Retrieving sub-pixel land cover composition through an effective integration of the spatial, spectral and temporal dimensions of MERIS imagery

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Abstract: MERIS on Envisat delivers imaging spectroscopy data at 300m spatial resolution. MERIS has demonstrated its great potential for regional and global land cover mapping. This paper illustrates that the combination of the spatial, spectral, and temporal dimensions of MERIS has, in addition, the potential to retrieve sub-pixel land cover composition. Three MERIS FR Level 1b scenes acquired over The Netherlands in April, July and August 2003 were used in this study to derive fractional composition of 9 main land cover types. Linear spectral unmixing (with an optimized number of endmembers per pixel) was applied in both a mono- and multi-temporal fashion. A morphological eccentricity index (MEI) was used to explore the MERIS spatial dimension and, subsequently, to support the selection of the endmembers. The Dutch land use database (LGN5) was used as a reference in this study. Classification accuracy was assessed both at sub-pixel and per-pixel level. The best classification results were obtained for the combined image of April and July with a classification accuracy above 58%. In general, sub-pixel and per-pixel classification accuracies were similar. Spectral confusion was detected for several classes and dates indicating that the phenological status plays an important role in choosing the optimal acquisition date combination.

1. Introduction

Information on land cover composition is essential to model and to understand the Earth system. Land cover maps are, for instance, a prerequisite to study spatial patters over large regions and to assess the impact of human activities over our environment or over the landscape condition. However, the current understanding of the global land cover and its dynamics is still far from complete. This is the reason why Earth observation missions have been focusing on land cover mapping since the very existing of the remotely sensed data.

In this framework, the use of the Medium Resolution Imaging Spectrometer (MERIS) on board of Envisat has proven to have a great potential to map land cover at regional scales (Clevers et al., 2005). MERIS fulfils the information gap between the current high and low spatial resolution sensors because it provides global coverage data with a high frequency (revisit time two to three days) and with a spatial resolution of 300m (in full resolution or FR mode). MERIS has also 15 narrow bands ranging from the visible to the near-infrared regions of the electromagnetic spectrum.

In general, traditional (per pixel) image classification methods have been applied to produce land cover classifications maps at regional to global scales. In this paper, the potential of MERIS to retrieve sub-pixel land cover composition is assessed. The spatial, spectral and temporal resolutions of MERIS FR data were combined to retrieve sub-pixel, or fractional, land cover information. This information is particularly interesting for very fragmented landscapes where distinct patters and changes can only be identified by using high spatial resolution data. Moreover, many of the land surface properties that are required to model the Earth system can be better derived from continuous composition maps than from traditional per pixel land cover maps.

2. Materials and Methods

A. Remotely-sensed data

A set of 3 MERIS FR level 1b (radiance TOA) images acquired over the Netherlands the 16th of April, the 14th of July and the 6th of August 2003 were used for this study. The images were first corrected from the smile effect and subsequently geo-referenced to the RD Dutch coordinate system using a nearest neighbor interpolation method. The quality of the geo-location metadata provided with the images was visually assessed by comparing the images with a reference dataset (a vector layer of province boundaries). As a result, a small shift in the image of August was discovered and corrected. After that, the images were layer stacked to create a multi-temporal dataset and a subset of 256 by 512 pixels covering the central part of the country was finally selected to perform all the analysis.

Finally, bands 1, 2, 11 and 15 of each image were removed from the analysis because the first two are heavily contaminated by atmospheric scattering (bands in the blue) and the last two fall in absorption features (O_2 and H_2O, respectively).

B. Reference data

The latest version of the Dutch land use database (LGN5), which was released in June 2005, was used as reference in this study (Hazeu, 2005). The LGN5 has 39 classes, 25 m resolution, and it is based on multi-temporal classification of high resolution satellite data and integration of ancillary data.

The overall classification accuracy of the LGN5 is still to be determined but preliminary results indicate that it will be, at least, equal to the one of the previous version which was between 85 and 90% depending on the land cover type. The original 39 classes of the LGN5 were aggregated into 9 main land cover classes: grassland, arable land, greenhouses, deciduous forest, coniferous forest, water, built-up areas, bare soil (mainly sand dunes), and natural vegetation. Next, a spatial aggregation (based on a majority filter) was done to match the MERIS FR pixel size. During the spatial aggregation process, the fractions of the different land cover types present in each MERIS pixel were computed so that a sub-pixel validation of the estimated fractional land cover composition could be done.

C. Selection of the Endmembers

Most of the methods that have been proposed in literature for the selection of pure land cover spectra, or endmembers, rely on the spectral information present in the image and, generally, they do not make use of the spatial information of the image that is going to be unmixed. In this paper, a spatial and spectral endmember extraction method called automated morphological endmember extraction (AMEE) was used (Plaza et al., 2002). The method is based on the use of multidimensional morphological operations. Its outcome is a morphological eccentricity index (MEI) at each pixel, which is used in this study to define spatially homogeneous areas from where spectral endmembers will be collected. Specifically, low MEI values belong to pixels situated in spectrally homogeneous areas whereas high MEI values are assigned to pixels whose spectral signature is different from the average signature of the surroundings of that pixel.

In this study, we computed the MEI for each MERIS scene and for the multi-temporal dataset using a sliding window of 3 by 3 pixels. After that, a threshold over the MEI values was set in order to define potential areas to search for endmembers. This threshold was empirically fixed to the lowest 10% values. Because the class greenhouses and bare soil occupy a very small proportion of the total surface (0.11% and 0.23%, respectively), a second threshold of the upper 10% of the MEI was used to identify these small and fragmented classes .

Pixels which were labeled as potential candidates to become endmembers were then grouped by class using the LGN5 as a reference. After this, an outliers removal algorithm namely the Grubbs' test was applied to each group. A final set of endmembers was generated by averaging the remaining pixels.

D. Spectral unmixing

Linear spectral unmixing was used in this study to derive fractional land cover composition because this method is relatively straightforward, and computationally fast. Furthermore, spectral unmixing has already demonstrated its capabilities to work with medium and low spatial resolution sensors (Lobell and Asner, 2004; DeFries et al., 2000).

In this study, the unmixing method described by Ramsey and Christensen (1998) will be used. This method iteratively optimizes the number of endmembers that are used to retrieve the fractional composition of each pixel. An unconstrained least squares inversion is first performed for each pixel. After this, the endmembers that yielded negative abundances are removed from the analysis of that pixel. This process is iteratively repeated until no negative fractions are found and then, the retrieved fractions are re-scaled to fulfill the two classical constraints that ensure the physical interpretation of the results: fractions must be positive and below 1 and the sum of all the fractions must add to unity.

This unmixing method was preferred because the algorithm is not "forced" to find abundances for all the endmembers in each pixel. Additionally, the removal of endmembers that yield negative fractions might result in a reduction of the spectral confusion of the remaining endmembers**.** In contrast, the residual errors might increase their value since the inversion will be performed with a limited number of endmembers (Ramsey and Christensen, 1998). Nonetheless, no large residuals are expected because no constraint is imposed during the least-squares inversion.

This iterative endmember selection spectral unmixing was applied to both the mono- and multi-temporal MERIS FR datasets. The unmixing of the multi-temporal image (or temporal unmixing) was selected because in this way the different land cover types will not only be defined by their spectral signatures, but also by their temporal profile. If the appropriated dates are selected, this should increase the discrimination of spectrally similar land cover types since the seasonal variations of their spectral responses will be accounted for.

The overall classification accuracy of the unmixed fractions was assessed both at sub-pixel and per-pixel level. To carry out the per-pixel assessment a mixed-to-pure-pixel-converter based on a majority rule was applied to the fractions.

3. Results

The spectral signatures of the main 9 land cover types of The Netherlands were identified using the MEI. Figure 1 illustrates, as an example, the endmembers for the 16th of April image.

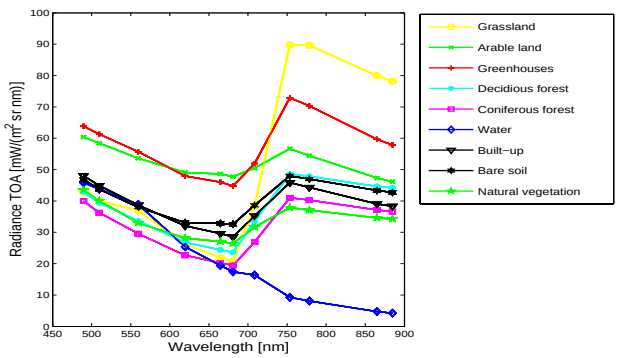

Figure 1. Endmembers for the 16th of April 2003.

The image of August, followed by July, presented the highest spectral confusion among endmembers. Arable land and grassland were the classes most confused.

The iterative spectral unmixing resulted in 9 images containing the fractional abundances of the main land cover

types, an image showing the spectral RMSE, and, finally, an image showing the number of endmembers that were used to unmix every pixel. By comparing this last image with the number of classes present in each (300m aggregated) pixel of the LGN5, it was concluded that the number of endmembers that were used during the unmixing was adequately identified.
Table 1 shows the results of the accuracy assessment both at a sub-pixel and a per-pixel level. Notice that because a high confusion was found between built-up and greenhouses, these two classes were combined into a single built-up class.
The best classification results were obtained for the combined image of April and July (Figure 2 (right)). This indicates the necessity of defining appropriates rules for the optimal selection of the number of dates and the dates that should be used in a temporal unmixing because, as shown in Table 1, increasing the number of dates does not imply a higher classification accuracy.

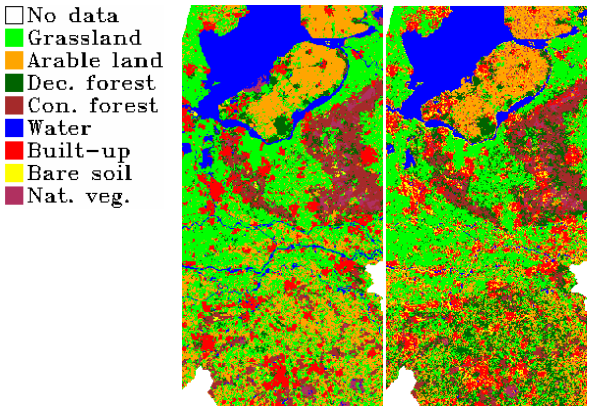

Figure 2. LGN5 (left) and hard classification of the April + July image (right).

Sub-pixel classification accuracy for the best classified image is illustrated in figure 3. Water has the best mean sub-pixel classification accuracy followed by grassland. However, most of the classes present a large variation in sub-pixel accuracy (Table 1). Bare soil and natural vegetation were the two worst classified classes.

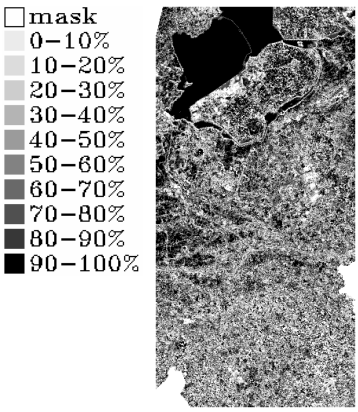

Figure 3. Sub-pixel classification accuracy for the April + July image

TABLE I. ACCURACY ASSESSMENT

	MSA (%)	OA (%)	Kappa
16th April	55.37 (33.27)	55.38	0.461
14th July	49.42 (34.22)	49.43	0.391
6th Aug	48.94 (33.95)	46.04	0.390
16th April + 14th July	57.79 (30.27)	58.03	0.486
16th April + 14th July + 6th Aug	47.84 (33.55)	47.72	0.375

MSA: mean sub-pixel classification accuracy; MSA standard deviation values are shown between brackets. OA: overall (per-pixel) classification accuracy.

4. Conclusions and Outlook

In this paper we have demonstrated that through an effective integration of the spatial, spectral and temporal dimensions of MERIS imagery it is possible to retrieve (regional) fractional land cover composition.
Despite the moderate classification accuracies obtained in this study, the results are considered to be promising because (in contrast to traditional classifiers) sub-pixel information on relevant land cover types was obtained. However, the selection of the dates (and the number of dates) to be used during the unmixing needs to be optimized. Moreover, operational ways to use the temporal dimension should be further explored.
The findings presented here should support the use of soft classifiers to map fragmented landscapes with medium to low spatial resolution sensors. Future research will investigate the use of (ground collected) spectral libraries, the use of the temporal information in an incremental/hierarchical way, and the use of fractional information to detect land cover changes at sub-pixel level.

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