Using MERIS fused images for land-cover mapping and vegetation status assessment in heterogeneous landscapes


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Using MERIS fused images for land-cover mapping and vegetation status assessment in heterogeneous landscapes

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In this paper we evaluate the potential of ENVISAT–Medium Resolution Imaging Spectrometer (MERIS) fused images for land-cover mapping and vegetation status assessment in heterogeneous landscapes. A series of MERIS fused images (15 spectral bands; 25 m pixel size) is created using the linear mixing model and a Landsat Thematic Mapper (TM) image acquired over the Netherlands. First, the fused images are classified to produce a map of the eight main land-cover types of the Netherlands. Subsequently, the maps are validated using the Dutch land-cover/land-use database as a reference. Then, the fused image with the highest overall classification accuracy is selected as the best fused image. Finally, the best fused image is used to compute three vegetation indices: the normalized difference vegetation index (NDVI) and two indices specifically designed to monitor vegetation status using MERIS data: the MERIS terrestrial chlorophyll index (MTCI) and the MERIS global vegetation index (MGVI).

Results indicate that the selected data fusion approach is able to downscale MERIS data to a Landsat-like spatial resolution. The spectral information in the fused images originates fully from MERIS and is not influenced by the TM data. Classification results for the TM and for the best fused image are similar and, when comparing spectrally similar images (i.e. TM with no short-wave infrared bands), the results of the fused image outperform those of TM. With respect to the vegetation indices, a good correlation was found between the NDVI computed from TM and from the best fused image (in spite of the spectral differences between these two sensors). In addition, results show the potential of using MERIS vegetation indices computed from fused images to monitor individual fields. This is not possible using the original MERIS full resolution image. Therefore, we conclude that MERIS–TM fused images are very useful to map heterogeneous landscapes.

1. Introduction

The Medium Resolution Imaging Spectrometer (MERIS) is one of the core instruments aboard the ENVISAT/European Space Agency (ESA) platform, the world’s largest environmental satellite (Bezy et al. 1999). MERIS provides hyperspectral data

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in 15 narrow bands and at two spatial resolutions: 300 m in the so-called full resolution (FR) mode and 1200 m in the reduced resolution (RR) mode. This imaging spectrometer was originally intended for monitoring coastal zones (FR mode) and for ocean applications (RR mode). For that reason, it was designed with a fine spectral and radiometric resolution and a high revisit time (2–3 days) (Curran and Steele 2005). Nevertheless, long before its launch a few modifications were introduced in its final design (e.g. the position of some bands) so that MERIS could also be used for atmospheric and land applications (Verstraete et al. 1999, Curran and Steele 2005).

The final MERIS spectral configuration, together with its high temporal resolution, has indeed proved to be very useful for land applications. For instance, MERIS data have been used to produce regional and global land-cover maps (Arino et al. 2005, Clevers et al. 2007). Furthermore, its unique spectral configuration allows the retrieval of canopy chlorophyll content through the red-edge position (Clevers et al. 2002). Other MERIS land products include leaf area index (LAI), fraction of absorbed photosynthetically active radiation (fAPAR) and fraction of vegetation cover (fCover) (Bacour et al. 2006). More recently, MERIS has been used to study solar-induced vegetation fluorescence (Ganter et al. 2007). In addition, two vegetation indices have been specifically designed for this sensor: the MERIS Terrestrial Chlorophyll index, MTCI (Dash and Curran 2004), which is linked to canopy chlorophyll content, and the MERIS Global Vegetation index, MGVI (Gobron et al. 1999), which is directly related to fAPAR. Both vegetation indices have been integrated in the processing chain of MERIS data and they are provided as MERIS level-2 datasets.

Although the above-mentioned products/applications show the potential of MERIS for monitoring at regional or global scales, the spatial resolution provided by this instrument might be too coarse to capture relevant details of fragmented landscapes. In such heterogeneous areas, at the MERIS spatial scale, pixels are very often the retrieved signal of more than one land-cover type.

In general, mixed pixels are difficult to handle and they limit the operational utility of medium and coarse spatial resolution imagery. For instance, mixed pixels are responsible for the so-called low resolution bias when estimating land-cover areas using medium and coarse spatial resolution data (Boschetti et al. 2004). High spatial resolution sensors, such as the multispectral scanner (XS) aboard the Satellite Pour l’Observation de la Terre (SPOT) or Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+), can be used to study heterogeneous or fragmented landscapes. However, their revisit time (26 days in the case of SPOT XS and 16 days for Landsat TM or ETM+) is not very appropriate for monitoring purposes. This is especially true for areas that have extensive cloud coverage throughout the year. For instance, in the UK, only one of every six Landsat TM images is usable (Legg 1991, Marshall et al. 1994). Clouds are also a problem for monitoring northern and tropical landscapes using Landsat data (Kontoes and Stakenborg 1990, Jorgensen 2000, Asner 2001).

Data fusion methods (Wald 1999) can be used to overcome both the mixed pixel and the cloud coverage problems. Fused images, i.e. images created by combining two or more types of data, can offer increased interpretation capabilities and more reliable results because the data collected by different Earth observation (EO) sensors are complementary (Pohl and Van Genderen 1998). Besides this, if successful data fusion methods are implemented, continuous time-series of vegetation status can be produced by combining all the EO data currently collected. Therefore, downscaling medium and coarse spatial resolution imagery will improve the optical remote sensing
(global) monitoring capabilities and help with the quantification of land-cover changes over heterogeneous areas where a Landsat-like resolution is required (Janetos and Justice 2000).

Several data fusion methods have been described in the literature (cf. Ehlers 1991, Pohl and Van Genderen 1998). However, most of them are operator- or data type-dependent (Zhang 2002, 2004). For instance, most of the recent data fusion methods based on wavelet transformation require that the ratio of the spatial resolution of the images to be fused is a power of 2 (Shi et al. 2005), or they require that the images to be fused are in the same spectral domain (Otazu et al. 2005). Furthermore, spectral normalization of the original data is required by several data fusion methods (Acerbi-Junior et al. 2006). Nevertheless, the main difficulty is that most of the current data fusion methods do not properly preserve the spectral information of the input images because they are concerned mainly with the visual enhancement of the images (Pellelman et al. 1993). The preservation of the spectral information is, for instance, a prerequisite to derive reliable land-cover maps because the classes that were spectrally separable in the original image should still be separable in the fused image. Additionally, it ensures a physical interpretation of the fused image and facilitates the retrieval of landscape properties using radiative transfer models.

In this respect, Zurita-Milla et al. (2008) have recently introduced a detailed implementation of the unmixing-based data fusion approach as initially introduced by Zhukov et al. (1999). This implementation succeeded in synthesizing fused images with the spectral resolution of MERIS but with the spatial resolution provided by Landsat TM.

In this paper, we further evaluate the performance of the unmixing-based data fusion approach by assessing the potential of MERIS FR fused images to derive spatially improved land products: land-cover maps and vegetation status assessment using the MTCI and the MGVI vegetation indices.

2. Unmixing-based data fusion

If a high and a low spatial resolution image are simultaneously available over a given study area, the linear mixing model (Adams and Gillespie 2006) can be used to combine the information provided by these images. This application is known as spatial unmixing or unmixing-based data fusion (Zhukov et al. 1999, Minghelli-Roman et al. 2001, 2006). The aim of this kind of unmixing is to downscale the spectral information of the low spatial resolution image to the spatial resolution provided by the high spatial resolution image.

Once the high and low spatial resolution images are co-registered, the selected unmixing-based data fusion approach can be summarized in four main steps (Zurita-Milla et al. 2008).

1. The high spatial resolution image is classified into $n$ unsupervised classes.
2. The fractional coverage of the high spatial resolution unsupervised classes is computed for each low spatial resolution pixel.
3. The spectral response of each of the $n$ unsupervised classes is unmixed using the fractional coverages obtained in the second step and the spectral information provided by the low spatial resolution image. This unmixing is done per band and using a neighbourhood of $k \times k$ low spatial resolution pixels.
4. Finally, a fused image is constructed by assigning the corresponding unmixed signals to the unsupervised classes present in the central pixel of each $k \times k$ neighbourhood.

The third step of the unmixing-based data fusion approach can be written as follows:

$$L_{i,k} = F^{k,n} S^{i,k,n} + E^i \quad i = 1, 2, ..., N,$$

where $L_{i,k}$ is a $(k^2 \times 1)$ vector that contains the low spatial resolution values (for band $i$) of all the low spatial resolution pixels present in the $k \times k$ neighbourhood. $F^{k,n}$ is a $(k^2 \times n)$ matrix containing their corresponding fractional coverages in terms of the $n$ unsupervised classes. $S^{i,k,n}$ is the $(n \times 1)$ unknown vector of spectrally downscaled values (band $i$) for each of the classes present in the $k \times k$ neighbourhood. $E^i$ is a $(k^2 \times 1)$ vector of residual errors. Finally, $N$ is the number of low spatial resolution bands.

It is worth noting that equation (1) is typically solved using a constrained least-squares method because the downscaled spectral information (DN, radiance or reflectance values) should fulfill the following two conditions: (i) all the spectral values must be positive and (ii) none of the spectral values can be larger than the saturation value of the low spatial resolution sensor.

3. Materials and methods

3.1 Study area and input datasets

The study area covers approximately 40 km by 60 km of the central part of the Netherlands (52.19° N, 5.91° E; figure 1). The selected study area includes the largest lowland natural area of north-western Europe as well as grasslands, croplands and some relatively important urban nuclei. The landscape of the natural area is characterized by a mixture of heather, woodlands and sand drifts. One of the largest and oldest national parks of the Netherlands, ‘De Hoge Veluwe’, lies in the southern part of the natural area. Part of the rivers Rhine and IJssel are located in the southern and eastern part of the Netherlands.

![Figure 1. Location of the study area within the Netherlands.](image-url)
study area. Finally, the north-western corner of the selected area corresponds to the province of Flevoland, a polder mainly used for agricultural purposes. The shallow lake known in Dutch as ‘Veluwemeer’ separates Flevoland from the mainland.

The study area was selected considering both the heterogeneity of the landscape and the availability of cloud-free high and medium spatial resolution satellite data acquired nearly simultaneously: a Landsat-5 TM image from 10 July 2003 and a MERIS full resolution level 1b image acquired 14 July 2003 were available over this area. Both images were in top of atmosphere (TOA) radiance and they were co-registered with a root mean square. error of 0.47 MERIS pixels. The main characteristics of the TM and the MERIS sensors are given in table 1.

3.1.1 Fused images. The unmixing-based data fusion approach formulated in equation (1) inherently requires the optimization of two parameters: the number of classes used to classify the high spatial resolution image (n) and the size of the neighbourhood used to solve the unmixing equations (k). As in our previous study (Zurita-Milla et al. 2008), 5 values of n (10, 20, 40, 60 and 80) and 14 values of k (from \( k = 5 \) to \( k = 53 \) in steps of 4) were used to generate a series of fused images. In that study, the quality of the fused images was quantitatively assessed at the TM and at the MERIS FR spatial resolutions by using the so-called ERGAS index (erreur relative global adimensionnelle de synthèse (global relative a-dimensional synthesis error); Wald 2002, Ranchin et al. 2003, Lillo-Saavedra et al. 2005) and by computing the average correlation coefficient between spectrally similar TM and MERIS bands. The results of this quality assessment indicated that a trade-off exists between the reconstruction of fused images at 25 and 300 m and suggested that a specific application should be used to select the best combination of n and k. In order to try to clarify this issue, here land-cover mapping was chosen as such an application.

Table 1. Comparison of the TM and the MERIS FR sensors.

<table>
<thead>
<tr>
<th>Band</th>
<th>TM centre (nm)</th>
<th>TM bandwidth (nm)</th>
<th>MERIS FR centre (nm)</th>
<th>MERIS FR bandwidth (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>485</td>
<td>70</td>
<td>412.5</td>
<td>9.9</td>
</tr>
<tr>
<td>2</td>
<td>560</td>
<td>80</td>
<td>442.4</td>
<td>10.0</td>
</tr>
<tr>
<td>3</td>
<td>660</td>
<td>60</td>
<td>489.7</td>
<td>10.0</td>
</tr>
<tr>
<td>4</td>
<td>830</td>
<td>140</td>
<td>509.7</td>
<td>10.0</td>
</tr>
<tr>
<td>5</td>
<td>1650</td>
<td>200</td>
<td>559.6</td>
<td>10.0</td>
</tr>
<tr>
<td>6</td>
<td>*</td>
<td>*</td>
<td>619.6</td>
<td>10.0</td>
</tr>
<tr>
<td>7</td>
<td>2215</td>
<td>270</td>
<td>664.6</td>
<td>10.0</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
<td>680.9</td>
<td>7.5</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td></td>
<td>708.4</td>
<td>10.0</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
<td>753.5</td>
<td>7.5</td>
</tr>
<tr>
<td>11</td>
<td></td>
<td></td>
<td>761.6</td>
<td>3.7</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td></td>
<td>778.5</td>
<td>15.0</td>
</tr>
<tr>
<td>13</td>
<td></td>
<td></td>
<td>864.8</td>
<td>20.0</td>
</tr>
<tr>
<td>14</td>
<td></td>
<td></td>
<td>884.8</td>
<td>10.0</td>
</tr>
<tr>
<td>15</td>
<td></td>
<td></td>
<td>899.8</td>
<td>10.0</td>
</tr>
<tr>
<td>Spatial resolution (m)</td>
<td>25</td>
<td>300</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revisit time (days)</td>
<td>16</td>
<td>2–3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*The 6th band of the TM sensor was not used in this study because it is located in the thermal domain and has a different spatial resolution (120 m).
3.2 **Land-cover classification**

All fused images, as well as the original TM image, were classified using a supervised maximum likelihood classification rule. Similar to other studies (Clevers *et al.* 2007, Zurita-Milla *et al.* 2007), the MERIS bands 1, 2, 11 and 15 were excluded from all the fused images before their classification. These bands are either very susceptible to atmospheric influences (bands 1 and 2) or they coincide with atmospheric absorption features (bands 11 and 15). Hence, they do not provide relevant information for land-cover mapping.

The latest version of the Dutch land-use database, LGN5, was used to support the selection of the training samples and to validate the classification results (figure 2). This dataset is based on a multi-temporal classification of high resolution satellite data and the integration of ancillary data (Hazeu 2005). LGN5, which is based on operator-supported interpretation of Landsat imagery from the year 2003 for the study site, has a spatial resolution of 25 m and a detailed legend consisting of 39 classes. In order to simplify the classification process and reduce spectral confusion, LGN5 was thematically aggregated into the eight main land-cover classes of the

![Figure 2. Thematically aggregated land-cover map (LGN5) over the study area.](image-url)
Netherlands: grassland, arable land, deciduous forest, coniferous forest, water, built-up area, natural vegetation and bare soil (including sand dunes).

Two additional experiments were designed to further assess the potential of the fused images for land-cover classification. First, the MERIS image was resampled from 300 m to 25 m using cubic convolution and then it was classified to evaluate the added value of the fusion process. In the second experiment, bands 5 and 7 of the TM image were omitted from the TM classification because MERIS does not collect information in the short-wave infrared (SWIR) region. This allows us to compare classification results of spectrally similar images. Finally, the overall classification accuracies, the user’s and producer’s accuracies, as well as the kappa coefficient, were used to compare the classification results.

### 3.3 Assessing vegetation status

As mentioned in §1, two vegetation indices are operationally produced to monitor vegetation status using MERIS data: the MTCI, which is related to canopy chlorophyll content, and the MGVI, which is directly linked to fAPAR. Traditional vegetation indices, such as NDVI, can also be computed from MERIS data. The NDVI was designed to enhance the vegetation signal and it is basically an indicator of the amount of vegetation and its ‘greenness’. Due to its simplicity, this index has found a large number of applications. For instance, NDVI has been related to fAPAR (Myneni and Williams 1994) and was also used to estimate crop and forest productivity (Maselli and Chiesi 2006, Moriondo et al. 2007). For this study, the advantage of computing this index is that it can also be derived from TM data so that we can compare results at 25 m.

The MTCI, MGVI and NDVI are easy to compute and, if the selected data fusion method preserves the MERIS spectral information, they can be used to study vegetation status at a much higher spatial resolution. The best fused image, as identified based on the land-cover classification accuracy, was selected to compute these vegetation indices. In addition to the vegetation indices, the spectral consistency of the best fused image was checked by comparing the average spectral signature of the training areas used during the land-cover classification with the corresponding signatures of the original MERIS FR data.

The NDVI was computed as follows:

\[
\text{NDVI} = \frac{L_{\text{NIR}} - L_{\text{RED}}}{L_{\text{NIR}} + L_{\text{RED}}},
\]

where \(L_{\text{NIR}}\) and \(L_{\text{RED}}\) are the TOA radiance values of the bands located in the near-infrared (NIR) and the red regions of the electromagnetic spectrum. In the case of MERIS, band 13 was used for \(L_{\text{NIR}}\) and band 7 for \(L_{\text{RED}}\), whereas for the TM sensor bands 4 (NIR) and 3 (red) were used.

The use of radiance data to compute the NDVI facilitates the inter-comparison exercise. Nevertheless, differences in sensor spectral configuration and sensor calibration will still play an important role when comparing indices computed using data from different sensors (Teillet et al. 1997). For instance, the TM sensor was designed to quantize the spectral information using 8 bits whereas MERIS uses 12-bits digitization.

Computation of the MTCI and MGVI indices requires that the data are transformed from TOA radiance \(L_{\text{TOA}}\) to TOA reflectance \(R_{\text{TOA}}\), also known as
planetary reflectance). Equation (3) shows the expression used for such a transformation. The average solar irradiance per band, \( S' \) (Wm\(^{-2}\) \( \mu \)m\(^{-1}\)), and the solar angle, \( \theta_s \), were obtained from the MERIS metadata.

\[
R^i_{\text{TOA}} = \frac{\pi L^i_{\text{TOA}}}{S' \cos(\theta_s)}.
\]  

The MTCI was computed using equation (4), where \( R_x \) is the TOA reflectance of the \( x^{\text{th}} \) MERIS band:

\[
\text{MTCI} = \frac{R_{10} - R_9}{R_9 - R_8}.
\]  

The MGVI uses the TOA reflectance in three MERIS bands: blue (band 2), red (band 8) and NIR (band 13). The information in the blue band is used to derive rectified red and NIR reflectances that are corrected for atmospheric effects. After that, the MGVI is computed as a polynomial function of the rectified red and NIR reflectances (Gobron et al. 2004).

4. Results and discussion

4.1 Land-cover classification

A supervised maximum likelihood classification rule was applied to: (i) the complete series of fused images, (ii) the Landsat TM images (all bands and 4 bands cases) and (iii) the original MERIS image resampled to 25 m using cubic convolution. First, homogeneous areas belonging to the eight main land-cover types were identified using the LGN5. These areas (\(< 0.4\% \) of the total pixels) were used to train the classifier. Subsequently, the land-cover classifications were validated using the whole LGN5 (figure 2) as a reference.

Figure 3 illustrates the relationship between the data fusion parameters \( k \) and \( n \) and the overall classification accuracies. In general, the larger the neighbourhood size, the higher the classification accuracies. Nevertheless, for larger neighbourhood sizes, an asymptotic value of about 60\% is found. This indicates that increasing the window size beyond the tested values will not result in an improved overall accuracy. The poor classification results obtained for small \( k \) could indicate that the unmixing solutions are not stable – especially if TM has been classified in a large number of classes. The use of regularization techniques (Golub et al. 2000) might be needed in these cases.

In addition, classification accuracies for \( n = 10 \) seem to be rather insensitive to the neighbourhood size and they are consistently lower than the rest of the accuracies. This could be because 10 unsupervised classes are not sufficient to properly characterize the heterogeneity of the study area.

The fused image obtained for \( n = 60 \) and \( k = 45 \) was selected as the best fused image because it maximizes the classification accuracy. Nevertheless, we recognize that other combinations of \( n \) and \( k \) provide very similar results. This is because a number of fused images yielded classification accuracies around the asymptotic value of 60\%.

Figure 4 shows a red–green–blue (RGB) colour composite of the best fused image and of a 25 \( \times \) 25 MERIS FR pixels subset together with the original TM and MERIS FR images. The selected subset corresponds to the north-western corner of the study area (Flevoland), where the individual agricultural fields can be identified easily at 25 m but not at 300 m.
Table 2 summarizes the overall accuracy and kappa coefficient of the best fused image as well as the ones obtained for the TM and the MERIS cubic convolution resampled images. Classification accuracies are moderate to good, especially considering the fact that the study area is very heterogeneous (even at the spatial resolution provided by the TM sensor).

The overall classification accuracy and the kappa coefficients of the original TM image were slightly better than the ones obtained for the best fused image. However, the classification results of the TM image without the SWIR bands were worse than the ones obtained for the best fused image. This indicates that (1) the SWIR bands, which are missing in MERIS, play an important role in the final classification accuracy and (2) that the MERIS spectral configuration offers an increased class separability with respect to TM (visible and NIR).

The best fused image performed much better than the cubic convolution resampling of the original MERIS FR image. This shows that the selected data fusion approach is very useful to downscale MERIS data. Figure 5 shows the classification results obtained with the best fused image and with the Landsat TM (all bands). The map produced using the best fused image offers a good representation of the main landscape features.

Finally, table 3 provides detailed information on the classification results of the best fused image through its confusion matrix. In comparison, the confusion matrix for the TM image with all six reflective bands is provided in table 4. In both cases a lot of confusions between classes are occurring, explaining the moderate overall classification accuracies and kappa coefficients in table 2. However, this is the order of magnitude of these accuracies to be expected if no multi-temporal satellite data and no ancillary information are used (Hazeu 2005).
In most cases, the classification confusion is quite similar for the fused and for the TM image. Noticeable are the low user’s and producer’s accuracies for arable land. This can be explained by the heterogeneity of the arable land class: for instance, in July, winter cereals are already mature and will look more like bare soil or urban areas but spring cereals and, in particular, crops like sugar beet and potatoes are still green. Due to this heterogeneity, mixing of the arable land class with many other classes occurred. In this respect, the major difference between the fused image classification and the TM classification is that in the fused image much more arable land pixels were labelled grassland, whereas in the TM image more pixels were assigned the label.

Table 2. Classification results.

<table>
<thead>
<tr>
<th></th>
<th>OA (%)</th>
<th>K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best fused image ( (n = 60; k = 45) )</td>
<td>61.59</td>
<td>0.519</td>
</tr>
<tr>
<td>Landsat TM 6 bands</td>
<td>63.32</td>
<td>0.550</td>
</tr>
<tr>
<td>Landsat TM bands 1–4</td>
<td>57.98</td>
<td>0.484</td>
</tr>
<tr>
<td>MERIS 25 m cubic convolution</td>
<td>40.57</td>
<td>0.295</td>
</tr>
</tbody>
</table>

OA is the overall classification accuracy; \( K \) is the kappa coefficient

Figure 4. RGB colour composite of bands 4, 3 and 2 of the TM image \( (a) \), \( (d) \), bands 13, 7 and 5 of the fused image for \( n = 60 \) and \( k = 45 \) \( (b) \), \( (e) \) and bands 13, 7 and 5 of the original MERIS FR image \( (c) \), \( (f) \). \( (a) \)–\( (c) \) show the whole study area, whereas \( (d) \)–\( (f) \) show a 25 by 25 pixel subset.
deciduous forest. Another noticeable class is water. This class had a very high user’s accuracy and a relatively low producer’s accuracy. This indicates that a significant number of water pixels was misclassified. An explanation for this can be remaining uncertainty in the co-registration and the presence of many narrow water bodies. In the fused image, many water pixels were classified as built-up area, whereas in the classified TM image many water pixels were classified as natural vegetation and arable land and not that much as built-up area.

Other major differences between the classifications of the best fused image and of TM are, in particular, the number of correctly classified pixels for the classes deciduous forest and bare soil (although the latter is a rather small class). For the bare soil class many more pixels were labelled as arable land in the classified fused image than in the classified TM image, at least relative to the size of this class.

4.2 Assessing vegetation status

Figure 6 illustrates the average spectral signatures of the areas used as training areas for the land-cover classification. Figure 6(a) was prepared using the best fused image, while figure 6(b) shows the signature of the corresponding areas in the original MERIS FR image. These signatures can be compared, since the training areas were taken from large homogeneous areas that correspond to ‘pure’ pixels at the original MERIS scale. The general shape of these spectral signatures corresponds to typical spectra of the respective classes. The first few bands show relatively high values due to atmospheric scattering in the blue. Bands 11 and 15 show low TOA reflectance values due to the oxygen and water absorption features located near those bands. Figure 6 confirms that the spectral differences between the best fused image and MERIS are very small. Thus, the unmixing-based data fusion approach succeeded in synthesizing the spectral characteristics of MERIS at 25 m. This should allow the calculation of vegetation indices from the fused images.

As an example, figure 7 presents the NDVI results computed over the 25 × 25 pixels MERIS FR subset that was used in figure 4. The index was computed from the TM
Table 3. Confusion matrix for the maximum likelihood classification of the best fused image ($n = 60; \ k = 45$).

<table>
<thead>
<tr>
<th>Classified class</th>
<th>Water</th>
<th>Built-up area</th>
<th>Grasslands</th>
<th>Coniferous</th>
<th>Arable land</th>
<th>Deciduous</th>
<th>Natural vegetation</th>
<th>Bare soil</th>
<th>Total</th>
<th>User’s accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>64542</td>
<td>40</td>
<td>669</td>
<td>11</td>
<td>24</td>
<td>8</td>
<td>0</td>
<td>37</td>
<td>65331</td>
<td>98.79</td>
</tr>
<tr>
<td>Built-up area</td>
<td>29007</td>
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<td>5714</td>
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<tr>
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<td>79117</td>
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<td>0</td>
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<td>449443</td>
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<td>226321</td>
<td>20079</td>
<td>3887977</td>
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<tr>
<td>Producer’s accuracy (%)</td>
<td>51.95</td>
<td>52.01</td>
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<td>72.52</td>
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<td>29.52</td>
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Table 4. Confusion matrix for the maximum likelihood classification of the TM image (6 bands).

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<th>Classified class</th>
<th>Water</th>
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<th>Coniferous</th>
<th>Arable land</th>
<th>Deciduous</th>
<th>Natural vegetation</th>
<th>Bare soil</th>
<th>Total</th>
<th>User’s accuracy (%)</th>
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<tr>
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<td>34</td>
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<td>Total</td>
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<td>226321</td>
<td>20079</td>
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</tr>
</tbody>
</table>

Producer’s accuracy (%)

63.03  53.22  63.38  75.08  34.54  74.28  84.06  51.49
image, from the best fused image and from the original MERIS FR image. A few negative 
NDVI values were identified in the NDVI images. These values, associated with bare soil, 
water or ‘edge effects’ (i.e. mixed pixels in between fields or at the interface land/water), 
were set to zero to facilitate the interpretation of the results. Figure 7 illustrates that it is 
possible to monitor individual fields using MERIS fused images. There is a good agree- 
ment between the spatial patterns found in the fused and in the original MERIS FR 
image. However, the dynamic range found for the fused and the MERIS NDVI values is 
smaller than the one of the TM image. This can be explained by differences in band centres 
and bandwidths. Cross-sensor calibration of vegetation indices is still an open issue for the 
remote sensing community (Fensholt et al. 2006). A detailed study by Teillet et al. (1997) 
identified that NDVI is very sensitive to the spectral configuration of the sensor and 
pointed out that the effects on the NDVI depend on the type of canopy under study. In 
this respect, the narrow spectral bands provided by MERIS should provide a better 
NDVI than the one computed using broad bands. More precisely, Teillet et al. (1997) 
concluded that a narrow band (less than 50 nm) located around 865 nm is optimal to 
compute the NDVI because this region is less sensitive to possible errors due to an 
improper atmospheric water vapour correction. MERIS band 13 (864.8 nm) is in the 
middle of this optimum region, whereas TM band 4 (830 nm) is a very broad band 
extending outside that spectral region.

Despite the differences in sensor spectral configuration (table 1), a good correlation 
\(R = 0.76\) was found between the NDVI computed from the TM and from the
MERIS fused image. In a recent study, Busetto et al. (2008) found a correlation of about 0.85 using NDVI computed from TM and fused MODIS images but these sensors have a much more compatible spectral configuration than TM and MERIS.

Finally, figure 8 shows the results for the MTCI and the MGVI vegetation indices. Notice that these indices were not computed for the large water body present in the scene since its MTCI and MGVI values are meaningless. For the land pixels, a small proportion (<1.2%) of unfeasible index values, or ‘outliers’, were identified and removed from the MTCI and MGVI images computed from the fused image. In this case, the outliers are defined as pixels that exceed more than 10% of the maximum or minimum index values as found in the original MERIS FR images (i.e. we assume that pixels at 25 m might have index values outside of the range found at 300 m, because at the MERIS original scale the signal is smoothed due to the mixed pixels). The ‘outliers’ mainly correspond with narrow linear features (e.g. roads or edges between agricultural plots). In figures 8(a) and (c), they can be seen as dark blue pixels because they were set to zero. These pixels could be removed easily using, for instance, a median filter. The appearance of these unfeasible index values might be attributed to errors during the unmixing because of residual errors in the co-registration and/or because the problem was ill-posed. In addition, the uncertainty of unmixing classes that have a very small fractional coverage inside the MERIS neighbourhood is
inherently higher than the unmixing of classes that cover a large proportion of the neighbourhood (Zhukov et al. 1999).

This example clearly illustrates the potential of monitoring individual fields using the fused products, whereas this is not possible using the original MERIS image. In the MERIS FR image each pixel seems to be a mixed pixel. In the fused images mixed pixels can still be observed at object boundaries, but individual fields are clearly identifiable.

5. Conclusions and recommendations

In this paper we have assessed the potential of MERIS–TM fused images to derive spatially improved MERIS land products. These fused images have the spatial resolution of TM, whereas the spectral and radiometric properties come solely from MERIS. The selected implementation of the unmixing-based data fusion approach requires the optimization of two parameters: the number of classes used to classify the TM image, \( n \), and the size of the MERIS neighbourhood, \( k \), used to solve the unmixing.

Here, a series of fused images generated with various combinations of \( n \) and \( k \) were used to produce land-cover maps of the eight main classes of the Netherlands. The image generated with \( n = 60 \) and \( k = 45 \) was chosen as the best fused image based on the land-cover classification results. Classification results for the TM image and for the best fused image were very similar (overall accuracies of 63.32% and 61.59%, respectively). However, the fused images outperformed the classification accuracies of a spectrally similar TM image (i.e. an image without the SWIR bands). This indicates that the fine spectral resolution of MERIS is better than a coarse spectral resolution for land-cover mapping and that the SWIR region plays an important role in the final classification accuracy. Classification accuracies might be improved further by making use of the changing phenology of some of the classes during the year. This would require a multi-temporal data fusion and classification approach.

The potential of the MERIS fused images to assess vegetation status was also evaluated in this paper. The NDVI, MTCI and the MGVI vegetation indices were computed from the best fused image (25 m) and from the original MERIS FR image (300 m). Results indicate that the best fused image can be used to successfully downscale these continuous variables. Despite differences in the spectral configuration of the TM and MERIS sensors, a good correlation \((R = 0.76)\) was found between the NDVI computed from TM and from the MERIS fused image. In addition, vegetation indices computed from the fused image were spatially consistent with patterns obtained from the original MERIS FR image. Moreover, the use of fused images allows one to study the vegetation status of individual fields because of their enhanced spatial resolution. This is not possible using original MERIS FR data over heterogeneous landscapes where most of the MERIS pixels are mixed pixels. Unsatisfactory vegetation index values are still obtained at object boundaries, because the data source for defining the object classes (a TM image) has many mixed pixels at these instances. This affected the TM unsupervised classification and resulted in deviating class labels from their neighbourhood. These deviating class labels yield deviating index values. This problem of mixed pixels at object boundaries may be solved by using an existing land-cover map instead of a remote sensing image for defining the thematic classes.

Another major advantage of using a land-cover map is that MERIS images of multiple dates may be fused with the same land-cover map. In the current study,
classes were obtained from a TM image and its classification will be different if an image from a different season is used. If the number of useful TM images is limited by cloud cover, the applicability of the proposed technique is also limited. However, the presented methodology also can be used with an existing, up-to-date land-cover map. This should be implemented as a next step.

Because of the spatial, spectral and potentially temporal resolutions of MERIS fused images, we believe that they are particularly interesting to monitor processes in both heterogeneous and frequently clouded areas. Further validation is, however, required in order to completely assess the possibilities and limitations of this data fusion method in other landscapes.

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References


