The use of vegetation indices and change detection techniques as a tool for monitoring ecosystem and biodiversity integrity

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Abstract: The use of satellite data has been widely applied to provide a cost-effective mean to analyse land cover changes over large geographic regions. The aim of this study was the multi-temporal change analysis of vegetation over the last 30 years, using freely available remote sensing data in three steps in Ilia Prefecture, Greece. In the first step, four vegetation indices were adopted to analyse the dynamic change of vegetation. At the second step, the investigation of the vegetation density changes was succeeded through thematic change detection techniques, and lastly, at the third step, a comprehensive change detection method (CCDM) was applied for mapping biomass progress/regress. Finally, after the catastrophic mega-fire of 2007 in Ilia, a change analysis of four vegetation indices focused on this affected region was implemented to investigate the vegetation restoration. Although some spatial changes of vegetation cover were observed during the study period, the state of biomass either improved or remained constant through time, demonstrating the high potential of Mediterranean ecosystems to recover after disturbance events.

Keywords: remote sensing; vegetation cover; multi-temporal analysis; change detection analysis; vegetation indices; sustainable management; informatics.


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1 Introduction

Land cover and its temporal dynamics play a major role in global patterns of climate and biogeochemistry cycles of the Earth (Lambin and Strahlers, 1994). Monitoring land cover and biomass changes is essential for planning and managing natural resources, modelling environmental variables, understanding the distribution of habitats and assessing biodiversity (Gómez et al., 2016; Hobi et al., 2017; Nieto et al., 2015).
Generally, according to Zhu and Woodcock (2014), land cover change can be distinguished into three categories. Seasonal change is driven by vegetation phenology caused by environmental and seasonal patterns. Trend change, caused by climate variability, change of vegetation state and land management. Abrupt change is caused by deforestation, floods, fire and urban expansion. In forest ecosystems, regarding carbon flux, biomass changes are predicted to happen both to the current forested areas and also to areas that are currently not forested (Bollandsås et al., 2013), as a result of climate and land use changes (Höhne et al., 2007). Deforestation affects biological diversity and results in soil degradation, mainly in the tropics (Matos et al. 2017; Sousa et al., 2017) but also in other areas (Burrascano et al., 2016). Wildfire occurrence and associated post-fire succession are the most critical drivers of vegetation changes (Jin et al., 2017), especially in Mediterranean ecosystems. These ecosystems show high resilience to fire, although the increasing rate of wildfire frequency and severity could cause serious ecosystem degradation (Ruiz-Gallardo et al., 2004). Remote sensing and GIS have been used extensively in post-fire applications, not only to estimate the burn areas (Mitri and Gitas, 2006) but also to evaluate post-fire recovery (Diaz-Delgado et al., 2005; Poirazidis et al., 2012).

The use of satellite data provides a cost-effective mean to analyse land cover, over large geographic regions (Lu, 2006; Lunetta et al., 2006). A fundamental advantage of remote sensing is the ability to collect and analyse time series images over large geographic areas easily and often at no cost (Hame et al., 1998). Digital change detection is a process of determining and quantifying change based on multi-temporal remotely sensed data (Jin et al., 2013), and it constitutes one of the most important applications of Earth-orbiting satellite sensors for natural resource management (Kennedy et al., 2009), providing multi-date digital imagery with consistent image quality, at short intervals, on any scale and during complete seasonal cycles (Rignot and van Zyl, 1993). The satellite image properties, such as spectral, spatial, temporal, and radiometric resolution, can affect significantly the success of the change detection assessment (Lu et al., 2014). Various researchers have described methods for change detection using remote sensing data, like transparency compositing, image differencing, image rationing, classification comparisons and image enhancement techniques (Jin et al., 2013, 2017; Kennedy et al., 2009; Matsushita et al., 2007; Munyati, 2000; Zhu and Woodcock, 2014). The most common change detection method amongst comparison techniques is the post-classification change method (Renza et al., 2017; Tewkesbury et al., 2015). Specifically, it refers to “the process of overlaying coincident thematic maps from different time periods to identify changes between them” (Tewkesbury et al., 2015).

Continuing, the capability of vegetation indices to enhancing features of interests can improve a change detection analysis, due to the reduction of variation caused by several conditions of topography, vegetation type and atmospheric characteristics (Lu et al., 2005, 2014). Lunetta et al. (2006) proposed an normalised differencing vegetation index (NDVI) based change detection technique, using MODIS data, which provides the capability to process temporal profiles of an index that track vegetation phenology on a continuous basis. For the same reason, Setiawan and Yoshino (2014) used enhanced vegetation index (EVI) to detect vegetation changes in the Java Island of Southeast Asia, which presents a highly productive intensive agricultural system. Regarding forest degradation, modified soil adjusted vegetation index (MSAVI) was selected by Wang et al. (2005) as the optimal vegetation index due to its linear relationship with green
canopy abundance. Finally, in a forest harvest type ecosystem, *normalised deferring moisture index* (NDMI) showed significantly high accuracy for detecting forestland changes (Wilson and Sader, 2002).

However, in cases were a systematic monitoring assessment of land cover changes is required for large-scale areas, researchers design and implement automated or semi-automated change detection models (Jin et al., 2013; Xian and Homer, 2010; Lv et al., 2017). These models offer not only the magnitude of land changes but also the direction of the changes (Bovolo and Bruzzone, 2007; Xian and Homer, 2010). Xian and Homer (2010) developed a method for radiometric change detection from paired Landsat images to update the US Geological Survey (USGS) National Land Cover Database (NLCD). Their implementation provided a baseline database to monitor surface changes useful for a study at a national and even regional scale. Lv et al. (2017) proposed a change detection system with three techniques (gaussian filter, threshold range prediction and region-growing algorithm). The experimental results showed that the framework achieved an enhanced change detection performance with high accuracies and is suitable for satellite images with median-low spatial resolution. Another important change detection method to detect changes related to forest regeneration and forest fire, which is a major component of our study, is zone model proposed by Jin et al. (2013) within the comprehensive change detection model (CCDM). Specifically, zone uses a combination of difference between normalised burned ratio (dNBR) of two time periods and difference between NDVI (dNDVI) of two time periods to capture a variety of forest changes (including regeneration and regrowth) efficiently.

The main goal of the study was to evaluate a multi-approach methodology for long-term analysis of vegetation changes as a tool to monitoring ecosystem and biodiversity integrity, using the Ilia region, Greece as a case study. The specific objectives of this study were to:

1. quantify vegetation changes using relative indices
2. investigate the changes of vegetation density classes
3. mapping biomass progress/regress using composite vegetation index
4. detect the forest recovery after wildfire.

2 Materials and methods

2.1 Study area

The study was carried out in the peripheral unit of Ilia (21°26’25.84”E and 37°40’7.244”N), located in southwest Greece. It covers 220,678 ha, of which 1,479 ha have been included in the Natura 2000 network (GR233002 – Oropedio Folois, GR2330004 – Olimpia, and GR2330005 – Thines and Paraliako Dasos Zacharos, Limni Kaifa, Strofilia, Kakovatos). The study area is characterised as a typical heterogeneous Mediterranean landscape, where forest stands (mainly by *P. halepensis* and *Quercus* species) of different sizes and ages are mixed with cultivations, primarily olives yards (Poirazidis et al., 2012).
2.2 Remote sensing data and pre-processing

In order to analyse the dynamic change of vegetation, we used 25 Landsat images acquired from 1984 to 2016 (Table 1). Twenty images were Landsat TM5, while five were Landsat 8 OLI/TIRS. The selected images were acquired between 15 July and 25 August of each year, except for 2007 which was acquired in September. The image of 2016, due to problems, was not used in the further analysis.

Table 1 The remote sensing images used in the study

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In certain circumstances, calibration of the image data is necessary prior to classification and change detection using multi-temporal images (Duggin and Robinove, 1990). Depending on the nature of research, atmospheric/radiometric correction can either convert a digital number to surface reflectance (absolute) or correct the same digital number values in order to represent some reflectance (relative), regardless of what the actual reflectance value may be on the ground (Song et al., 2001). In our case, we applied an absolute atmospheric correction using an ENVI 5.4 software routine.

2.3 Quantitative and multi-temporal analysis of biomass using vegetation indices

The first objective was to quantify the vegetation changes using vegetation indices. For this reason, four vegetation indices were calculated for each study year:

1. EVI
2. MSAVI
3. NDMI
4. NDVI.

Then, the mean values of those indices were calculated and evaluated in all the time-series (1984–2015) on two zone levels based on the LPIS-GIS:

1. forest zone, abandoned zone and olive grove zone
2. natural zone (the combination of the previous three zones).
2.3.1 Enhanced vegetation index

EVI [equation (1)] was developed to optimise the vegetation signal with improved sensitivity in high biomass areas and improved vegetation monitoring through a decoupling of the canopy background signal and a reduction in atmospheric influence (Jiang et al., 2008):

\[
EVI = G \frac{N - R}{N + C_1 - C_2 B + L}
\]

where \(N, R\) and \(B\) are near-infrared, red and blue bands respectively, \(G\) is a gain factor, \(C_1, C_2\) are the coefficient of the aerosol resistance term and \(L\) functions as the soil-adjustment factor. The coefficients adopted in the Landsat EVI algorithm are \(L = 1, C_1 = 6, C_2 = 7.5\) and \(G = 2.5\). EVI has been used in various studies including those on land cover change, estimation of vegetation biophysical parameters, phenology, evapotranspiration and other (Lo and Yang, 2002; Matsushita et al., 2007; Sims et al., 2006; Wardlow and Egbert, 2010).

2.3.2 Modified soil adjusted vegetation index

MSAVI [equation (2)] is a modified version (Qi et al., 1994) of the soil adjusted vegetation index (SAVI) developed by Huete (1988). The basic idea of MSAVI is to provide a variable correction factor \(L\). This adjustment factor depends on the observed level of vegetation cover and the product of other vegetation indices, such as NDVI and WDMI (Matricardi et al., 2010).

\[
MSAVI = N + 0.5 - \sqrt{N + 0.5^2 - 2(N - R)}
\]

where \(N\) and \(R\), are near-infrared and red band, respectively.

2.3.3 Normalised difference moisture index

NDMI [equation (3)] is very useful for detecting vegetation water liquid (Xu, 2006). This index produces accurate results in the forest conditions and is more accurate than NDVI in detecting forest disturbance (Wilson and Sader, 2002).

\[
NDMI = \frac{(N - S1)}{(N + S2)}
\]

where \(N\) is near-infrared band and \(S1\) is the infrared band between 1.55–1.75μm.

2.3.4 Normalised difference vegetation index

Whereas NDVI [equation (4)] correlates directly with the vegetation productivity, there are numerous possible applications of the index for ecological purposes (Pettorelli et al., 2005). The NDVI provides information about the spatial distribution of vegetation communities, vegetation biomass, CO2 fluxes, vegetation quality and the extent of land degradation in various ecosystems (Ferrari 2010; Pettorelli et al. 2005; Reed et al. 1994; Thiam 2003).
where $N$ is near-infrared band and $R$ is the red band.

2.4 Dynamic change of vegetation density

By using unsupervised classification (ISO DATA algorithm) based on the normalised difference bare soil index ($NDBSI$) [equation (5)] three thematic classes of vegetation density were estimated for all study years

1. high density vegetation – forest, shrubs, olive groves
2. low density vegetation – transitional ecosystems, sclerophyllous vegetation
3. open and rocky areas.

$NDBSI$ aims at enhancing bare soil areas, fallow lands, and vegetation with marked background response (Baraldi et al., 2006) and it was found to separate well the above density classes (Poirazidis et al., 2012).

\[
NDBSI = \frac{(S1 - N)}{(S1 + N)}
\]

where $S1$ is the shortwave infrared band with wavelength from 1.55 to 1.75 μm and $N$ is near infrared band of wavelength 0.76 to 0.90 μm.

By using thematic change detection techniques, a map of changes and net change diagram was produced to evaluate the relative changes for the whole period (1984–2015) (Figure 1).

**Figure 1** Flowchart of dynamic change vegetation density

2.5 Change detection using composite vegetation index

The comprehensive change detection method (CCDM) using a composite vegetation index was adopted to map the progress/regress (decrease/increase) of biomass. The CCD method was proposed by Jin et al. (2013) and includes three major components:
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1. MICCA, a change detection method for a full range of land cover disturbance.
2. Zone, a change detection method that is specifically designed to detect the changes related to forest.
3. Combination, the knowledge-based combination of change map derived from the MIICA and zone methods.

The first two methods generate a map of changes with two classes: biomass increase and biomass decrease. To analyse the biomass changes in the natural zone, the zone method was implemented (Figure 2). This method was applied by using two indices $dNBR$ [equation (6)] and $dNDVI$ [equation (7)]. These indices based on the difference between two time slots, are not only sensitive to the magnitude of the related forest change but also to the direction of the changes (Jin et al., 2013).

\[
dNBR = \frac{(N_{t1} - S_{t1}) - (N_{t2} - S_{t2})}{(N_{t1} + S_{t1}) - (N_{t2} + S_{t2})}
\] (6)

\[
dNDVI = \frac{(N_{t1} - R_{t1}) - (N_{t2} - R_{t2})}{(N_{t1} + R_{t1}) - (N_{t2} + R_{t2})}
\] (7)

where $N_{t1}$ and $N_{t2}$ are the near-infrared band of early and late date, respectively. $S_{t1}$ is the shortwave infrared band of the early date, and $S_{t2}$ is the shortwave infrared band of the late date. $R_{t1}$ and $R_{t2}$ are the red bands of the first and the second study year, respectively.

**Figure 2** Flowchart of CCDM zone model

The input indices of each time were the mean of two successive years (e.g., 2006 is the average of 2005 and 2006) to minimise the yearly variation of the estimated values. The estimation of biomass change direction was based on the reclassification of the differences of both indices using the mean value and standard deviation in four classes as:

- Change Map A
- Change Map B
- Change Map C
- Change Map D
pixels with no change [mean + 0.5 * std]
2 pixels with no change [mean – 0.5 * std,]
3 pixels with biomass decrease [>= mean + 0.5 * std]
4 pixels with biomass increase [< = mean –0.5 * std].
The reclassified indices were then combined to obtain an image with a total of 16 classes, where class 33 represents biomass decrease, and class 44 represents biomass increase.

2.6 Analysis of post-fire vegetation restoration

Post-fire regeneration process differs among regions since different environmental factors play a critical role in regeneration patterns (Poirazidis et al., 2012). In Ilia’s peripheral unit, in 2007, a catastrophic fire damaged 22,678 ha, mainly covered by Pinus halepensis forest. Through remote sensing techniques, we investigated the current vegetation status in this area to evaluate the level of recovery (Figure 3). The methodology approach followed by this analysis had two main components. The first one refers to the comparison of the four vegetation indices, which were used in section “Quantitative and multi-temporal analysis of biomass using vegetation indices”, for the years 1986, 2006 (before the fire), 2007 (year of fire occurrence) and 2015 (post-fire year). The second component contains post-classification change detection techniques, using the NDBS index and ISO DATA unsupervised classification, as shown in section ‘Dynamic change of vegetation density’. The change detection maps refer to the time periods 2006–2015, 2006–2007 and 2007–2015.

Figure 3 Flowchart of post-fire vegetation analysis

3 Results

3.1 Quantitative and multi-temporal analysis

The multi-temporal analysis of the vegetation indices (1984–2015) for the combined natural zone of Ilia’s region, showed small fluctuations during the study period, where EVI and MSAVI seem to be more stable over the years while NDMI and NDVI showed greater fluctuations (Figure 4). A general small increasing trend was observed from 1984 to the recent times. The average values for EVI, MSAVI and NDMI were around 0.4 and NDVI’s mean value around 0.7. In 2007, all indicators due to the big fire in the region
were dropped down, but their values were returned close to the initial level (before fire) in 2015. Results from the three specific zones (forest zone, abandoned zone, olive grove zone) showed the same pattern as the natural’s zone (where the mean values are a bit higher, i.e., 0.5 for EVI, MSAVI and NDMI, and 0.75 for NDVI for the forest and abandoned zones).

Figure 4   Vegetation indices of natural zone (1984–2015) (see online version for colours)

3.2 Dynamic change of vegetation density

In the natural zone, high density vegetation was appeared to have the highest percentage of a mean value 49%, maximum value 57% in 2011 and a minimum value 29% in 2007 (Figure 5). Following high density vegetation, low density vegetation class has a mean value 38%, maximum value 44% in 2008 and a minimum value 35% in several years. Lastly, open and rocky areas had the lowest coverage in all years with a mean value 13%, maximum 33% in 2007 and minimum 11% in 2011. Variations in rates per year were small as they did not exceed 8% of net changes, with an exception in 2007 where the dense vegetation had lost 26% of its coverage, with a consequent increase by 25% of open and rocky areas. The dense areas recovered their rates in 2011, after 2007’s wildfire, as the period 2011–2015 highly vegetated areas covered approximately 55–57%.

In forest zone, as expected, the high density vegetation was the main class, with a mean value 74% and minimum value of 65%, while the remaining 26%, referred to the sparse vegetation category. At the abandoned and olive grove zones, the main class was the low density vegetation (28% to 47% and 48% to 52%, respectively) but they had the highest variation among density cover classes.
The produced map of changes showed that for the period 1984–2015 (Figure 6 and 7) in the natural zone of Ilia, major changes were not observed, as 74% of the region was classified as ‘no change’ areas, ‘low density’ area was improved to ‘high density’ vegetation at 10%, but at the same time 7% of ‘high density’ areas were degraded to ‘low density’ vegetation. Changes occurred mainly in the eastern-mountainous areas leading to improved vegetation density and in the southern part of the region where a clear pattern (improvement or deterioration of the vegetation state) was not obvious.
3.3 Change detection of biomass using composite vegetation index

The comprehensive change detection method – zone model was implemented in four time periods

4. D: 2006–2015 to analyse spatial patterns within the overall studied period (Figure 8).

A similar pattern was observed in the periods B and C, where biomass had a total increase of 60% and a relative decrease of 40%, resulting in a similar result for the overall period (A). This pattern was reversed in the last period (D), mainly by the effect of 2007’s mega-fire. The main reduction of biomass was observed in the southern section of Ilià’s region while biomass growth appeared in the mountainous areas of the eastern part as well as in areas that belong to the abandoned zone.
Looking at the LPIS zones, the pattern at the forest and olive groves zones is similar with a difference at their intensity. At the forest zone the relative rates of biomass were constantly increasing from 1984 to 2006, which was estimated at 68% for the first period (B) to 73% for the second (C), but a high decrease rate was found for the third period (D), which reached 67%. Overall, in the studied period (A), a total increase of biomass (67%) appeared in the forest zone. In the Olive grove zone, results showed that biomass decrease outmatched biomass increase in almost all studied period. Specifically, in the period 1986–1996 (B) biomass decrease and increase had a value of 50%, and in the periods A, C and D biomass decrease had 52, 51 and 56% respectively. At all periods in the abandoned zone, biomass had an increasing trend. Overall, in period A, the relative rates of biomass increased to 75%. The first periods (B and C) the increase rates were 69% and 60% respectively, and finally, at the period D, there was a biomass decrease of 49%.

3.4 Analysis of vegetation restoration after fire in 2007

The post-fire analysis of vegetation cover after the mega-fire of 2007 indicated the rapid recovery of the burnt forested area. Despite the almost complete disappearance of the forest vegetation in 2007, eight years later, most of the indices showed a better or similar picture compared to 2006 and better than 1986 [Figure 9(a)]. Only the NDMI did not fully recovered, possibly due to the sensitivity of this index in the more mature forest stands which they burnt in 2015. Similar results were found in the analysis of density.
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classes, where the presence of high density vegetation cover (from 86% in 1986 and 88% in 2006), was restored again in 2015 reaching 85% [Figure 9(b)].

Figure 9  (a) Changes of vegetation indices and (b) Density class at burned forest zone in mega-fire of 2007, for the years 1986, 2006, 2007, 2015

From the classification of $NDBS$ index for the pre-fire study years, it is evident that in this zone the presence of high density vegetation is very high, as in any year this percentage is not less than 85%. At the year of fire, the areas with high density vegetation
cover only 9% of the study area. The open/rocky areas in the years before and after the fire do not exceed 3.5%, while in 2007 these areas amounted to 80%.

Comparing the vegetation conditions between 2006 and 2015, one can see an excellent recovery rate since 92% of the area appears with no changes and only 8% of the burnt area has changed mainly in less vegetated areas. Specifically, 5.5% of ‘high density’ vegetation in 2006 transformed into ‘low density’ vegetation (4.5%) and ‘open and rocky’ areas (1%) in 2015. Concerning open and rocky areas, no more than 0.3% changed into another type. Opposite, areas with ‘low density’ vegetation in 2006 had changed to ‘high density’ vegetation and ‘open and rocky’ areas in 2015 by approximately 1% in each density class (Figure 10).

Figure 10  Change detection analysis at the burnt forest zone for the period 2006–2015 (see online version for colours)

4 Discussion-conclusions

Remote sensing is an appealing technology when estimating vegetation dynamics as it provides a vast range of data and tools (Galidaki et al., 2017). Many automated algorithms (Jin et al., 2013; Kennedy et al., 2009) have been successfully developed to detect land cover/use changes using mid-resolution images, such as Landsat images. Specifically, Pflugmacher et al. (2012) found a strong relationship between post-disturbance vegetation cover and recovered forest structure from analysing Landsat
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time series metrics which is crucial when detecting the time of disturbance and therefore, the change of vegetation’s state. Furthermore, vegetation indices are useful for detecting land change patterns with high accuracy as stated by Wilson and Sader (2002), who used multi-date Landsat images to identify forest change accurately. Many studies use Landsat image data due to their utility and historical record that cover more than a 40-year period (Nagendra et al., 2013), which makes it, even more, easier to include satellite data into monitoring processes. The aim of this study was the development of a multi-level methodology of temporal analysis of vegetation changes using remote sensing data. This methodology could be used as a proxy for monitoring ecosystem and biodiversity integrity through a time scale.

All of the vegetation indices showed stability, with small fluctuations but also a slightly increasing trend, with a relatively similar pattern for all study zones. In 2007, a significant reduction of biomass was counted, but most of the burnt forests consist of mature pine forest. Veraverbeke et al. (2012), assessed the post-fire vegetation recovery three years after the catastrophic fires on the Peloponnese peninsula using 13 vegetation indices. Their study suggests that NDVI is the optimal measurement for applications related to areas with variability between vegetation types and found that at 2010, vegetation regrowth was evident. These results are similar to ours since indicators values after 2011 are near to values found at pre-fire periods. The effective protection of natural regeneration both from Forest Service and locals allows the ecosystem to quickly recover and revegetate the burnt area within eight years since the fire event.

Concerning the study of vegetation densification, the results showed a rather stable condition. In all study years (except 2007) and all study zones, the areas with high density vegetation remained constant, which shows the high value of ecosystems in the natural zone of Ilia’s region (forest and olive groves parcels). In contrast, results from the implementation of CCDM – zone method, showed a spatial vegetation dynamic (progress or regress) in the natural zone, as the method captures a full range change, including all kind of disturbances (e.g., fire, deforestation). For the periods 1986–1996, 1996–2006 and 1986–2015 there was a significant increase of biomass in contrast to the biomass decrease at the period 2006–2015. Although the applied model shows an increase or decrease of biomass, it did not clarify its origin, but additional data (e.g., polygons of the burnt areas, other pressures) could be overlaid to analyse cause–effect problems.

As the methodology produces spatial data, any scale of investigation could be used from Forest Services to monitor in a systematic way the integrity of local ecosystems and consequently the effectiveness of these ecosystems to support and maintain local biodiversity and ecosystem services. Newly available satellite sensors with better spatial and spectral resolution (e.g., Sentinel-2 with 10m pixel size) could help ecosystems monitoring with better accuracy, and these sensors have already been used for global monitoring of the environment (Drusch et al., 2012).

Finally, it is essential to emphasise the dynamic of Mediterranean ecosystems. This type of ecosystems has the ability to recover quickly, in case of a disastrous intervention (e.g., fire) but not in the case of repeated events (Keesstra et al., 2017; Poirazidis et al., 2012). Thus the early recognition of urgent intervention is a cost-effective method for economic and ecological benefits. Monitoring, observation, and interpretation of historical changes in land cover will significantly help the understanding of spatial dynamics and lead to a sustainable management of those sensitive ecosystems.
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The use of vegetation indices and change detection techniques


