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Mapping and monitoring net primary productivity with AVHRR NDVI time-series: statistical equivalence of cumulative vegetation indices

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Abstract

In the last two decades, numerous investigators have proposed cumulative vegetation indices (i.e., functions which encode the cumulative effect of NDVI maximum value composite time-series into a single variable) for net primary productivity (NPP) mapping and monitoring on a regional to continental basis. In this paper, we investigate the relationships among three of the most commonly used cumulative vegetation indices, expanding on the definition of equivalence of remotely sensed vegetation indices for decision making. We consider two cumulative vegetation indices as equivalent, if the value of one index is statistically predictable from the value of the other index. Using an annual time-series of broad-scale AVHRR NDVI monthly maximum value composites of the island of Corsica (France), we show that the pairwise linear association among the analysed cumulative vegetation indices shows coefficients of determination (R^2) higher than 0.99. That is, knowing the value of one index is statistically equivalent to knowing the value of the other indices for application purposes.

Keywords: Corsica; cumulative vegetation indices; Fourier transform; NDVI; net primary productivity

1. Introduction

The quantitative description of broad-scale net primary productivity (NPP) patterns in time and space is a key element for ecologists studying the Earth as a global system (e.g., Dungan et al., 1994). Terrestrial NPP is the net gain in dry matter production by plant photosynthetic tissues per unit time. Since terrestrial NPP is directly linked to the rate of atmospheric CO_2 uptake by vegetation through the process of net photosynthesis minus dark respiration, which in turn significantly influences the Earth's climate system, global assessment of interannual changes in terrestrial NPP is a fundamental input for models of global climate and global change (Lambin and Strahler, 1994; Ruimy et al., 1994). However, at broad spatial scales, direct estimation of NPP obviously cannot be considered. In this context, remote sensing appears the appropriate tool as the International Geosphere Biosphere Programme Data Information System (IGBP-DIS) in cooperation with the European Space Agency (ESA), National Aeronautics and Space Administration (NASA), National Oceanic and Atmospheric Administration (NOAA), and the US Geological Survey (USGS) already provides a time series of 1-km AVHRR NDVI monthly maximum value composites of the Earth surface

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(Eidenshink and Faundeen, 1994; Loveland and Belward, 1997). The data set is intended for monitoring seasonal variations in vegetation conditions and provides a foundation for studying long-term changes in vegetation resulting from global climate alterations and human interactions (Eidenshink, 1992). The maximum-value composite procedure (MVC) is based on the NDVI, which is the normalised ratio of near-infrared and red surface reflectances. Although the NDVI itself is not an intrinsic physical quantity (Ruimy et al., 1994; Carlson and Ripley, 1997), extensive research, since the pioneer work of Rouse et al. (1973), has shown that NDVI can be used for accurate description of vegetation cover due to its strong relationship to certain physical properties of the vegetation, such as the amount of absorbed photosynthetically active radiation (APAR), leaf area index (LAI), fractional vegetation cover, and biomass (e.g., Cihlar et al., 1991 and references therein).

The MVC method considers the maximum value assumed by the NDVI in a time period as a good estimate of the entire period (Taddei, 1997). MVC requires that a series of multitemporal georeferenced satellite data be processed into NDVI images. On a pixel-by-pixel basis, each NDVI value is examined and only the highest value is retained for each pixel location. A final MVC image is produced after all pixels have been evaluated. In this way, NDVI MVC imagery minimises problems common to single-date remote sensing studies, such as cloud contamination, atmospheric attenuation, surface directional reflectance, and view and illumination geometry (Holben, 1986).

For a given region, the sequential NDVI observations can be plotted against time to quantify remotely sensed vegetation seasonality and dynamics. To summarise the phenological cycle of vegetation, many techniques have been applied with varying degrees of success. Some authors have used few simple parameters to evaluate the time-series of vegetation indices, like mean and standard deviation of NDVI profiles (Ramsey et al., 1995), the amplitude of the NDVI profiles, the onset and peak of greenness and the length of the growing season (Odenweller and Johnson, 1984; Lloyd, 1990; Loveland et al., 1991; Reed et al., 1994; Running et al., 1994). In addition, principal component analysis has been extensively used to characterise long sequence time-series of NDVI profiles (Townshend et al., 1985; Tucker et al., 1985; Eastman and Fulk, 1993; Benedetti et al., 1994; Anyamba and Eastman, 1996; Hirosawa et al., 1996). Other studies proposed some NDVI modelling based on logarithmic or exponential expressions (Badhwar and Henderson, 1985; Baret and Guyot, 1986) and Fourier transformation (Menenti et al., 1993; Andres et al., 1994; Sellers et al., 1994; Taddei, 1997). To quantitatively describe the pattern of annual NDVI time-series, Samson (1993) proposed two additional indices, a skew index and a range index, based on the magnitude and shape of the NDVI profiles, respectively. Lambin and Strahler (1994) and Lambin (1996) used the multitemporal change vector approach to compare the differences in the NDVI profiles for two successive hydrological years for a Sudanian–Sahelian region in Western Africa.

Furthermore, since the work of Tucker et al. (1981), extensive research has shown that the time-wise integration of sequential NDVI observations is directly related to the NPP of the analysed land cover (e.g., Asrar et al., 1985; Tucker and Sellers, 1986; Box et al., 1989). In the last decade, due to the effectiveness of the integral of NDVI time-series (ΣNDVI) in detecting and quantifying interannual changes in NPP broad-scale patterns, ΣNDVI has become the principal tool for broad-scale remotely sensed NPP mapping and monitoring on an annual basis.

However, besides the ΣNDVI, other ''cumulative indices'' (i.e., multitemporal indices derived from the cumulative effect of NDVI over the period during which the data were compiled) based both on vectorial representation of NDVI sequential observations in a multidimensional space and Fourier analysis have been adopted for remotely sensed NPP monitoring (e.g., Andres et al., 1994; Lambin and Strahler, 1994). Although these indices have been considered roughly equivalent to ΣNDVI, as far as we know, accurate studies investigating the relationships among different cumulative indices have never been performed. Thus, the aim of our paper is to investigate the relationships among different cumulative indices derived from annual NDVI time-series expanding on the definition of equivalence of remotely sensed vegetation indices of Perry and Lautenschlager (1984).

2. Deriving cumulative vegetation indices from NDVI profiles

2.1. Fourier analysis

Any arbitrary function can be either represented in the physical domain as $x(t)$ or in the frequency domain as $X(f)$. The representation in the frequency domain as $X(f)$ is obtained using the Fourier transform of $x(t)$. Although the Fourier transform is basically a decomposition of $x(t)$ into an integral over sine and cosine terms, it is most easily described with complex exponential functions in place of sine and cosine functions (Hastings and Sugihara, 1993):

$$X(f) = \int_{-\infty}^{\infty} x(t)\mathrm{e}^{-2\pi i f t}\mathrm{d}t \tag{1}$$

where f is the frequency and $i = \sqrt{-1}$. $X(f)$ is generally a complex number that determines both the amplitude and the phase of the signal. Rewriting $X(f)$ as:

$$X(f) = |X(f)|\mathrm{e}^{i\phi(f)} \tag{2}$$

$|X(f)|$ is called the amplitude of $x(t)$ and $\phi(f)$ is the phase angle of the Fourier transform. For Fourier analysis of discrete series, such as spectral–temporal NDVI profiles, the infinite integration interval has to be truncated on both sides and the integral discretised. This leads to what is called the discrete Fourier transform (DFT). The discrete Fourier transform $X(k)$ of a series $x(n)$ of length N is defined as:

$$X(k) = \sum_{n=0}^{N-1} x(n)\mathrm{e}^{-2\pi i n k/N} \tag{3}$$

with $k = 0,1,\ldots,N-1$. The amplitudes $|X(f)|$ are usually represented by the power density spectrum $S(f)$, which represents the ‘‘energy’’ associated with each frequency. The power spectrum $S(f)$ of $x(t)$ is just the sequence of squares of amplitudes (Hastings and Sugihara, 1993):

$$S(f) = |X(f)|^2 \tag{4}$$

Thus, substituting Eq. (3) in Eq. (4), we obtain the expression for calculating the power density spectrum of finite time series, such as the NDVI time-series of any pixel of a multitemporal AVHRR image:

$$S(k) = \left|\sum_{n=0}^{N-1} x(n)\mathrm{e}^{-2\pi i n k/N}\right|^2 \tag{5}$$

Since vegetation phenological cycles generally occur on a 1-year time scale, we assume annual NDVI profiles as our basic unit (Andres et al., 1994). Furthermore, assuming monthly composited NDVI MVC data, 12 successive NDVI images will be available for each profile.

As shown in Eq. (4), the power density spectrum of a time series $x(n)$ is the sequence of squares of the amplitudes of its Fourier transform. Therefore, the components of $S(k)$ describe the behaviour of $x(n)$ at temporal scales corresponding to their respective frequencies. Furthermore, Eq. (5) clearly shows that the zero frequency, i.e., the first component of the power density spectrum ($\mathrm{NDVI_S}$) is related to the integral of the annual NDVI time-series and can therefore be considered as a cumulative vegetation index in the frequency domain (Andres et al., 1994).

2.2. Vectorial representation of NDVI profiles

Alternatively, for any pixel of a multitemporal AVHRR image, the annual time-series derived from sequential monthly NDVI MVC observations can be represented by a point in a 12-dimensional space defined by the vector (Lambin and Strahler, 1994; Johnson and Kasischke, 1998):

$$NDVI = \begin{bmatrix} h_1 \\ h_2 \\ \ldots \\ \ldots \\ h_{12} \end{bmatrix} \tag{6}$$

where $h_1, h_2, \ldots, h_{12}$ represent the monthly NDVI observations. The magnitude of NDVI,

$$|NDVI| = \left(h_1^2 + h_2^2 + \ldots + h_{12}^2\right)^{0.5} \tag{7}$$

measures the accumulated value of the NDVI through the year (Lambin and Strahler, 1994) and is therefore conceptually similar both to the integral of the annual time-series ΣNDVI and to the first component of the power density spectrum $\mathrm{NDVI_S}$.

3. An equivalence definition for cumulative vegetation indices

The equivalence definition for cumulative vegetation indices we use in our paper was introduced in remote sensing literature by Perry and Lautenschlager (1984). Therefore, to place the current work in context, a brief explanation of this method may be instructive.

As mentioned above, we defined cumulative vegetation indices as functions which encode the cumulative effect of a NDVI MVC time-series into a single (real) variable. Furthermore, since cumulative vegetation indices are generally used for NPP mapping and monitoring purposes, it is appropriate to consider cumulative vegetation indices as equivalent if, and only if, knowing the value of one index is equivalent to knowing the value of the other index for decision making, as proposed by Perry and Lautenschlager (1984). However, Perry and Lautenschlager (1984) made this definition in a rigorous algebraic sense. That is: ''The equivalence of vegetation indices means the value of one index can be (biunivocally) computed from the value of the other index''.

Conversely, since ΣNDVI, $\mathrm{NDVI_S}$ and $|\mathrm{NDVI}|$, although conceptually similar, are not equivalent in a rigorous algebraic sense, we will expand the former definition and consider equivalence of cumulative vegetation indices in a more empirical way. In other words, we will consider two cumulative vegetation indices as equivalent, if the value of one index is statistically predictable from the value of the other index, so that, for any specific application, the same decision results regardless of the index employed.

In the following paragraphs, we will test statistical equivalence of ΣNDVI, $\mathrm{NDVI_S}$ and $|\mathrm{NDVI}|$, using an annual time series of 5-km AVHRR NDVI monthly maximum value composites of the island of Corsica (France).

4. Material and methods

4.1. Study area

The island of Corsica (France) was chosen as test site. Corsica (8748 km^2) is located between 41°20′N and 43°00′N latitude and between 8°30′E and 9°30′E longitude. The island is characterised by a complex physical geography, with extreme heterogeneity in geological, morphological and climatic features. Approximately 90% of the island is mountainous. The highest elevation is at Monte Cinto (2710 m). Several other peaks exceed 2500 m.

According to the classification of Rivas-Martinez (1996), Corsica's bioclimate ranges from the Mediterranean Pluviseasonal-Oceanic to the Temperate Oceanic-Submediterranean. However, due to its complex physical conditions, Corsica is subject to a strong micro-climatic variability, which is reflected in the high plant biodiversity of the island consisting of 2621 natural taxons, 282 of which are endemic (Gamisans, 1991).

Land-use in the flatter areas along the coast is dominated by traditional crops (e.g., vine, lemons, olives, and vegetables). In the hilly areas, chestnut (*Castanea sativa*) stands combined with pastures prevail. At lower altitudes, natural vegetation is composed by Mediterranean species (e.g., *Quercus ilex*, *Quercus suber*, *Pinus pinaster*). Conversely, the upper-Mediterranean landscape is dominated by deciduous mixed woods with *Quercus pubescens*, *Ostrya carpinifolia*, *Acer monspessulanum*, *Acer obtusatum*, *Fraxinus ornus*. In the mountain domain, *Fagus sylvatica* prevail. Above the timberline, the landscape is dominated by a scattered distribution of shrubs and herbaceous species.

4.2. Data collection and analysis

The 1-km AVHRR NDVI monthly composites of Corsica for April 1992 through March 1993 were extracted from the Eurasian monthly composite data set accessible through the World Wide Web: //edcwww.cr.usgs.gov/landdaac/ (Loveland and Belward, 1997). The original NDVI database is geometrically registered to a Lambert Azimutal equal area projection optimised for Europe. The computed NDVI ranges from -1 to 1 but was rescaled to a 0–200 range with a value of 100 equal to a computed NDVI of 0. Furthermore, a value of zero was assigned to pixels representing water bodies to eliminate NDVI data from the 12-monthly composites where the meaning of NDVI values is ambiguous.

The 1-km AVHRR pixels were resampled into 351 larger pixels of 5×5 km^2 size by averaging the original non-zero NDVI values. Notice that this operation is conceptually similar to a low-pass filtering. The dimension of the resampled pixels was chosen empirically as a compromise between overcoming the spatial degradation of AVHRR composite data resulting from misregistration and off-nadir viewing (Meyer, 1996) and preserving the image features.

To test the statistical equivalence of the above-mentioned cumulative vegetation indices, the initial step involves the calculation of ΣNDVI, NDVI$_S$ and |NDVI| for each 5×5 km^2 pixel of the multitemporal sequence. Second, the three cumulative vegetation indices were linearly correlated against each other. Scattergrams were generated to indicate the nature of the analysed relationships and linear correlation coefficients were calculated to quantify the magnitude of the relationships.

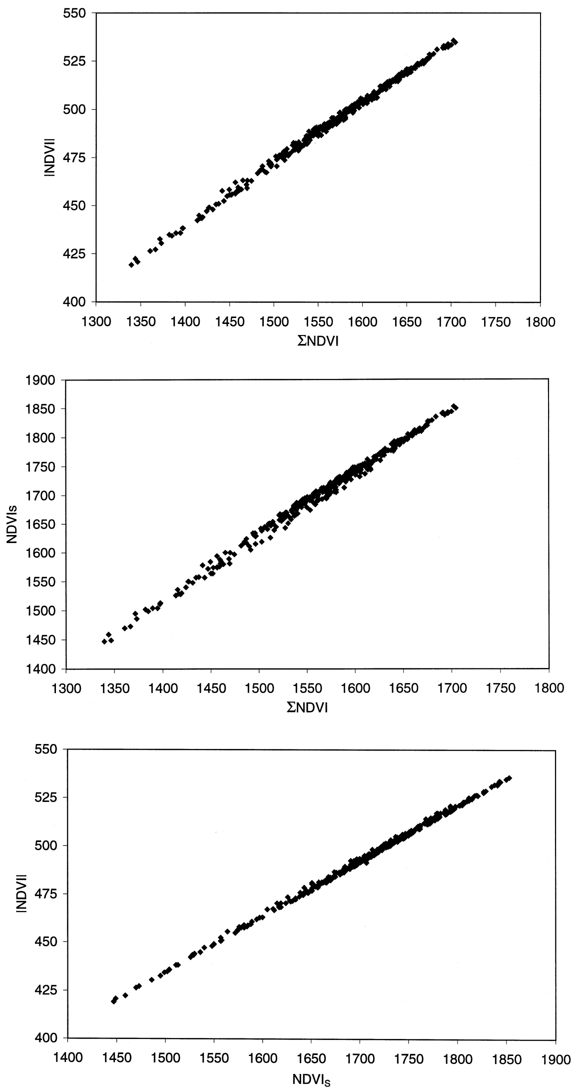

Fig. 1. Scattergrams of the pairwise linear relationships between the three analysed cumulative vegetation indices: (a) ΣNDVI vs. |NDVI|, (b) ΣNDVI vs. NDVI$_S$, (c) NDVI$_S$ vs. |NDVI|.

Table 1
Coefficients of determination (R^2) of the pairwise linear relationships among the three analysed cumulative vegetation indices

	ΣNDVI	NDVI$_S$	|NDVI|
ΣNDVI	1.000	0.993	0.996
NDVI$_S$		1.000	0.998
|NDVI|			1.000

The pairwise relationships among ΣNDVI, NDVI$_S$ and |NDVI| are presented in Fig. 1(a–c) and the associated correlation matrix is given in Table 1. Inspection of Fig. 1 and Table 1 reveals a strong linear association among the three analysed cumulative vegetation indices. Notice that all coefficients of determination (R^2) of Table 1 are higher than 0.99 with a significance level $p > 0.001$.

Furthermore, there does not seem to be much difference in the strength of linear association between Fig. 1(a), (b) and (c). This is quantified by the small differences between the single coefficients of determination of Table 1 confirming that the cumulative vegetation indices ΣNDVI, NDVI$_S$ and |NDVI| are fully equivalent for decision making.

5. Conclusions

Since the early work of Tucker et al. (1981), numerous investigators have developed cumulative vegetation indices (i.e., functions which encode the cumulative effect of NDVI MVC time-series into a single number) for broad-scale NPP mapping and monitoring. In this paper, we firstly summarised three of those indices based on the integral of the NDVI MVC profile (ΣNDVI), vectorial representation of NDVI sequential observations in a multidimensional space (|NDVI|) and Fourier analysis (NDVI$_S$), respectively. Secondly, we investigated the (statistical) relationships among ΣNDVI, NDVI$_S$ and |NDVI| expanding on the definition of equivalence of remotely sensed vegetation indices of Perry and Lautenschlager (1984). We considered two cumulative vegetation indices as equivalent, if the value of one index is statistically predictable from the value of the other index. In this sense, unlike the original definition of Perry and Lautenschlager (1984), the relationship among cumulative vegetation indices is intended in a more empirical rather than rigorous algebraic way. Using an annual time series of broad-scale AVHRR NDVI monthly maximum value composites of the island of Corsica (France), we showed that, under the conditions of our experiment, the analysed cumulative vegetation indices are fully equivalent for decision making. That is, for any specific application, the same set of decisions result regardless of the index employed.

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