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Research Article

The performance of vegetation indices for operational monitoring of CORINE vegetation types

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Abstract

Vegetation monitoring has been performed using remotely sensed images to secure food production, prevent fires and protect natural ecosystems. Recent satellite sensors, such as MODIS, provide frequent wide scale coverage in multiple areas of the spectrum, allowing the estimation of a wide range of specialized vegetation indices (VIs), each offering several advantages. It is not, however, clear which VI performs better during operational monitoring of wide scale vegetation patches, such as CORINE Land Cover (CLC) classes. The aim of this work was to investigate the performance of several VIs in operational monitoring of vegetation condition of CLC vegetation types, using Terra MODIS data. Comparison among the VIs within each CLC class was conducted using the sensitivity ratio, a statistical measure that has not been used to compare VIs and does not require calibration curves between each VI and a biophysical parameter. In addition, the VI's sensitivity to factors such as the aspect, viewing angle, signal saturation, and partial cloud cover was estimated with correlation analysis in order to identify their operational monitoring ability. Results indicate the Enhanced Vegetation Index as superior for monitoring vegetation condition within the CLC types, but not always optimum in the performance tests for operational monitoring.

Keywords: vegetation indices; performance evaluation; operational monitoring; sensitivity ratio; MODIS

1. Introduction

Vegetation is monitored from Earth observation satellites at large scales in order to provide knowledge about the condition of natural ecosystems, the productivity of crops and the assessment of risks, such as fire and drought. Monitoring plant phenology has helped identify deforestation in Brazil and improved management for yield potential in maize production (Ferreira *et al.* 2003, Vina *et al.* 2004). Vegetation monitoring has been used to aid risk prevention and management of drought in agricultural crops and fire prevention in the Mediterranean forest and maquis (Maselli *et al.* 2003, Unganai and Kogan 1998). More recently, monitoring terrestrial ecosystems has aided climate change assessment regarding estimation of carbon fluxes and ecosystems capacity to act as carbon sinks (Gonzalez-Alonso *et al.* 2006, Potter *et al.* 2009).

Often, monitoring of vegetation condition with remotely sensed data is performed by utilizing vegetation indices (VIs), which are spectral transformations of two or more bands. Their ability to detect vegetation quantity and quality is based on the high reflectance of green vegetation in the near-infrared spectrum and the low reflectance in the red spectrum. The usefulness of using VIs is immense, as they offer easy calculation and interpretation, and minimisation of radiometric, atmospheric and topographic effects (Silleos *et al.* 2006). A large number of VIs has been designed, providing certain advantages. Among the numerous vegetation indices available, the Simple Vegetation Index (SVI) was developed first and is one of the simplest to calculate (Tucker 1979). The Normalized Difference Vegetation Index (NDVI) (Townshend *et al.* 1987) offers several advantages such as the confined range of values which facilitates interpretation, and is probably the most widely used for monitoring vegetation condition (Baret and Guyot 1991, Huete *et al.* 1985). More recently, the Enhanced Vegetation Index (EVI) has been proposed by the MODIS Land Discipline Group for use with MODIS data to overcome issues related to soil background and atmospheric influence (Huete *et al.* 1999). Large scale programmes related to monitoring vegetation condition with VIs include the Fire Prevention System of the Greek Civil Protection Agency at the national scale and FAO's Global Information and Early Warning System (GIEWS) at the continental scale (FAO 2000, Gitas *et al.* 2004).

Following the development of more than thirty VIs, comparisons among different VI have been performed using the probability theory (Vaiopoulos *et al.* 2004), regression analysis (Lawrence and Ripple 1998), multivariate analysis of variance (Price *et al.* 2002) and sensitivity analysis (Ji and Peters 2007). Also, simulation data have been used (Bouman 1992), as well as comparison with reference datasets of biophysical parameters such as capability to estimate leaf area index (LAI) (Elvidge and Chen 1995), forest biophysical parameters (Peddle *et al.* 2001), and crop height (Payero *et al.* 2004). Specifically for MODIS, the performance of various indices has been performed from radiometric and biophysical perspectives, both pre-launch with simulated images from Landsat TM (Huete *et al.* 1997) and post-launch (Huete *et al.* 2002) using MODIS, airborne radiometric measurements, Landsat ETM+ and in situ field biophysical data collected over validation test sites.

Each VI offered several advantages over the existing ones, justifying its development. However, unless tested under specific conditions (scale and geographic region) their actual performance is unknown. Thus, it is not clear which VI performs better during operational monitoring of wide scale vegetation patches, such as CORINE Land Cover (CLC) classes, since no comparative analyses have been performed. The aim of this work was to investigate the performance of several VIs in operational monitoring of vegetation condition of CLC vegetation types, using MODIS/Terra data. The specific objectives were: (i) to investigate the performance of various VIs for monitoring homogeneous CLC vegetation types using the sensitivity ratio, and (ii) to investigate the VIs' sensitivity to factors that influence operational monitoring.

2. Study area

The study area consists of the vegetated areas of Greece, which covers 131,000 km^2 including the mainland and numerous islands which vary in size (Figure 1). Greece is located in the Mediterranean climatic zone, with monthly average temperatures ranging from 5^{o}C in the winter to 28^{o}C in the summer. The mean annual precipitation varies throughout the country, ranging from 400 to 1800 mm/year, corresponding to the strongly undulating terrain. The wet months are March, April and November, while July and August are very dry.

[Figure 1 about here]

Vegetation cover of the area is typically Mediterranean and can be classified into two major categories: natural (59%) and managed (41%), based on the CLC map of Greece (EEA 2004).

The managed (agricultural) vegetation consists of irrigated annual crops (maize, cotton, alfalfa and others) concentrated around lowland irrigation systems, rainfed cereals located on the hillsides, and orchards scattered around villages (classes 2.1, 2.2, 2.3 and 2.4 in Table 1). The phenological cycle of managed agricultural vegetation is repeated on an annual basis. Development phases include seeding, growth, maturity and harvesting, which can largely be controlled by modern agricultural practices. Factors such as current meteorological conditions, irrigation status and availability of equipment influence the timing. Generally, there is one growing season from early spring to early autumn. The agricultural vegetation in the study area is monitored by the Hellenic Agricultural Insurance Agency for yield prediction and crop damage assessment using, among others, the NDVI vegetation index (Silleos *et al.* 2002).

The natural vegetation consists of coniferous and deciduous forest, shrubs and pastures (classes 3.1, 3.2 and 3.3 in Table 1). The phenological cycle of the natural vegetation is relatively stable throughout the year, except in the case of extreme weather conditions. Generally, the various types of vegetation leaf-out, grow to maturity and senesce at approximately the same time each year. The most notable changes occur after the dormant phase of winter, when rapid growth takes place in the spring, followed by senescence in late summer or early autumn. The natural vegetation in the study area is monitored by the Civil Protection Agency, mainly for fire prevention (Gitas *et al.* 2004).

3. Materials and methods

3.1 Data acquisition and pre-processing

The main dataset used in this study was acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra satellite. The CLC map was also used to identify areas of homogeneous land cover. In specific, the datasets used were:

- The MODIS/TERRA daily surface reflectance product (MOD09GHK) at 500m pixel resolution. This product was selected in preference to the 250m MOD09GQK because it included the spectral bands necessary for the calculation of the examined VIs. A sample image is provided in Figure 2.
- The MODIS/TERRA 8day LAI product (MOD15A2) at 1km pixel resolution.
- The MODIS/TERRA daily geolocation angles product (MODMGGAD) at 1km pixel resolution.
- The Digital Elevation Model (DEM) of Greece at 127m resolution (Figure 3), derived from interpolation of elevation contours at 100m intervals.
- The CORINE Land Cover (CLC) map of 2000 is a vector file that characterizes the type of land cover in 44 categories. It was digitized on screen at a 1:100,000 scale with minimum mapping unit of 0.25 km^2 using Landsat 7 images acquired throughout Europe in 2000. The CLC project was jointly managed by the Joint Research Centre and the European Environment Agency (EEA 2010). CLC has a hierarchical structure, of which the 2nd level was used, as it was in a similar scale to the above

mentioned raster datasets. The classes that were considered in this study are provided in Table 1.

[Table 1 about here]

[Figure 2 about here]

[Figure 3 about here]

The MODIS images acquired on the following dates were used: 13/05/2003, 14/08/2003, 25/10/2003, 16/02/2004, 13/05/2004, 14/08/2004, 24/10/2004, and 18/02/2005. All the MODIS data were downloaded from the Earth Observing System Data Gateway (http://edcimswww.cr.usgs.gov/pub/imswelcome/). They were reprojected from the Sinusoidal projection to the Greek coordinate system, and the tiles covering the study area were mosaiced and masked. The MODIS Reprojection Tool was used to identify the pixels flagged as low quality in the MODIS images and they were removed from further processing.

Three VIs were examined in this study: the Simple Vegetation Index SVI (Tucker 1979), the Normalized Difference Vegetation Index NDVI (Townshend *et al.* 1987), and the Enhanced Vegetation Index EVI (Huete *et al.* 1999). These three indices were included in this work for their diverse properties: SVI is simple in its calculation and requires low computational power, NDVI is widely used and long time series exists, and EVI overcomes several sources of noise and is promoted as the new standard index. All these VIs were created by using MODIS surface reflectance products, at 500m pixel size. Factors used in EVI calculation were adopted from Huete et al. (1999): L=1, C1=6, C2=7.5, and G= 2.5.

The equations for estimating these indices are:

$$SVI = \frac{NIR}{R} \tag{1}$$

$$NDVI = \frac{NIR - R}{NIR + R} \tag{2}$$

$$EVI = 2.5\left(\frac{NIR - R}{NIR + 6R - 7.5B + 1}\right) \tag{3}$$

Where: *NIR* is the reflectance in the near-infrared wavelength, *R* is the reflectance in the red, and *B* is the reflectance in the blue.

Since the two main vegetation categories of the study area (natural and managed vegetation) are different in their phenological cycles, it was decided to study them separately and provide results for each main vegetation category. These two categories were defined using the CLC map. The map’s scale (1:100,000) was adequate for a nationwide study, and its production date (2000) was not expected to create any problems at this level of generalization, as no major changes had been recorded in fire and agricultural statistics (YPAAT 2013, YPEKA 2013).

3.2 Evaluation of VIs for monitoring CLC vegetation types

The basic assumption for the first objective was that monitoring vegetation condition at the CLC type level would be better performed with VIs that are responsive to the variability of vegetation reflectance. A VI that is more responsive, or sensitive, to vegetation variability than another VI would be preferred. Several different measures of the relative sensitivity of two VI have been proposed. Becker and Choudhury (1988) suggested using $R=|dY/dX|$, the first derivative of two rescaled VI, Y and X where Y is preferred if $R>1$. Gitelson (2004) used $S_R= (d\hat{y}/dx)(\Delta x/\Delta y)$, where $\hat{y}=f(x)$ was the regression function of VI y on x, $d\hat{y}/dx$, the derivative and $\Delta x/\Delta y$, the ratio of the ranges of the two VI and where VI Y was preferred if $S_R >1$. Unfortunately, both measures R and S_R are somewhat limited since neither accounted for random variability of the VI. Ji and Peters (2007) proposed the relative sensitivity $s_{y|x} = (d\hat{y}/dx)/\sigma_{\hat{y}}$, the derivative of a nonlinear regression function $(d\hat{y}/dx)$ divided by the standard error of the prediction $\sigma_{\hat{y}}$ where two VI were compared by plotting $s_{y|x}$ vs x and $s_{x|y}$ vs y. Although $s_{y|x}$ incorporates random variation via $\sigma_{\hat{y}}$ and allows a comparison of two VIs, the method is somewhat cumbersome requiring two regressions and a rather ad hoc visual assessment of the relative sensitivities with unknown mathematical properties.

The SR, proposed by Mandel (Mandel 1964, Mandel and Stiehler 1954) is a measure of relative variation useful for comparing different methods of measuring the same property and is especially useful when the methods have different scales and the relationship between the scales is either unknown or complex. The SR is similar in concept to the relative sensitivity of Ji and Peters (2007), but is easier to compute and has well-developed mathematical properties and statistical tests (Mandel 1964, Otto-Hanson *et al.* 2009). The SR for two VI, M and N, is developed by assuming both VI are functions of the same property Q. Specifically, $M=f(Q)$ and $N=g(Q)$ where the functions are both differentiable and the inverses f^{1} and g^{-1} exist. Then for VI M, $Q=f^{1}(M)$ and using the delta rule the variance of Q is $\sigma^2_{Q(M)} =[df^{-1}/dM]^2\, \sigma^2_{\mathrm{M}}$ where σ^2_M is the variance of M. The sensitivity of VI M is the inverse of the standard deviation of Q as measured by M which is $1/\sigma_{Q(M)} = (df/dQ) / \sigma_M$ since $df^{-1}/dM = 1/(df/dQ)$. Similarly it can be shown that the sensitivity of VI N is $1/\sigma_{Q(N)} = (dg/dQ) / \sigma_N$. Specifically, this is a measure of sensitivity of the VI relative to its standard deviation. The ratio of the two sensitivities results in the sensitivity ratio

$$SR\left(\frac{M}{N}\right)=\left|\frac{dM}{dN}\right|/\left(\frac{\sigma_{\mathrm{M}}}{\sigma_{\mathrm{N}}}\right) \qquad (4)$$

If $SR(M / N) > 1$ the sensitivity of M is superior to N, if $SR(M / N) < 1$ the sensitivity of N is superior and the methods have equal sensitivities if $SR(M / N) = 1$. The physical explanation of using SR to compare the performance of two VIs, say M and N, is that if $SR\left(\frac{M}{N}\right)> 1$ then VI M is more responsive relative to its standard deviation in each CLC type than VI N, i.e. VI M is relatively more responsive within each group of CLC polygons. It is important to emphasize that the SR applies to any biophysical parameter Q, as long as both M and N are monotonic, invertible and differentiable functions of Q. This remarkable property means that the superiority or inferiority of a VI relative to another does not depend on a specific biophysical parameter as required by previously used techniques, and as such allows global superiority statements relative to any possible biophysical parameter. For example, the comparison of the sensitivities of EVI and NDVI can be made without fitting calibration curves of EVI and NDVI in terms of a biophysical parameter, for example LAI. In addition, the SR is invariant to any scale transformation of *N* or *M*. For example, any scale transformation EVI will have no effect on the SR between EVI and NDVI. To the authors' knowledge, no other method proposed used for evaluating VIs has these properties. For details on SR, see Mandel and Stiehler (1954), Mandel (1964), Otto-Hanson et al. (2009).

The derivative in (4) was computed by regressing each VI against each other (NDVI vs SVI; NDVI vs EVI; EVI vs SVI) over the CLC classes for each vegetation class and date. The standard deviations for each VI were estimated as the average standard deviation within CLC class for each vegetation class and date. A random sample of 1000 points was selected per CLC class to estimate means and standard deviations. Scatter plots of each VI against each other for each vegetation type and date indicated that for nearly all cases, an approximate linear relationship existed between the VI over the CLC classes. The regression results are given in Table 2. Predicted vs. actual values of NDVI of the worst fitting model (NDVI vs. SVI) is displayed in Figure 4 to give a visual representation of the model fitting. The other models followed a similar pattern (data not shown).

For each CLC type and date, the mean values of *NIR*, *R* and *B* were used in formulas (1)-(3) to compute the VIs: SVI, NDVI and EVI.

[Table 2 about here]

[Figure 4 about here]

3.3 Evaluation of indices for operational vegetation monitoring

The basic assumption for the second objective was that VIs should be usable under normal conditions, thus performing well for operational vegetation monitoring. Therefore, a VI would be most useful in operational monitoring if it was not affected by the factors that usually hinder large scale Earth observation monitoring. The performance of the VIs as affected by various factors was examined using performance tests.

- *Aspect*: Aspect is a factor reported to influence the sensor’s return signal, depending on the relief and sun azimuth and elevation (Goodin *et al.* 2004). Moreover, it is affecting the state of vegetation as it relates to the incoming solar energy and resistance to droughts (Bennie *et al.* 2006). The criterion used to investigate the influence of aspect was the level of correlation between the VIs and the aspect. The VI with the lowest correlation coefficient with aspect was the most appropriate for operational monitoring. In order to assess the relation of VIs in relation to aspect, a random sample of 1000 points was selected throughout Greece. Then an aspect raster was created at 500m pixel using the DEM and was represented by 8 classes (N, NW, W, WS, S, SE, E, NE). For each point of the random sample the values of each VI and the aspect class were recorded and correlated in pairs. The analysis was repeated per CLC vegetation type to exclude the influence of the latter, as it may be related to aspect.

- *Viewing angle*: Wide coverage satellite images are mostly influenced by sensor viewing angle, displaying variable reflection from nadir to off-nadir locations (Zhang *et al.* 2003). Specifically for vegetation canopies, NIR is affected more by multiple scattering than red reflectance, which causes an increase of the spectral contrast between the NIR and red band, resulting in higher VI values off-nadir (Kimes *et al.* 1985, Verrelst *et al.* 2008). In this work, the criterion for the investigation of influence of viewing angle was again the level of correlation between the VIs and the sensor's zenith azimuth. The VI with the lowest correlation coefficient with the sensor's zenith azimuth was the most appropriate for operational monitoring. The dataset used to compute the correlations of the VIs against the viewing angles was the same as for the aspect.
- *Saturation*: A major limitation of confined ratio vegetation indices, such as NDVI and EVI, is that they asymptotically approach a saturation level after a certain biomass density or LAI (Gao *et al.* 2000, Huete *et al.* 1997, Todd *et al.* 1998, Tucker 1977). In high density vegetation canopies, the amount of red light that can be absorbed by leaves reaches a peak, while NIR reflectance will increase because an addition of leaves results in multiple scattering, thus yielding a poor relationship between the VI and biomass (Kumar *et al.* 2001, Thenkabail *et al.* 2000, Tucker 1977). In this work, the criterion to investigate the saturation of the VIs was the variability of a VI at the areas of high biomass, where LAI was highest. The MODIS/TERRA 8day LAI product (MOD15A2) at 1km pixel resolution was used to identify the areas of high vegetation biomass density (LAI > 2), where VI saturation is mostly expected. In high biomass densities, the relationship between NDVI and LAI has been identified as nearly linear (Myneni *et al.*, 1997; Thenkabail *et al.*, 2000). The VI displaying the highest correlation with LAI at these areas of high vegetation density was considered the least saturated VI. The correlation was computed using the same dataset used for aspect and viewing angle, after resampling the VIs to 1km. Values of LAI lower than 2 were excluded from this analysis leaving a sample size of 399 points. The reported accuracy of MODIS/TERRA 8day LAI is 0.66 m^2/m^2.
- *Partial cloud cover*: Partial cloud cover is a factor influencing VIs in images of large pixel sizes (Liu *et al.* 2004, Zhang *et al.* 2003). The criterion used to investigate the influence of partial cloud cover was the correlation of VI values of partially cloud covered pixels of the examined day with the corresponding pixels of the previous or next cloud free day. The VI with the highest correlation between the two days was considered the most appropriate for operational monitoring, as this VI would be the least affected from partial cloud cover. The methodology followed for this purpose was to isolate some pixels at the perimeter of clouds, thus potentially partially cloud covered, which were cloud free at the previous or the next day of satellite acquisition. This criterion was based on the assumption that the changes in vegetation condition were not significant between two days, which has already been proven in the study area (Alexandridis *et al.* 2008). Gridding artifacts and variable viewing angles have been reported to influence daily MODIS observations (Tan *et al.* 2006, Wolfe *et al.* 1998, Xin *et al.* 2012). To minimize their influence on the results of this test, only near-nadir observations were used (viewing angle < 10^o) in the analyses for this test.

The test of significance of the correlations was selected for two-tailed probabilities because the direction of association of the two variables was not known in advance (Fisher *et al.* 1970).

4. Results and discussion

4.1 Performance of VIs for monitoring vegetation condition within CLC types

Results for all vegetation types (Table 3 a) show that EVI displayed a higher performance for monitoring the condition of CLC vegetation types on most of the examined dates. The high performance of EVI may be due to the design of this VI to overcome known problems of older VIs related to interference of soil background and atmosphere. Indeed, this VI has a soil adjustment factor, uses the blue to correct for atmospheric aerosol scattering, and has improved sensitivity to high biomass regions (Huete *et al.* 2002). An exception to these results was noted during a single date in mid-summer (14/8/2003), when EVI had almost equally low performance as NDVI, both inferior to SVI. This could be due to the higher errors in vegetation parameters estimation noted in high values of LAI, thus at high levels of vegetation cover (Liu *et al.* 2007). In these cases, various leaf layer conditions at the same percent vegetation cover is misinterpreted as changes in the estimate of vegetation cover amount and yield variable VI values (Purevdorj *et al.* 1998).

In general, SVI had the lowest performance as compared with EVI and NDVI. This VI appeared to be relatively less homogeneous within an area with uniform vegetation type. The large potential range of values of SVI $[0, +\infty)$ could not be the reason for this lower performance, as SR is designed to overcome differences in the scale of the examined methods. However, there is a very high correlation of SVI with NDVI and EVI, according to the scatter plots and the R^2 values from the regressions across the CLC types (Table 2).

Repetition of the analyses for managed and natural vegetation separately (Table 3 b and c) showed results similar to the previously mentioned ranking for the combined all vegetation types. An exception was the mid-summer dates of both years (14/8/2003 and 14/8/2004) when SVI was superior to EVI for natural vegetation only. A possible reason is the full development and high levels of biomass of natural vegetation, which in combination with the lack of atmospheric disturbances in the arid Mediterranean summer amplified the advantage of SVI to remain unsaturated in full vegetation cover conditions. During these days, SVI was marginally better than EVI, thus lowering the confidence of the results.

[Table 3 about here]

4.2 Performance of indices for operational vegetation monitoring

There was a very weak relation between the examined VIs and aspect, as most correlation coefficients were smaller than 0.1 (Table 4a). Moreover, detailed analysis per CLC vegetation type did not reveal any increase in the relations (results not shown). Therefore, aspect plays a negligible role as an influencing factor for any of the examined indices. This is a positive characteristic of all slope-based VIs, for which the problem of variable surface illumination as a result of topography is minimized because of division of satellite spectral bands (Silleos *et al.* 2006). These results agree with previous similar observations for wheat crops in Italy (Pinter Jr *et al.* 1987). Nevertheless, aspect has been reported as an important factor influencing vegetation monitoring with remote sensing, especially in mountainous environments (Deng *et al.* 2007), for which correction algorithms have been proposed (Gitas and Devereux 2006).

All three VIs displayed relatively low correlation coefficients with sensor's viewing angle (<0.5). However, SVI had the lowest correlation coefficients in most of the examined dates, followed by NDVI. EVI was for all dates the most highly correlated (Table 4b). Therefore, SVI is the VI least influenced by the sensor's viewing angle. According to previous studies, the effect of variable viewing angle of wide viewing satellites is exacerbated by most VIs, which may show strong isotropic behaviour (Pinter Jr *et al.* 1987). Small differences were also noted between SVI, NDVI and ARVI (Atmospherically Resistant Vegetation Index) in other studies (Verrelst *et al.* 2008). Nevertheless, the effect of viewing angle on VIs is dependent on vegetation type and percent of coverage (Kaufmann *et al.* 2000; Pocewicz *et al.* 2007).

Regarding the influence of saturation, the results showed that SVI had the highest correlation with high values of LAI, where saturation was expected (Table 4c). This was probably because SVI is designed to have a large potential range of values $[0, +\infty)$. However, an equally high performance was expected for EVI, since it has been reported to display good sensitivity in monitoring high biomass conditions (Huete *et al.* 2002). However, SVI had higher correlations in 6 of the 8 dates considered. A similarly higher performance of SVI had been noted in a previous comparison with NDVI and TVI (Transformed Vegetation Index); nevertheless it has been suggested that the red edge reflectance bands minimise the issue of saturation (Mutanga and Skidmore 2004).

Finally, partial cloud cover had generally the lowest influence on EVI over all the examined days as demonstrated by the generally large correlation of VI pixels between cloudless and partly cloudy days (Table 4d). EVI has been previously reported to perform better than NDVI under the influence of atmospheric aerosols both at local and continental scales (Huete *et al.* 1997, Xiao *et al.* 2003). This insensitivity was probably because EVI was designed to be resistant to atmospheric influences (Huete *et al.* 2002). EVI's design was based on the difference of blue and red band reflectance due to aerosol scattering, which was used to stabilize the index value against variations in aerosol concentration levels (Huete *et al.* 1999). This was first used in the design of the Atmospherically Resistant Vegetation Index (ARVI), which utilizes the difference in radiance between the blue and the red channel to correct the radiance in the red channel and stabilize the index to temporal and spatial variations in atmospheric aerosol content (Kaufman and Tanre 1992).

[Table 4 about here]

4.3 Discussion and implications for vegetation monitoring

The examined VIs are based on the same principle: they show the contrast between the high reflectance of near-infrared wavelength because of internal leaf scattering and no absorption, and the low reflectance of chlorophyll at red. Generally they are sensitive to the abundance and activity of the absorbers of radiation, which can be quantified with derivatives (Myneni *et al.* 1995) or more complex equations that connect the spectral reflectance with biophysical properties of leaves and canopy (Pinty *et al.* 1993). However, differences in the various VIs' response derive from the mathematical design of each VI and the inclusion of additional spectral bands in order to minimize the soil and atmospheric interference. It has been demonstrated that certain VIs can perform better than others in large scale vegetation monitoring, while their performance can change when tested under operational conditions. EVI seems to perform better, as discussed in recent literature (Huete *et al.* 2002, Ji and Peters 2007, Xiao *et al.* 2003). However, it was only in the last decade that EVI was being used, so comparative results with NDVI and SVI cannot be quantified on equal terms. Although SVI performed worse in monitoring homogeneous CLC vegetation types, it was superior to the other VIs in two out of four tests for operational performance. This result demonstrates that although the more recent EVI is designed to overcome several known issues of VI performance, it cannot outperform the simple SVI under all conditions. Potential users could take into account the findings of this study to select the appropriate VI for monitoring vegetation under the specific conditions of their study area.

Considering the major differences in the phenology of managed and natural vegetation, these two broad types of vegetation were studied separately. Results displayed a relative consistency across the two vegetation types, which were similar to the combined all vegetation types category. This consistency appeared to indicate that all three VIs can identify the differences across a wide range of vegetation states and quantities of biomass, regardless of the vegetation type (Mutanga and Skidmore 2004, Peters *et al.* 2002, Silleos *et al.* 2006) The implication is that a single vegetation index could be used to monitor all types of vegetation at a national or regional scale, which could be implemented by a central monitoring organization (e.g. FAO-GIEWS, ESA-GMES).

Local users and agencies involved in vegetation monitoring can benefit from this work to optimise the efficiency of their monitoring programmes. National users who use the VIs for monitoring agricultural production, subsidies control, environmental assessment of protected areas, and for assessing the fire risk, as well as continental or global international programmes such as FAO's Global Information and Early Warning System (GIEWS) could evaluate their vegetation monitoring using similar tests on the selected VIs. GIEWS continuously monitors and reports the food supply and demand situation around the world, using NDVI to provide an indication of the amount and state of vegetative ground cover, and thus the effect of weather conditions on plant growth (FAO 2000). The issue of continuity of such long time series has played an important role in the use of NDVI in parallel with more advanced VIs, such as the case of MOD13 product (Huete *et al.* 1999).

Comparison of different VIs using the SR has several advantages over previously proposed approaches. The SR does not require data on a particular biophysical parameter (e.g. LAI, biomass) or the need for calibration curves between the VIs and the parameter. This property means that SR results apply to any biophysical parameter as long as both VIs are functions of the parameter. Thus, the SR can operate successfully at various vegetation types and phenological stages. Such global assessment of VIs can result in considerable cost savings since biophysical data are usually costly to collect. Also, the SR is unit-less in the sense that it is not influenced by scale transformation of the VI thus relieving the researcher from specifying the 'correct' function of the underlying property.

There are certain limitations to the applied methods. First, we assumed that CLC vegetation types were mapped correctly as homogeneous patches. According to the CLC validation report (EEA 2006), an overall thematic accuracy of 87% was succeeded, thus meeting its aims. Moreover, the two largest CLC classes (arable land and forest) which were of interest to this work were estimated to have a higher level of reliability, reaching between 90 and 95%. Therefore, our assumption is true at a high level of certainty. Second, one of the methods used in performance evaluation, the SR, was based on the assumptions of a linear relationship between the two VIs (M and N) and that the independent variable in the regression was measured without error. Although the data in this study roughly adhered to both of these assumptions, if other datasets deviate considerably from these assumptions, substantial bias could result. Third, we derived our results using eight seasonal observations during two consecutive years, for which significant correlations were obtained. Although seasonal observations have demonstrated the advantages and disadvantages of the presented methodology, plant response varies substantially from year to year, and a much larger time series would be required to capture and model all this variance, which may be a source of uncertainty for this work. Finally, MODIS daily observations have been reported to be influence by geolocation errors, gridding artifacts, and viewing geometry (Tan *et al.* 2006, Wolfe *et al.* 1998, Xin *et al.* 2012). It is important to acknowledge that despite the careful experimental design, not all these factors can be easily excluded, and their influence may be inserted in the results for the VIs performance. Future communication may concentrate on the influence of CLC scale level and VI's spatial resolution on their monitoring performance, it may use simulation data to avoid interference among the tested parameters (Xin *et al.* 2012), and may expand to a wider range of VIs such as EVI2, which can be calculated at 250m using MODIS data (Jiang *et al.* 2008).

5. Conclusions

In this paper the evaluation of SVI, NDVI and EVI for operational monitoring of vegetation condition was performed using descriptive statistics estimated from MODIS satellite images at various CLC vegetation types using for the first time the sensitivity ratio (SR) as performance metric. EVI was better at monitoring vegetation condition since it was relatively more homogeneous within CLC vegetation types during most of the examined dates than the other two VIs.

Regarding the VIs' use in operational monitoring, EVI was less affected by partial cloud cover, however, SVI and NDVI were less sensitive to conditions of saturation and variable viewing angles. Based on these three VI, a single VI was not consistently overcoming all the potential problems met at monitoring vegetation conditions at these scales using MODIS data.

Results have been mostly consistent between the two major vegetation types examined (managed and natural vegetation), indicating that a single VI could be used for monitoring all vegetation types at the national or regional level.

Finally, the results of this work can help local and international agencies involved in vegetation monitoring to optimise the efficiency of their monitoring schemes.

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Tables

Table 1. The 2nd level CORINE Land Cover classes that were used

ID	Class name
2.1	Arable land
2.2	Permanent crops
2.3	Pastures
2.4	Heterogeneous agricultural areas
3.1	Forests
3.2	Scrub and/or herbaceous vegetation associations
3.3	Open spaces with little or no vegetation

Table 2. Slope and R^2 results from regression model y = a + bx for three major vegetation categories: all CLC vegetation types, managed vegetation types, and natural vegetation types.

	Model y = a + bx		All vegetation types		Managed		Natural	
Date	y	x	R^2	slope (b)	R^2	slope (b)	R^2	slope (b)
13/05/2003	EVI	SVI	0.67	0.06	0.85	0.04	0.63	0.04
13/05/2003	NDVI	EVI	0.84	1.14	0.87	1.63	0.82	1.12
13/05/2003	NDVI	SVI	0.57	0.04	0.97	0.07	0.66	0.05
14/08/2003	EVI	SVI	0.92	0.07	0.98	0.08	0.85	0.05
14/08/2003	NDVI	EVI	0.90	1.25	0.89	1.18	0.94	1.35
14/08/2003	NDVI	SVI	0.79	0.05	0.92	0.10	0.95	0.07
25/10/2003	EVI	SVI	0.82	0.10	0.99	0.06	0.61	0.05
25/10/2003	NDVI	EVI	0.93	1.61	1.00	1.63	0.89	1.61
25/10/2003	NDVI	SVI	0.71	0.05	0.99	0.10	0.77	0.09
16/02/2004	EVI	SVI	0.75	0.14	0.99	0.10	0.52	0.10
16/02/2004	NDVI	EVI	0.70	0.99	0.51	1.12	0.74	1.04
16/02/2004	NDVI	SVI	0.66	0.11	0.47	0.10	0.84	0.15
13/05/2004	EVI	SVI	0.72	0.14	0.76	0.08	0.60	0.11
13/05/2004	NDVI	EVI	0.52	0.89	0.30	0.80	0.31	0.62
13/05/2004	NDVI	SVI	0.72	0.12	0.72	0.12	0.59	0.12
14/08/2004	EVI	SVI	0.93	0.08	0.99	0.09	0.90	0.05
14/08/2004	NDVI	EVI	0.94	1.25	0.94	1.16	0.96	1.33
14/08/2004	NDVI	SVI	0.83	0.06	0.93	0.11	0.96	0.08
24/10/2004	EVI	SVI	0.93	0.10	0.99	0.07	0.84	0.05

24/10/2004	NDVI	EVI	0.93	1.63	1.00	1.75	0.93	1.68
24/10/2004	NDVI	SVI	0.80	0.05	1.00	0.12	0.95	0.09
18/02/2005	EVI	SVI	0.87	0.13	0.99	0.06	0.83	0.11
18/02/2005	NDVI	EVI	0.97	1.49	0.97	1.48	0.94	1.40
18/02/2005	NDVI	SVI	0.86	0.09	1.00	0.09	0.86	0.17

Table 3: Sensitivity ratio[a] of vegetation indices used to monitor the condition of all CLC vegetation types (a), managed vegetation (b) and natural vegetation. Last column shows the ranking of VIs.

a. All vegetation types

Date	SR(NDVI/SVI)	SR(NDVI/EVI)	SR(EVI/SVI)	Ranking
13/05/2003	0.86	0.72	1.00	EVI=SVI>NDVI
14/08/2003	0.90	0.95	0.83	SVI>EVI~NDVI
25/10/2003	1.65	0.65	2.27	EVI>NDVI>SVI
16/02/2004	1.41	0.46	2.44	EVI>NDVI>SVI
13/05/2004	2.06	0.62	2.41	EVI>NDVI>SVI
14/08/2004	1.63	0.92	1.63	EVI>NDVI>SVI
24/10/2004	2.61	0.88	2.65	EVI>NDVI>SVI
18/02/2005	2.93	0.72	3.99	EVI>NDVI>SVI

b. Managed vegetation

Date	SR(NDVI/SVI)	SR(NDVI/EVI)	SR(EVI/SVI)	Ranking
13/05/2003	0.99	1.02	0.84	SVI~NDVI~EVI
14/08/2003	1.14	0.95	1.18	EVI~NDVI>SVI

25/10/2003	1.79	0.68	2.64	EVI>NDVI>SVI
16/02/2004	1.05	0.51	2.16	EVI>NDVI~SVI
13/05/2004	1.67	0.55	1.71	EVI>NDVI>SVI
14/08/2004	3.99	0.90	4.42	EVI>NDVI>SVI
24/10/2004	2.49	0.99	2.50	EVI~NDVI>SVI
18/02/2005	2.35	0.70	3.30	EVI>NDVI>SVI

c. Natural vegetation

Date	SR(NDVI/SVI)	SR(NDVI/EVI)	SR(EVI/SVI)	Ranking
13/05/2003	0.78	0.71	0.97	SVI~EVI>NDVI
14/08/2003	0.87	1.00	0.81	SVI>EVI~NDVI
25/10/2003	1.51	0.64	1.96	EVI>NDVI>SVI
16/02/2004	1.59	0.48	2.23	EVI>NDVI>SVI
13/05/2004	1.73	0.44	2.24	EVI>NDVI>SVI
14/08/2004	0.99	0.94	1.00	SVI~EVI>NDVI
24/10/2004	2.73	0.88	2.82	EVI>NDVI>SVI
18/02/2005	3.34	0.68	4.69	EVI>NDVI>SVI

[a] SR(M/N) > 1 (<1) implies VI M is preferred (less preferred) to VI N

Table 4: Correlation coefficients of VIs with: (a) aspect, (b) viewing angle, (c) LAI in values of LAI greater than 2.0 (saturation), and (d) correlation of partially cloud covered pixels with the cloud free pixels of the previous or the next day (partial cloud cover). Bold text shows VI with highest performance at each examined date.

(a) Influence of aspect

Date	SVI	NDVI	EVI
13/05/2003	-0.054	**-0.020**	-0.068*
14/08/2003	-0.095**	-0.096**	**-0.083****
25/10/2003	0.044	**-0.018**	-0.043
16/02/2004	**0.009**	-0.032	-0.011
13/05/2004	-0.033	-0.060*	**-0.014**
14/08/2004	**-0.111****	-0.135**	-0.117**
24/10/2004	**-0.062***	-0.078*	-0.084**
18/02/2005	**0.014**	0.086**	0.042

(b) Influence of viewing angle

Date	SVI	NDVI	EVI
13/05/2003	0.038	**0.013**	0.019
14/08/2003	**0.338****	0.420**	0.386**
25/10/2003	**-0.214****	-0.430**	-0.393**
16/02/2004	0.086**	**0.065****	0.144**
13/05/2004	**-0.200****	-0.260**	-0.402**
14/08/2004	**0.269****	0.281**	0.381**
24/10/2004	**0.202****	0.209**	0.361**
18/02/2005	**-0.025**	-0.143**	-0.132**

(c) Influence of saturation

Date	SVI	NDVI	EVI
13/05/2003	**0.211****	0.111	0.198**
14/08/2003	**0.403****	0.361**	0.163**
25/10/2003	**0.123**	0.027	0.011
16/02/2004	**0.110**	-0.023	-0.084
13/05/2004	**0.127***	**0.127***	-0.025
14/08/2004	**0.338****	0.236**	0.228**
24/10/2004	-0.050	-0.072	**0.287***
18/02/2005	0.029	0.046	**0.139**

(d) Influence of partial cloud cover

Date	SVI	NDVI	EVI
13/05/2003	-0.051	-0.026	**0.213***
14/08/2003	0.210*	0.198	**0.511****
25/10/2003	0.123	0.061	**0.538****
16/02/2004	0.128**	0.400**	**0.611****
13/05/2004	0.458**	0.651**	**0.810****
14/08/2004	0.562**	0.394*	**0.784****
24/10/2004	0.248**	0.319**	**0.683****
18/02/2005	0.369**	0.478**	**0.721****

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Figures

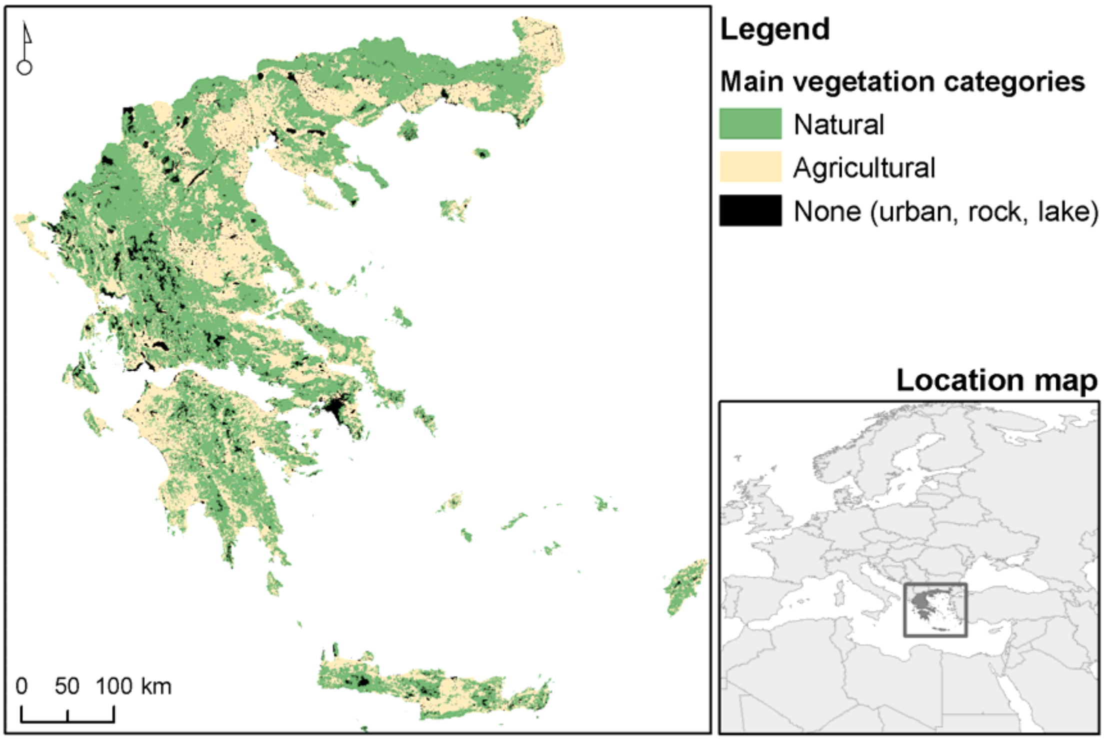

Figure 1: Vegetated areas of Greece according to CORINE Land Cover 2000 (Level 2).

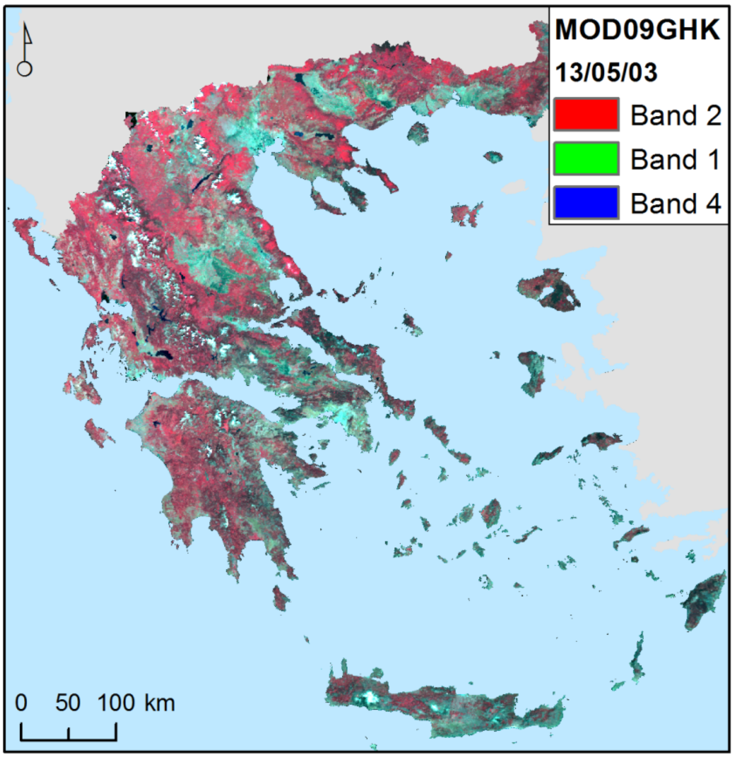

Figure 2: MODIS satellite image acquired on 13/05/03 (R,G,B = 2,1,4).

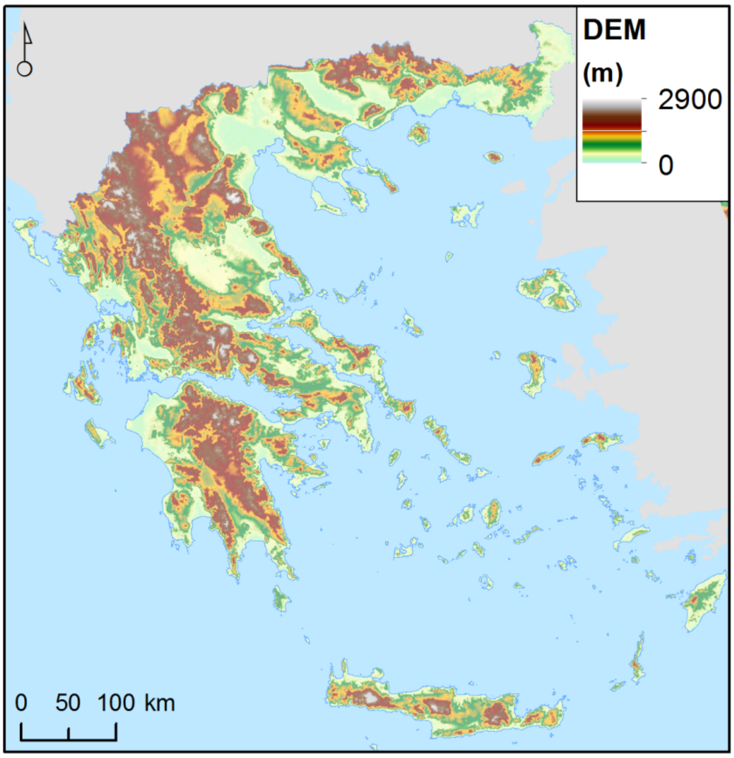

Figure 3: The DEM of the study area.

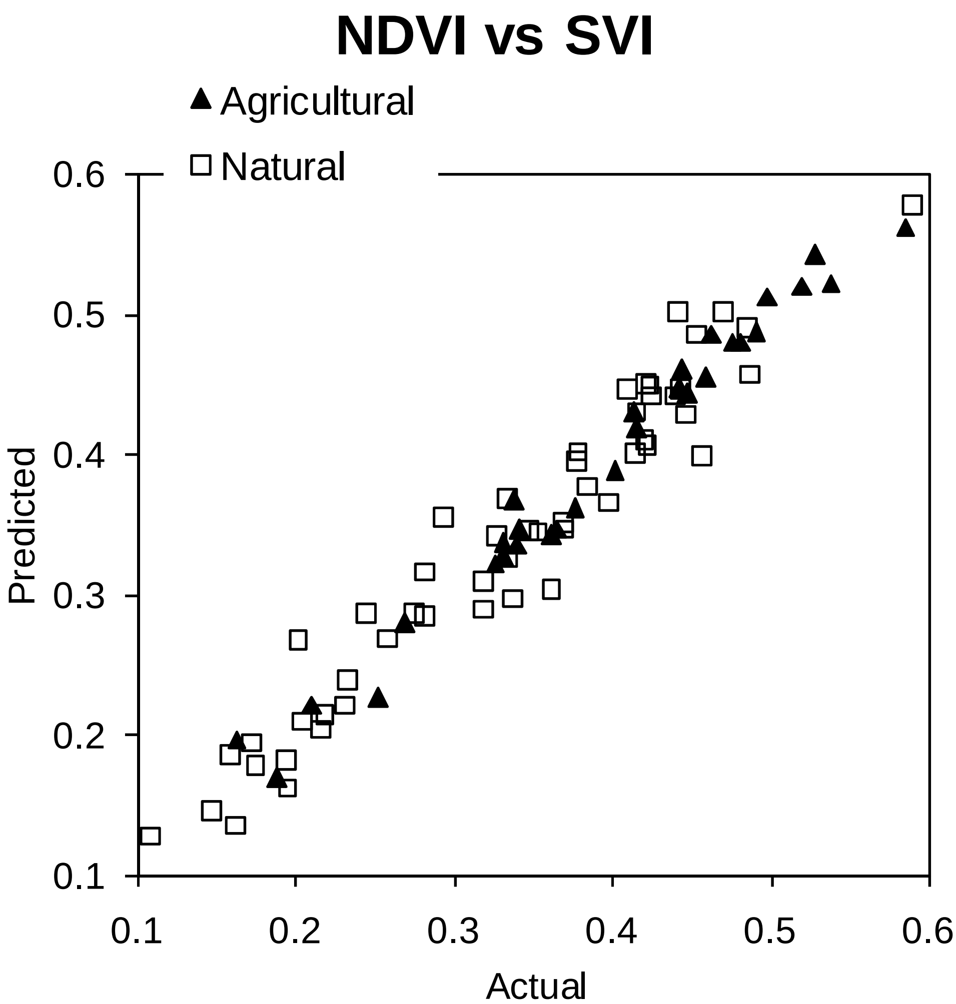

Figure 4: Predicted vs. actual NDVI values, where predictions are based on models from Table 2 for NDVI vs. SVI for all dates and CLC vegetation types.