CHARACTERIZATION OF TEMPORAL VARIATIONS OF SAVI SPATIAL PATTERNS

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ABSTRACT

Remotely sensed data are widely used to gain information about biophysical parameters characterizing the Earth surface. Among the others, the Soil Adjusted Vegetation Index (SAVI) is commonly used to monitor the distribution and the health of the green cover. The vegetation usually shows a certain level of spatial correlation, that is expected to be present also in the related SAVI maps. Moreover, also the temporal evolution of vegetation is not a random phenomena, but its growth follows the natural phenological seasonal cycle, if human intervention or unexpected natural phenomena such as landslides, fires or floods are excluded. Accordingly, the SAVI information derived from remotely sensed data should also contain a corresponding pixel-by-pixel temporal correlation. In this work a preliminary characterization of the spatial and temporal correlation of a multi-temporal series of SAVI maps derived by Landsat-TM imagery is presented and a characterization of the temporal information stability is evaluated.

INTRODUCTION

Remotely sensed data have been widely used for many years to gain information about biophysical parameters characterizing Earth surface and related ecosystems (Foody, 1994) [1], and satellite gathered data have proved to be particularly useful to this purpose because of their wide spatial coverage and suitable revisiting time. Many vegetation indexes (*VI*s) based on linear combinations of different spectral bands have been proposed in literature, aimed at assessing and monitoring vegetation characteristics. Among the others, the Soil Adjusted Vegetation Index (Huete, 1988) is commonly used to evaluate the distribution and the health of the Earth vegetation coverage. The vegetation cover affects many natural phenomena, therefore SAVI maps with suitable temporal and spatial resolutions are very useful in many scientific and applicative tasks for the control, monitoring and management of the environment. The spatial distribution of vegetation cover patterns, is, at a given time, generally characterized by a spatial correlation that should be present also in the corresponding SAVI maps obtained by satellite data. Moreover, also the temporal evolution of vegetation patterns is not a random phenomena but follows the natural phenological cycle of the seasons, if human intervention or unforeseen natural phenomena such as landslides, fires, floods or others are excluded. As a consequence, the related multi-temporal sequence of SAVI images should also highlight a corresponding temporal correlation. In this work a multi-temporal series of Landsat TM multispectral images acquired over two years (2009-2010) on an area situated in Central Italy have been considered, and the related SAVI maps were produced. The temporal stability of the SAVI spatial patterns have been then characterized on the basis of the variability in the time domain of the high and low SAVI spatial frequency components. In the following, after the description of the data set and of the adopted pre-processing procedures, the methodological approach is presented. At first the considered SAVI index and the concept of temporal stability of spatial patterns are introduced. Afterwards, the method and the procedures used to characterize the temporal stability of SAVI patterns are described and, at last, the results of the analysis are presented and the conclusions are summarized.

DATA SET AND PREPROCESSING

A multi-temporal series of eight multispectral Landsat-TM5 images acquired between march 2009 and july 2010 on the same area (path 191, row 030) situated in the central part of Italy was used in this study. The date of acquisitions are reported in Table 1 together with the corresponding names and temporal indexes used in the work. The images were downloaded from the *Earth Resources Observation and Science (EROS) Center* site (http://glovis.usgs.gov) by the Global Visualization Viewer (GloVis). Only some images of good data quality have been found, limited to the June-August period and the month of March of both 2009 and 2010 years. Thus, the multi-temporal sequence of imagery doesn't represent completely all the four seasons, but includes only the summer period and marginally the winter and spring seasons (images on March).

Table 1: Acquisition date of the TM temporal series

Image	TM5(1)	TM5(2)	TM5(3)	TM5(4)	TM5(5)	TM5(6)	TM5(7)	TM5(8)
Time index	1	2	3	4	5	6	7	8
date	**2009-03-26**	**2009-06-30**	**2009-07-16**	**2009-08-17**	**2010-03-13**	**2010-06-01**	**2010-07-03**	**2010-07-19**

The original reflective bands have been calibrated and converted to reflectance values, and reprojected by a bilinear interpolation procedure to a 15 m sampling step. Afterwards, the images were orthonormalized by means of a 10 m grid DEM, and taking into account a selection of 10 GCPs, found by using a Terraitaly™ frame of 0,5 m spatial resolution as reference image. At last, a window of 748 x 1040 pixels (11.22 by 15.6 Km) has been extracted from the TM5 images, by considering an area that covers a part of the Tiber river near Collazzone town (in the middle of Italy). Such an area includes part of the Tiberine plain and of the hills around, and diversifies its coverage spanning from bare soils to fully vegetated ones and small urban areas. A preliminary multispectral classification of the selected test area, carried out from an Ikonos-2 image acquired on 2005, reported a percentage of 33% of fully vegetated area, a bare soil of 6.5% and urban area percentage of 2%. Due to the very high spatial resolution of Ikonos image, the effects of mixed pixels can be considered as negligible in comparison with the blur caused by the spatial resolution of TM5. A visual inspection of the images proved however that the soil coverage on the 2009-2010 years were, for our purpose, still consistent with those of 2005.

METHODOLOGY

The SAVI index

Vegetation indexes extracted from multispectral data acquired by satellite platforms have been long used to gain information about biophysical parameters of vegetation and to characterize vegetation canopies. The Soil adjusted Vegetation index (SAVI) introduced by Huete [2], is the enhanced version of the well-known NDVI (Normalized Differential vegetation index), and is defined as:

$$SAVI = \frac{(NIR - RED)}{(NIR + RED + L)}(1 + L)$$

where NIR and RED are respectively the Near InfraRed and the red bands, and L represents a corrective factor whose optimal value depends on the vegetation density, measured with the *LAI* (Leaf Area Index). L spans from 0.25 to 1, but it has been found that for any corrective factor in this range the soil background effect is significantly reduced, and a value of L=0.5 should offer a performance better than the NDVI for the most part of vegetation conditions. Therefore, a SAVI with a corrective factor of 0.5 has been here considered.

Spatial and temporal persistence of SAVI patterns

Many studies focusing on the spatial and/or temporal correlation of vegetation indexes exist in literature. The intra-annual persistent behaviour of NDVI were analysed in the work of Telesca and Lasaponara (2006) [3], in which the local vegetation fluctuations are studied. Bradley (2007) [4] defined a fitting procedure for the NDVI inter-annual series along the time domain, and Mao (2011) [5] analysed the correlation between NDVI temporal evolution and climatic parameters. Spatial correlation of the NDVI is instead studied specifically for the soil-wheat system in Yang (2011) [6]. Most of the works however focused only on the analysis of the spatial or the temporal correlation, but never both of them.

At a given time, it is reasonable to make the assumption that distribution of the green coverage has a certain level of spatial correlation, that should be present also in the corresponding SAVI image if the pixel size is lower than a given threshold related to the considered vegetation type. As a matter of fact, by considering a pixel imaging the leafage of a tree, it is possible to make the hypothesis that also the surrounding pixels have a high probability to belong to the same leafage, if the pixel covered area is lower than the leafage dimension. Similarly, if the pixel represents a bare soil area, the probability that the surrounding pixels also belong to bare soil is higher than that to belong to a different class type. Woodcock and Strahler (1987) [7] showed how the local variance of a remotely sensed image changes by varying its spatial resolution, and therefore they highlighted a dependence of spatial correlation on pixel size, which should be expected also in the SAVI images sequence. On the other hand, if we consider the temporal evolution of the environment, it is reasonable to make the assumption that a certain level of temporal correlation could exist between two different times, and this correlation should again be present also in the corresponding SAVI images. As a matter of fact, by considering in the image pixels corresponding to a certain canopy or a bare soil, we can also assume that in a subsequently images of the multi-temporal sequence the most part of them will be referred to the same coverage, if the time interval between the images doesn't exceed a suitable threshold and unexpected antrophic or natural phenomena are excluded. Such temporal correlation should therefore be present also in the corresponding SAVI multi-temporal sequence and, as hypothesized for the spatial correlation, should be dependent on the temporal resolution. Differently from the most part of literature, this work jointly takes into account both the spatial and temporal correlation of multi-temporal SAVI images by analyzing the temporal correlation (that is the similarity) among the multi-temporal SAVI sequence with the spatial resolution.

Assessment of the spatio-temporal correlation of SAVI map sequence

SAVI map series (S^i, i =1,8) were derived from the considered multi-temporal series of multispectral TM5(*i*) images, using a corrective factor value of 0.5. In order to exclude possible outliers, the SAVI values have been then clipped in the range [–1.5÷1.5]. Then, a set of images $S^i_{Ln\times n}$ of decreasing spatial resolution was generated from each original SAVI image by applying a suitable set of 17 low-pass convolution filters. The decreasing spatial resolution was obtained by applying square sliding windows of increasing *nxn* size, from 3x3 up to 141x141 (tab 2), having all the elements set to 1 and normalized to the total number of elements of each window. By this way, the first 3x3 sliding window produces a slightly smoothed version of the original SAVI map ($S^i_{L3\times 3}$), and as the window size *n* increases, more and more blurred images $S^i_{Ln\times n}$ are obtained (tab. 2).

Table 2: Dimension of the sliding windows used to produce the smoothed SAVI images, together with the k index adopted to numerate them.

window size (pixel)	3	5	7	9	11	13	15	17	19	21	23	41	61	81	101	121	141
Index (k)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17

Each SAVI image is then splitted in two components accordingly to:

$$S^i = S^i_{Hn\times n} + S^i_{Ln\times n},$$

where $S^i_{Ln\times n}$ represents the low frequencies components of the original SAVI image S^i, obtained with the blurring procedure, whereas $S^i_{Hn\times n}$ indicates the complementary high frequencies. The subscript *nxn* specifies the filter window size and the *i* apex indicates the image time position in the time series series (*i* =1;8).

Since In this work 17 smoothed versions $S^i_{Ln\times n}$ have been obtained from the original one S^i, a corresponding series of 17 high frequencies images $S^i_{Hn\times n}$ have been therefore produced by a simple subtraction pixel-by-pixel. The two images $S^i_{Ln\times n}$ and $S^i_{Hn\times n}$ are discriminated in the spectral domain of the spatial frequencies by a moving threshold which position depends on the *n* value. For small n value, a low blurring is performed on the SAVI map, and the most part of the information is conveyed by $S^i_{Ln\times n}$. On the contrary, for high values of the window dimension *n* the threshold moves itself to the low spatial frequencies, and the most part of the information falls in the image $S^i_{Hn\times n}(x, y)$.

At this point, for each pixel $p(x, y)$, the temporal series $S^i_{Hn\times n}(x, y)$ obtained by varying the *i* index is considered from the statistical point of view as a population. A temporal mean $\bar{S}_{Hn\times n}(x, y)$ was then evaluated for each pixel of the high frequency frames $S^i_{Hn\times n}$, according to:

$$\bar{S}_{Hn\times n}(x, y) = \frac{1}{N}\sum_{i=1}^{N} S^i_{Hn\times n}(x, y)$$

obtaining 17 $\bar{S}_{Hn\times n}$ images, one for each 17 used filtering windows size.

Such set of $\bar{S}_{Hn\times n}$ images represents, the temporal low frequencies (i.e. the slow variations) of the high spatial frequencies, related to each *nxn* used window. Then, the temporal stability of the high spatial frequencies in the SAVI images have been evaluated by comparing the original high freunecy $S^i_{Hn\times n}$ image with the $\bar{S}_{Hn\times n}$ temporal mean. A quantitative evaluation of such stability has been assessed for each pixel by considering the standard deviation along the time domain computed for each *nxn* window size:

$$\sigma_{Hn\times n}(x, y) = \frac{1}{8}\sqrt{\sum_{i=1}^{8}\left[S^i_{Hn\times n}(x, y) - \bar{S}_{Hn\times n}(x, y)\right]^2}$$

It is possible to notice that lower the values of $\sigma_{Hn\times n}(x, y)$ is, the greater the temporal stability of the high spatial frequency of the SAVI map is in the (*x,y*) point. Finally, a global quantitative evaluation has been obtained by considering, for each *nxn* combination the spatial mean $\mu[\sigma_{Hn\times n}(x, y)]$ of the images $\sigma_{Hn\times n}(x, y)$, defined as:

$$\mu[\sigma_{Hn\times n}(x, y)] = \frac{1}{XY}\sum_{x=0,y=0}^{X,Y} \sigma_{Hn\times n}(x, y)$$

Maximum, median, mode and standard deviation statistical parameters were also evaluated on the $\sigma_{Hn\times n}(x, y)$ image set corresponding to the 17 different *nxn* filter size used.

The same procedure could be also repeated for the temporal stability of the low spatial frequencies, by considering the standard deviation image $\sigma_{Ln\times n}(x,y)$, obtained by evaluating the temporal mean of $S^i_{Ln\times n}(x,y)$ and the corresponding standard deviation image $\sigma_{Ln\times n}(x,y)$. In this work, however only the $\sigma_{Hn\times n}(x,y)$ has been computed for all the 17 *nxn* combinations, whereas the $\sigma_{Ln\times n}(x,y)$ has been evaluated for comparison purpose for the 7x7 sliding window case only.

RESULTS

Table 3 reports the statistical parameters evaluated on the temporal variance map $\sigma_{Hn\times n}(x,y)$ of the high spatial frequencies for all the 17 *nxn* combinations and on the temporal variance map of the low spatial frequency $\sigma_{Ln\times n}(x,y)$ but only for the 7x7 filtering sliding windows.

Table 3: Statistical parameters evaluated on the high frequency $\sigma_{Hn\times n}(x,y)$ and low frequency $\sigma_{Ln\times n}(x,y)$ variance maps.

sliding window size (pixels)	Max	Mean	STD	Median	Mode
3x3	0.031796	0.002	0.001	-0.0037333	-0.0037333
5x5	0.048299	0.004	0.002	0.00066945	0.00066945
7x7	0.026759	0.006	0.003	-0.0046607	-0.0046607
9x9	0.033682	0.007	0.004	-0.00444	-0.00444
11x11	0.037616	0.009	0.004	0.001471	0.001471
13x13	0.039647	0.01	0.005	0.002501	0.002501
15x15	0.041801	0.011	0.005	0.001037	0.001037
17x17	0.045002	0.012	0.006	0.008348	0.008348
19x19	0.047672	0.013	0.006	0.002846	0.002846
21x21	0.049719	0.014	0.006	0.008578	0.008578
23x23	0.050955	0.014	0.007	0.004554	0.050955
41x41	0.051352	0.018	0.008	0.014768	0.014768
61x61	0.053	0.019	0.009	0.015694	0.015694
81x81	0.053843	0.02	0.009	0.007804	0.007804
101x101	0.055695	0.02	0.009	0.012535	0.012535
121x121	0.055821	0.021	0.009	0.007288	0.007288
141x141	0.055781	0.021	0.01	0.009029	0.009029
7x7 ($\sigma_{Ln\times n}(x,y)$)	0.4	0.101	0.04	0.091705	0.079085

Table 4 reports the spatial mean and standard deviation of the 8 original SAVI images S^i together with their temporal averages, to be used for comparison purpose.

Table 4: Mean and standard deviation (STD) of the 8 original SAVI images

Date	**2009-03-26**	**2009-06-30**	**2009-07-16**	**2009-08-17**	**2010-03-13**	**2010-06-01**	**2010-07-03**	**2010-07-19**	**Temporal mean**
SAVI mean	0.225	0.347	0.338	0.271	0.269	0.4	0.333	0.272	**0.306**
SAVI STD	0.1	0.149	0.138	0.12	0.096	0.131	0.13	0.112	**0.122**

It is possible to notice that the mean and the standard deviation for all the 17 *nxn* combinations are smaller than those of the original SAVI map (about factor 10 for n < 15), with a slighty increase with the dimension of the filtering sliding window. The maximum value is also low, but with a less regular trend. On the contrary, the same parameters are higher than about a factor of 10 if the stability of the low frequency variance map $\sigma_{Ln\times n}(x,y)$ is considered.

CONCLUSION

The analysis performed on the TM5 multi-temporal image series acquired during 2009 and 2010 on an area located in the central part of Italy shows that the high spatial components of the SAVI images have a strong temporal correlation, with a mean value of the temporal standard deviation considerably lower than spatial standard deviation of the original SAVI. As a matter of fact it has been found that for the high spatial frequencies, the higher is the frequency, the higher is the temporal stability. On the other hand, SAVI low spatial frequencies show a greater variability along the time domain. This suggests that the most part of the time-varying information in a multi-temporal series of SAVI images is conveyed by the low spatial frequencies, whereas the high spatial frequency components mainly account for scene details that concern time-stable or slowly changing information.

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