A novel approach to produce NDVI image series with enhanced spatial properties

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Abstract

A novel multi-step method is presented to improve the spatial properties of MODIS NDVI data series based on one or few single-date higher spatial resolution (HR) images. This method does not rely on the classification of the HR imagery, which is often inadequate in characterizing all main vegetation types that are present in the observed area. An unmixing strategy is instead applied to identify these vegetation types from the low spatial resolution (LR) MODIS imagery, which offers a more effective description of seasonal NDVI evolutions. In particular, an annual multitemporal MODIS NDVI data series is preliminarily decomposed by an automatic technique, which produces abundance images representative of the main vegetation types. These images are then used to extract spatially variable NDVI endmembers. Next, a statistical method is applied to improve the spatial features of the abundance images based on these endmembers and the available HR NDVI imagery. The final recombination of the spatially enhanced abundance images and NDVI endmembers allows the production of synthetic imagery, which maintains the temporal information of the MODIS NDVI data and most spatial properties of the HR images. The new method is preliminarily tested using an annual MODIS NDVI data series and five Landsat 8 OLI images taken in a study area of Tuscany (Central Italy). The results obtained support the potential of the method and indicate some possibilities for future methodological advancement.

Keywords: NDVI, MODIS, OLI, Image enhancement.

Introduction

Remote sensing techniques offer great potential to monitor and analyze terrestrial vegetation with various spatial and temporal resolutions. Several vegetation parameters can be remotely detected (i.e. plant species, density, green biomass, etc.) which can be useful alone or used as inputs for models of ecosystem processes (transpiration, photosynthesis, productivity, etc.). The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used indices to represent vegetation greenness and vigor [Huete et al., 2002]. Therefore, NDVI image series are appropriate for studying the spatial and temporal dynamics of ecosystem responses to human induced or natural environmental disturbances [Busetto et al., 2008].
When accomplishing these tasks, however, major problems arise due to the lack of satellite data series with both high spatial and temporal resolutions [Gao et al., 2006; Zhu et al., 2010]. This is due to both technological and budget limitations, which have created a trade-off within remote sensing instruments between spatial resolution and revisiting time [Hilker et al., 2009a]. While, in fact, information with high time frequency has been obtained by using data from low spatial resolution (LR) sensors, the relevant pixel size (generally around 1 km) is insufficient for properly defining the previously mentioned ecosystem dynamics. On the other hand, satellite sensor images characterized by higher spatial resolution (HR) have generally been acquired less frequently and more expensively [Coppin et al., 2004]. This trade-off is worsened by the effect of clouds and other atmospheric disturbances, which reduce the number of usable images [Ju and Roy, 2007]. Thus, finding several good HR images in a growing season is a non trivial task, particularly during rainy periods. The advent of the Moderate Resolution Imaging Radiometer (MODIS) system, which yields NDVI imagery at 250 m spatial resolution with relatively high temporal frequency (8-16 days), has provided only a partial solution to the problem. Most ecosystems affected by human induced disturbances, in fact, should be observed at higher spatial resolution, typically around 50-100 m [Houghton, 2005]. The spatio-temporal resolution trade-off should be mostly overcome by the launch of new generation satellites, such as the EU Sentinel 2, but the construction of long-term data series from these systems will require several years. Thus, also in the next future retrospective high resolution archives will remain of fundamental importance for ecological studies.

This situation has promoted the development of methods to integrate data with different spatial and temporal resolutions, which have had various degrees of success [Maselli and Chiesi, 2006; Hilker et al., 2009b]. In particular, several methods have been developed and tested for blending MODIS and Landsat TM/ETM+/OLI data [Gao et al., 2006; Zhu et al., 2010; Walker et al., 2012; Maselli, 2012; Hazaymeh and Hassan, 2015]. Most of these methods are based on the linear unmixing principle, in which the fractional cover of each vegetation class is provided by the Landsat imagery [Zhu et al., 2010; Rao et al., 2015]. This imagery is used to produce HR maps whose classes are assumed to have homogeneous NDVI evolutions during the examined prediction periods. Such a property, however, is difficult to obtain from one or even few single-date HR images, since vegetation types can show complex, unsynchronized NDVI developments which make them fully distinguishable only considering several dates. In fact, vegetation classes having homogeneous NDVI at the base date may evolve differently during the prediction periods. This is especially frequent in fragmented, heterogeneous environments, where vegetation development is constrained by several driving factors which produce temporally diversified NDVI developments. These situations are typical of Mediterranean areas, where thermal and water limitations act together with agricultural and forestry activities in shaping complex, multi-modal vegetation evolutions. The inappropriate characterization of these evolutions through the high resolution maps can lead to predict erroneous NDVI values at some dates.

The current work aims at presenting a new unmixing-based method able to improve the spatial properties of MODIS NDVI data series through the use of one or few single-date HR images. The new method overcomes the mentioned drawback by introducing a novelty in the classification of the main vegetation types, which is conventionally based on the HR imagery. The new integration procedure instead identifies these types from
the multitemporal MODIS images, which offer a more complete description of the most important annual NDVI evolutions. The multitemporal MODIS NDVI data series is first decomposed by an automatic technique, which produces abundance images representative of the main functional vegetation types. A statistical method is then applied to improve the spatial properties of these images based on the available HR NDVI imagery. The final recombination of spatially enhanced abundance images and NDVI endmembers allows the production of synthetic imagery which maintains all temporal information of the MODIS NDVI data and most spatial properties of the HR images.

The paper is organized as follows. First, the multi-step integration method is briefly presented. Next, a case study is described where the method is applied in a rural area in Tuscany (Central Italy). The results obtained are discussed and commented in the final section.

**Integration methodology**

The proposed methodology consists of four sequential steps which are schematically represented in Figure 1 and briefly described in the next subsections. Basically, the NDVI of both LR and HR pixels at time $t$ ($NDVI_t$) is defined as:

$$ NDVI_t = \sum_{i=1}^{C} AF_i \cdot EM_{i,t} \quad [1] $$

where $AF_i$ and $EM_{i,t}$ are the LR or HR abundance fraction of vegetation class $i$ and the corresponding NDVI endmember at time $t$, respectively. Assuming that the spatial variability of the NDVI endmembers is limited and can be estimated from the low resolution data, the NDVI at any spatial resolution can be predicted if the relevant abundance fractions are correctly known.

**Identification of low spatial resolution abundance images**

The first step consists of applying the Sequential Maximum Angle Convex Cone (SMACC) algorithm to spectrally decompose the multitemporal MODIS NDVI data series. SMACC finds spectral endmembers and their abundances throughout previously calibrated multispectral or hyperspectral data [Gruninger et al., 2004]. Endmembers that represent reflectance spectra must satisfy a positivity constraint and other physically-based constraints, such as a sum-to-unity one. SMACC uses a convex cone model (also known as Residual Minimization) with these constraints to identify image endmember spectra. Extreme points are used to determine a convex cone, which defines the first endmember. A constrained oblique projection is then applied to the existing cone to derive the next endmember. The cone is increased to include the new endmember. The process is iterated until a projection derives an endmember that already exists within the convex cone or until the desired number of endmembers are found. In practice, different numbers of endmembers can be tested, looking for minima of residual spectral error. SMACC also provides abundance images descriptive of the fractions of all resulting endmembers. When applied to multitemporal NDVI data series the method identifies classes which have homogeneous phenological (NDVI) evolutions during the prediction period and can therefore be associated to functional vegetation types.
Estimation of spatially variable NDVI endmembers

The NDVI endmembers previously identified by SMACC assume a spatial stationarity in the properties of the vegetation classes considered. The method can therefore be suboptimal when applied to relatively large areas, where the NDVI evolution of each class can vary spatially due to a series of environmental factors (mainly differences in climate and topography).

The spatially weighted regression procedure proposed by Maselli [2001] addresses this issue by using the abundance images to estimate different endmembers for each image pixel. These spatially variable endmembers can efficiently reproduce within-class spatial
NDVI variations and are therefore suitable for the current application. In this case the method decomposes each MODIS NDVI image of a time series into a variable number of spatially variable NDVI endmembers based on the SMACC abundance images.

**Spatial enhancement of the abundance images**

The third step of the proposed method consists of enhancing the spatial properties of the SMACC abundance images by the use of single date HR images. This operation can be accomplished by several methods, which present advantages and limitations. The method currently chosen benefits from the availability of spatially variable NDVI endmembers, whose abundances can be modified for each HR pixel. The process does not have a unique solution, since several NDVI endmember combinations can produce the same single-date NDVI value. An approximate solution can however be found which reproduces the HR NDVI image minimizing the change of the SMACC abundance images. The method proposed to achieve this goal consists of iteratively modifying the abundances corresponding to each HR pixel depending on the difference between HR and MODIS NDVI values. In case of positive difference, the abundances of the classes with NDVI endmembers higher than the local average are increased by a small value, while the others are decreased; the opposite is the case for a negative difference. This is obtained by adding or subtracting to each abundance fraction the NDVI difference between the respective endmember and the endmember average, multiplied by a constant (0.01). The modification is constrained by the uncertainty of the original SMACC abundances, which is maximum for values close to 0.5 (when more classes are present within the LR pixel) and tends to 0 as the abundance approaches 0 or 1 (when the class is completely absent or pure). This uncertainty is approximated by the product $AF_i \times (1 - AF_i)$, which, multiplied by the previous NDVI difference, nullifies the modification of each abundance fraction as it approaches 0 or 1. In this way, the NDVI obtained combining the endmembers and the modified abundance fractions will increase or decrease converging towards the HR NDVI. The iterative process ends when the relevant NDVI difference is minimized to a desired tolerance (e.g. 0.001 NDVI) or when the abundance fractions are stabilized.

**Recombination of abundance images and NDVI endmembers**

The spatially variable NDVI endmembers and enhanced SMACC abundance images are finally recombined through Equation [1] to produce a synthetic NDVI image series with HR spatial properties and MODIS temporal frequency.

**Case study**

**Study area and data**

The study area is located in Tuscany (Central Italy) (Fig. 2), and was selected on the basis of two criteria. First, the area had to be environmentally complex, with the presence of fragmented vegetation cover types showing different NDVI evolutions. Second, the area had to be covered by several Landsat 8 OLI acquisitions completely unaffected by atmospheric disturbances during a growing season. The selected area (11.65-11.84° E, 42.81-42.94° N) is a hilly land, with elevation ranging from 300 to 650 m a.s.l.
The climate is Mediterranean warm (mean annual rainfall of about 900 mm and temperature of 11-13°C), and becomes more temperate humid following the altitudinal gradient [Rapetti and Vittorini, 1995]. According to the CORINE land cover map of Italy, the main cover types are deciduous and evergreen forests, alternated with winter/spring crops and olive groves; small urban areas are also present.

MODIS images are collected daily by sensors on the Terra and Aqua satellites and are freely distributed in a pre-processed format by the NASA's Goddard Space Flight Center. The current study utilizes the MOD13Q1 product of 2013, which corresponds to 23 16-day NDVI images having a spatial resolution of 250 m. The window on the study area has a size of 60x90 MODIS pixels.

The Operational Land Imager (OLI) sensor mounted onboard Landsat 8 provides a continuation of the TM/ETM+ functionalities with some enhanced spectral and spatial
features (more details at http://landsat.usgs.gov/landsat8.php). Five OLI images were selected, taken on 13 April, 16 June, 3 August, 4 September and 7 November 2013. These images were already geometrically and atmospherically corrected, which allowed the computation of NDVI from bands 4 and 5. Figure 3 shows a false colour composition of the OLI NDVI images of April, August and November.

![Figure 3 - RGB composition of the OLI NDVI images taken in April, August and November 2013.](image)

**Data processing**

The available MODIS imagery was first corrected for residual noises as described in Maselli et al. [2006]. Next, both MODIS and OLI images were reprojected to a common geographical reference system with a pixel size of approximately 50 m. To this aim, the MODIS images were simply enlarged five times, while the OLI images were reprojected by a bilinear interpolation algorithm. MODIS and OLI NDVI values present some differences due to both radiometric factors and the application of different pre-processing steps [Houghton, 2005]. These differences were addressed by adjusting the OLI NDVI values through a linear regression equation defined on a regional scale using all available imagery. The identification of vegetation classes with homogeneous NDVI evolution was carried out by applying SMACC to the 23 16-day MODIS NDVI images. The optimum number of classes was found by looking at the residual NDVI error. The obtained endmembers were associated to functional vegetation types based on both visual interpretation and the CORINE map. The corresponding abundance images were then used to estimate spatially variable NDVI endmembers from all MODIS images; details on this operation can be found in Maselli [2001]. Next, the abundance images were spatially smoothed by a Gaussian filter to reduce image blockiness and were enhanced by the described method using one or more OLI NDVI images. In the latter case, multiple-date abundance images were produced by averaging the single-date images. Finally, synthetic NDVI images were obtained through Equation [1] from the various combinations of spatially variable endmember and enhanced abundance images and assessed through comparison with the original OLI images.
Results
The visual examination of Figure 3 reveals that the cover types of the study area are spatially heterogeneous and have temporally irregular NDVI evolutions, with minima and maxima in different periods. This is confirmed by the examination of the 23 MODIS NDVI images, which obviously show less spatial detail but similarly complex NDVI evolutions. When applied to these 23 images, the SMACC algorithm identified five main NDVI endmembers; the consideration of additional endmembers led to only marginal reductions of residual NDVI error (Tab. 1). The five NDVI endmembers are shown in Figure 4 together with the corresponding inter-class standard deviations.

![Figure 4](image_url)

Figure 4 - NDVI endmembers identified by applying SMACC to the multitemporal MODIS data series (lines) and relevant standard deviations (histogram) (the asterisks on the x axis indicate the periods corresponding to the OLI acquisitions).

The first and second endmembers have constantly high and low annual NDVI values, respectively; the former corresponds to evergreen forest, the latter to urban and bare lands. The third endmember has an unique spring peak and corresponds to winter/spring crops. The fourth endmember has a brief winter minimum and a long summer plateau and is associated to Mediterranean deciduous forest. The fifth endmember, which shows two NDVI peaks in spring and fall, mostly corresponds to olive groves. The endmember standard deviation, which indicates their mean separability, has a minimum in spring and a maximum in late summer-fall. In general, these results confirm that the cover classes of the study area have temporally complex and unsynchronized NDVI evolutions.

Examples of abundance images are shown in Figure 5. These are the original SMACC images of class 1 (evergreen forest) derived from MODIS data and enhanced by the use of the August OLI NDVI image.
Table 1 - SMACC NDVI errors found considering increasing numbers of endmembers.

| N  | 1    | 2    | 3    | 4    | 5    | 6    |
|----|------|------|------|------|------|------|
| NDVI Error | 0.811 | 0.531 | 0.224 | 0.164 | 0.156 | 0.155 |

An increase of spatial detail is clearly visible in the enhanced image (Fig. 5b). The same is the case for the exemplary synthetic NDVI image of September obtained by applying the current method to the August OLI image, which is shown in Figure 6 together with the original OLI image.
Figure 6 - NDVI images of September taken by OLI (a) and obtained by applying the current method to the August OLI image (b). NDVI ranges from 0 (black) to 1 (white).

Figure 7 shows the RMSE averages and standard errors obtained applying the method to all HR image combinations, which indicate the improvements obtainable over the entire NDVI data series by considering one or more HR images. A limit to the accuracy achievable is given by the discrepancy between spatially degraded MODIS and OLI images (i.e. at 250 m resolution), which corresponds to a root mean square error (RMSE) of about 0.068 NDVI. The NDVI RMSE between downscaled MODIS and OLI images is notably higher than this (0.106), and is decidedly reduced by the use of single-date OLI images. The consideration of additional OLI images improves the estimates and reduces the error in a regular way. According to what mentioned above, the improvement in spatial detail obtainable by the current method can be hypothesized to depend on the separability of the five NDVI
endmembers in the different seasons. The relationship between the previously seen inter-class MODIS NDVI standard deviations at the five OLI dates (Fig. 4) and corresponding RMSEs of the enhancement method is shown in Figure 8.

![Figure 7 - NDVI RMSE averages and standard errors of the downscaled MODIS images and of the synthetic images produced by the current method using increasing numbers of spatially enhanced abundance images (see text for details).](image1)

![Figure 8 - Scatter plot of the NDVI RMSEs obtained by applying the current method to the five OLI images versus the corresponding inter-class MODIS NDVI standard deviations (* = significant correlation, P<0.05).](image2)
The linear regression is negative and significant, and the periods with the lowest and highest NDVI separability (April and September) correspond to the highest and lowest NDVI errors, respectively.

**Discussion and conclusions**

The current methodological investigation addresses an issue which affects the methods for fusing NDVI data with different spatial and temporal resolutions based on the unmixing paradigm. Such methods, in fact, generally rely on maps of vegetation classes having homogeneous NDVI evolutions which are difficult to obtain from one or even few single-date HR images. This is due to the difficult discriminability of the classes at some dates, which is particularly frequent where vegetation growth is constrained by several contrasting factors. The decomposition of the multitemporal LR image series is proposed as an alternative, followed by a spatial enhancement of the obtained abundance images based on the single-date imagery.

The algorithm currently applied for decomposing the NDVI data series (SMACC) has shown good potential to identify vegetation classes with homogeneous and easily interpretable NDVI evolutions. The application of this algorithm, however, might be problematic in regions where pure low spatial resolution pixels are very rare or absent. In these cases other methods could be applied for the identification of NDVI endmembers, such as those examined by Plaza et al. [2004].

In general, identifying NDVI endmembers of the observed vegetation classes from LR images is a critical point of unmixing-based spatio temporal fusion methods. The utilization of the SMACC abundance images to produce spatially variable NDVI endmembers can efficiently cope with the spatial nonstationarity which commonly affects remotely sensed estimates of vegetation properties [Maselli, 2001].

The availability of different NDVI endmembers for each HR pixel facilitates enhancing the spatial properties of the SMACC abundance images, which must be modified to converge towards the single-date HR NDVI images. The success of this process, which is necessarily approximated, depends on the efficiency of the enhancement method applied. The current iterative algorithm has provided satisfactory results, improving the spatial properties of the LR images in practically all cases. Other algorithms could be envisaged and tested, for example applying to the HR imagery classification or regression techniques trained on the LR abundance images [Maselli et al., 2014].

The final results are affected by the temporal proximity of the base and synthetic HR images but are mainly dependent on the information content of the HR data, which varies during the growing season. The enhancement method in fact produces partly different results in relation to the inter-class NDVI separability at the study dates. In any case, also HR images containing poor spatial details for class discrimination bring some contribution to enhancing the properties of the LR abundance images, and, consequently, of the final synthetic imagery, as is testified by the NDVI errors of Figure 8.

As mentioned previously, the current preliminary testing should be completed by a more in-depth and extensive error analysis of several methodological options. Such future research should be conducted in areas which show variable mosaics of land use/cover types and, consequently, different spatial NDVI patterns and temporal evolutions. All these issues will be dealt with in a follow-up of the current investigation.
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