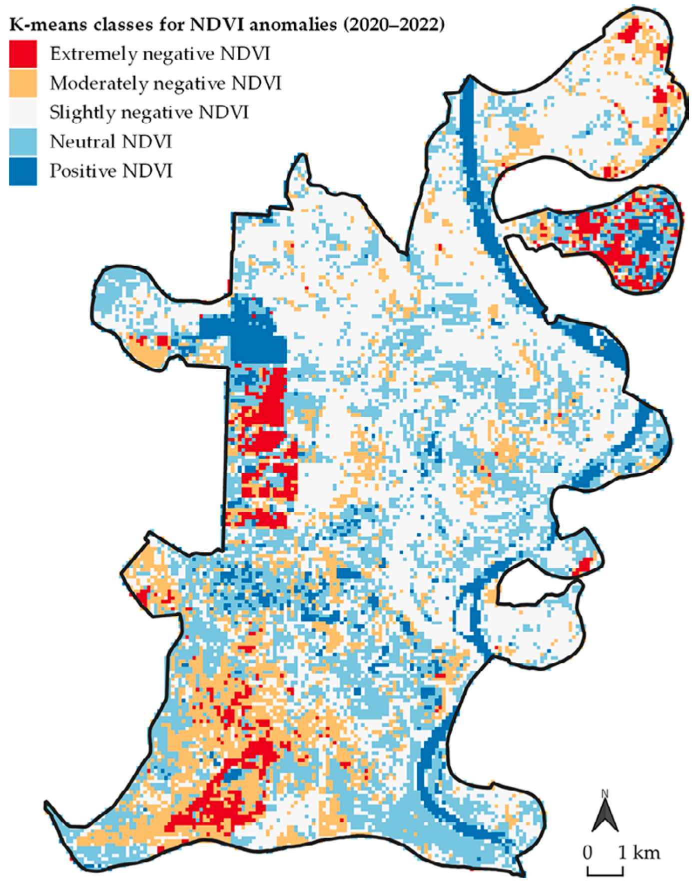

Figure 6. The five vegetation activity classes produced by k-means unsupervised classification based on the sum of monthly NDVI anomalies during test period

Discussion

The results from this study proved that the combination of Landsat 8 data with the NDVI allows for phenology analysis to identify anomalies and track vegetative dynamics in protected areas. The vegetation anomalies were determined individually for years 2020, 2021 and 2022 based on the reference period between 2013 and 2019. The long-term phenology studies provide insights into ecosystem health, resilience, and responses to environmental stresses, particularly in protected regions where conservation efforts are paramount (Cumming et al., 2015). Understanding these dynamics can guide management strategies aimed at preserving biodiversity and mitigating the impacts of climate change. Since NDVI obtained from satellite imaging is sensitive to both chlorophyll content and canopy structure, it was a reliable indicator of plant health and vitality (Garroutte et al., 2016). The notable application of the proposed approach is that it significantly reduces the need for extensive fieldwork in phenological studies, allowing biologists to focus their efforts on areas with detected abnormal vegetation activity. This allows monitoring large areas consistently and efficiently, capturing spatiotemporal patterns of vegetation without the logistical challenges associated with ground surveys (Zeng et al., 2020). This allows biologists to prioritize field investigations in specific locations that show significant anomalies, thus optimizing resource allocation and enhancing the effectiveness of conservation efforts. This targeted approach not only streamlines research processes but also improves data quality by focusing on areas where ground truthing is most needed to validate satellite observations and refine ecological models (Azizan et al., 2021). However, in diverse landscapes or smaller-scale land use areas, the spatial resolution of Landsat 8 imagery may not be sufficient to detect minor changes in plant dynamics. To enhance the detection capabilities of vegetation phenology anomalies, additional multispectral datasets with higher spatial resolutions, such as Sentinel-2 with spatial resolutions up to 10 m (Phiri et al., 2020), or commercial high-resolution imagery like PlanetScope with resolutions as fine as 3 meters, can be integrated (Panđa et al., 2024). Moreover, the creation of continuous time series records over several decades aids in identifying long-term environmental changes in these protected areas. The integration of Landsat 7 and Landsat 5 data ensures consistency and reliability in the long-term monitoring of vegetative changes, allowing for improved continuity in phenology analysis. By enabling more comprehensive evaluations of vegetation dynamics at smaller spatial scales, these higher-resolution datasets allow for the identification of changes in smaller land cover features or fragmented landscapes. Furthermore, the inclusion of supplementary data, such as meteorological characteristics obtained from weather stations or reanalysis datasets, strengthens the analysis by providing insights into the environmental forces that impact vegetation dynamics (Pardela et al., 2020). The phenology of vegetation is influenced by variables such as temperature, precipitation, and soil moisture, which can be used to explain abnormalities identified through multisensory analysis (Radočaj et al., 2024). To ensure effective anomaly identification in multisensory phenology analysis, the temporal resolution of accessible multispectral images is just as important as their spatial resolution (Sedona et al., 2021). Sentinel-2's frequent revisit time allows for more frequent observations than Landsat 8, which is particularly useful for monitoring vegetation dynamics at finer temporal scales. To comprehend the intricate relationships between climatic variability and ecosystem responses, it is promising to establish a link between monthly anomalies in vegetation dynamics and climate data rasters for the years 2020-2022. However, this attempt faces difficulties when climate data rasters are regularly provided with a time buffer (Fick & Hijmans, 2017; Karger et al., 2017), resulting in temporal misalignment between the two datasets. To align climatic data with vegetation observations, several techniques can be used, such as statistical modeling to account for temporal misalignment, time lag analyses to identify delays between climatic events and vegetation responses, temporal aggregation or interpolation of climate data to match the temporal resolution of vegetation anomalies, and long-term trend analyses to find consistent patterns over several years (Zhao et al., 2020). Resolving the temporal discrepancy between vegetation anomalies and climate data has the potential to clarify the complex connections between ecosystem dynamics and climate variability (Jiao et al., 2021). This can ultimately improve comprehension of how ecosystems adapt to environmental change, despite the difficulties involved.

For phenology analysis in protected areas, using multispectral satellite images that cover periods longer than ten years can likely be beneficial, providing more complete insights into long-term vegetation dynamics and ecosystem changes (Li et al., 2017). This allows for more detailed identification of trends, patterns, and anomalies in vegetation phenology by tracking phenological variations over extended periods of time and establishing thorough baseline information by utilizing historical satellite data. Long-term phenology studies can enhance the understanding of ecosystem health, resilience, and responses to environmental stresses as well, particularly in protected regions where conservation efforts are crucial (Cumming et al., 2015). Continuous time series records can be created for several decades, aiding in the identification of long-term patterns and changes in the environment in protected regions. The integration of Landsat 7 and Landsat 5 data ensures consistency and dependability in the long-term monitoring of vegetative changes, allowing for an improved continuity in phenology analysis.

The classified maps produced from the NDVI analysis can be utilized by Nature Park management for monitoring vegetation health, ecologists for research purposes and policymakers for informed decision-making. The maps indicate that significant positive and negative NDVI anomalies may be influenced by natural events such as droughts and flooding, as well as human activities like deforestation and urbanization, which should be further explored in the field. However, this research relies on statistical outputs without adequately exploring the ecological implications of these anomalies. The study acknowledges several limitations that could affect the results. First, months with little or no data can introduce biases in NDVI calculations, leading to inaccurate assessments of vegetation health. Second, challenges in collecting ground truthing data due to accessibility issues may impact the validation of remote sensing accuracy. Third, the lack of integration of climate data is a significant gap, as NDVI changes can result from natural variability rather than abrupt disturbances; incorporating data from nearby meteorological stations could clarify how climatic factors influence vegetation dynamics. These limitations should be addressed in future studies, which should include ground truth data collected in the field.

Conclusion

This study proposed the method of detecting vegetation changes based on phenology analysis using Landsat 8 multispectral images, utilizing phenology analysis for NDVI anomalies detection and unsupervised k-means classification for the determination of vegetation management zones. Overall, the multispectral imagery acquired during the 10-year study period in Nature Park Kopački rit in eastern Croatia, divided into seven-year reference (2013–2019) and three-year test periods (2020–2022) produced the following observations and conclusions:

- the zones based on NDVI anomalied can be utilized by Nature Park management to monitor vegetation health and changes over time, enabling better conservation strategies;
- the areas which produced highest and lowest NDVI anomalies are recommended to be analyzed comprehensively during fieldwork to determine the cause of abnormal vegetation activity;
- the phenology analysis based on the long-term Landsat 8 multispectral imagery using "npphen" R package successfully harmonized temporally uneven images into systematized monthly NDVI rasters without spatial gaps;
- high heterogeneity was observed for both monthly NDVI values and NDVI anomalies after the phenology analysis;
- the results of unsupervised k-means classification ensured the determination of five vegetation activity classes, with three of these classes having considerably high negative NDVI anomalies as class centers;
- a comprehensive field observation is required to determine the potential environmental and/or anthropogenic causes of vegetation changes on areas with extremely negative and moderately negative NDVI anomalies;
- longer study periods using the proposed methodology and combining earlier Landsat images with Landsat 8 would likely produce additional and more complete information on the vegetation activity and anomalies indicating vegetation changes to produce more informed land management plants of protected areas.

Acknowledgements

This research was supported by the Tech4All program, under project "Wetland and wildlife monitoring using technology and acoustics".

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