SPECTRAL UNMIXING OF LOW RESOLUTION IMAGES FOR MONITORING SOIL SEALING

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ABSTRACT:

The expansion of urban areas has a negative impact on the environment. The increase of impervious or sealed surfaces is directly proportional to this expansion. The estimation of sealed surfaces has often been executed using remote sensing imagery, although only on a local to regional scale, using medium and recently available high resolution images like LANDSAT TM and IKONOS. In order to develop a global policy and strategy on urban expansion matters, consistent time series of area statistics on urban land use on a national and global level will become indispensable. This research explores the possibilities of SPOT VEGETATION imagery, with a spatial resolution of 1 km, for urban monitoring in order to generate statistics of sealed surfaces over larger zones. While low resolution imagery offers the advantage of covering a large area in small temporal intervals, its spatial resolution is too coarse to monitor most urban objects. In order to tackle this problem, a sub-pixel classification was applied and unmixed sealed surface area statistics were produced. Endmember selection is a key element in the sub-pixel classification process in which the spectrally complex sealed surface class should be distinguished from other general classes. To find the most favourable temporal interval or period for endmember selection, several datasets were developed and explored. SPOT-VEGETATION images were acquired in summer and winter for Flanders (Belgium). This region is characterised by a highly fragmented urban land-cover and large availability of reference data. Spectral unmixing of the multitemporal datasets illustrates that the endmember spectra differs for three different endmember selection techniques, affecting the quality of the final sub-pixel classification. The paper argues that the unmixing result is more sensitive to the endmember selection technique than to the period of image acquisition. It was found that with regard to the tested endmember selection techniques, the Average of Pure Pixels technique gave the best results with an overall accuracy of 81 %, while the combined winter/summer image performed better than the individual summer or winter images.

1. INTRODUCTION

The Earth's land cover is in constant evolution with urban developments continuously expanding world wide. The increase of sealed surfaces is one of the main characteristics of this expansion and is likely to be sustained due to growing population pressure. Keeping up to date with these changes at acceptable costs is a necessity for regional planners and managers of natural resources. In the past, land cover/use information was gathered mainly by field measurements and interpretation of aerial photographs. But these approaches are labour intensive, require expertise for interpretation and can only be applied to relatively small areas. The same is true when applying medium to high resolution satellite imagery like Landsat TM and IKONOS images to monitor land cover/use. The estimation of sealed surfaces has often been executed using digital image data of these instruments, although only on a local to regional scale (Small, 2003). However, to develop a global policy and strategy on urban expansion matters, consistent time series of area statistics on urban land cover/use on a national and global level will become indispensable.

Although low resolution (LR) imagery, like those provided by the SPOT VEGETATION and AVHRR sensors, contains less geographical detail, it presents attractive features as they cover large areas at short time intervals (Lillesand and Kiefer, 2000). In order to produce a land cover/use geodataset, with the emphasis on sealed surface identification, the imagery of these instruments has to be classified. Typical hard classifiers, such as maximum likelihood and parallelepiped operators, mostly do not provide satisfactory results because the spatial resolution of LR imagery is too coarse to monitor most urban objects. Soft classifiers on the contrary are more eligible to deal with LR imagery because they recognise, in contrast to hard classifiers, that pixels can cover more than one real-world feature or land cover/use type (Settle and Drake, 1993). Several methods have been proposed to characterize land cover/use at the sub-pixel level, including Linear Mixture Models (Verhoeye and De Wulf, 2000; Lu and Weng, 2004), Artificial Neural Networks (Paola and Schowengerdt, 1995; Swinnen *et al.*, 2001), Fuzzy Classifiers (Zang and Foody, 2001), Maximum Likelihood Classifiers (Häme *et al.*, 2001), Hierarchical Linear Unmixing (Newland, 1999) and Support Vector Machines (Brown *et al.*, 1999).

The work presented here will make use of the Linear Mixture Model, assuming that the spectral response recorded for a pixel is a linear combination or mixture of pure spectral responses of the objects present in the pixel. These pure spectral responses are called endmembers. Once the present classes and their spectral responses are known, the contribution of these endmember spectra to the overall spectral signature of the pixel and, ultimately, their fraction within the pixel area, can be estimated. Following this 'unmixing' approach, a.o. Settle and

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Drake (1993), Verhoeye and De Wulf (2000) and Lu and Weng (2004) have shown that it is possible to estimate the area proportion of different features or land cover/use types within single pixels of satellite imagery. According to Van Der Meer and De Jong (2000), the endmember selection is a key element in this sub-pixel classification process. The aim of this research is to explore the possibility of linearly unmixing SPOT VEGETATION imagery to obtain area statistics of sealed surfaces over a large area. Herewith emphasis is on the identification of the spectrally complex sealed surface class with respect to other classes and on the investigation of the effect of the period of image acquisition and the endmember selection technique.

2. STUDY AREA AND DATA

The northern part of Belgium, including the regions of Flanders and Brussels, with a total area of 13682 km^2 was selected for the unmixing analysis. This area is characterised by a highly fragmented land cover, with cities interconnected by a dense road network along which ribbon development is pertinently present (Ministerie van de Vlaamse Gemeenschap, 1998).

The VEGETATION instrument is a large scale Earth observation sensor with a resolution of 1000 m * 1000 m on board of both the SPOT 4 and the SPOT 5 satellite with a field of view of 2200 km and gathers information in 4 spectral bands (blue, red, NIR and SWIR). A summer and winter 10-daily synthesis (S10) image of the VEGETATION instrument were selected from the year 2001 and downloaded for free from the webpage http://free.vgt.vito.be/. An S10 image is composed by 10 daily-taken VEGETATION images. The composition is based on the highest Normalized Difference Vegetation Index (NDVI) for every pixel to remove possible cloud pixels, which generally have low NDVI values (Ledwith, 2002).

The reference data used for the endmember selection and validation process is an available land cover/use geodataset produced by the governmental organization OC GIS-Vlaanderen, with resolution of 15 m * 15 m and a K-statistics of 0.88. The geodataset has been derived from two Landsat images and ancillary vector data of 2001, covering the entire study area. (OC GIS Vlaanderen, 2001).

3. METHODOLOGY

3.1 Data preparation

The summer and winter VEGETATION images were clipped to the study area and geographical transformed from Plate Carrée to the national Lambert conformal conical coordinate system of Belgium. The cloud pixels around the coastal zone, i.e. the “coastal ring”, caused by the synthesis procedure of the S10 images were masked, using the land borders of the reference image. Both images had an error in the form of white stripes in the MIR-band, due to blind/or aberrant MIR detectors (Ledwith, 2002). This error, together with the noise from the other bands, was removed in the final stage of the data preparation by means of the minimal noise fraction (MNF) transformation.

MNF transformation projects the original image in a space where the new components are sorted in order of signal to noise ratio (Green *et al.*, 1988; LU and Weng, 2004). Its procedure consists of a combination of two principal component analyses (PCA), rotating the original coordinate system such that most of the variation in the data is found along a limited number of axes. The first PCA de-correlates and rescales the noise in the data based on an estimated noise covariance matrix established under the assumption that the spatial autocorrelation of the signal is high compared to the noise’s one. The second step is a standard PCA of the noise-whitened data resulting in a two-part dataset, one part associated with large eigenvalues and coherent eigenimages, and a second part with near-unity eigenvalues and noise-dominated images. The MNF transformation was applied to the summer, winter and a stacking of the summer and the winter image. The single and combined period datasets resulted in eigenvalues bigger than unity for the first 3 and respectively 4 MNF bands, leaving the apparent noise in the other bands. The latter were excluded from the endmember selection and the linear unmixing procedure.

3.2 Linear unmixing

Assuming that the signal received at the sensor is composed of a linear mixture of pure-element reflections (endmembers) coming from different land cover/use types, the general linear unmixing equation for one pixel can be written as follows:

$$x = M * f + e \tag{1}$$

with the column vector x = $[x_1,\ldots,x_n]^T$ to denote the MNF transformed reflectance values of the spectral bands (n) of a VEGETATION-pixel; the column vector f = $[f_1,\ldots,f_c]^T$ to denote the proportions of area within each pixel occupied by each of the land cover/use types (c). Each column of the matrix M is the endmember spectrum of one pure land cover/use class and e is an observation error, both expressed in MNF values (Settle and Drake, 1993). The area fraction (f) is estimated for each pixel such that:

$$\|M * f - x\|^2 \tag{2}$$

is minimized subject to:

the sum to one constraint: $\sum_{i=1}^{c} f_i = 1$

positivity constraint: $0 \succ f_i \succ 1$

Before applying this linear programming problem using the Matlab optimization toolbox (Grace, 1999), the endmember spectra were to be estimated.

3.3 Endmember selection

Because the final goal is to generate area statistics on sealed surfaces, the two broad category endmembers “sealed” and “non-sealed” were selected as endmembers. This implies that the condition of identifiability for equation (1) is met since the number of land cover/use types (c=2) is smaller than the number of MNF spectral bands (n=3 or n=4). To estimate the MNF band values for these endmembers, three estimation techniques were applied. They each made use of the reference geodataset from which area fractions of the sealed and non-sealed classes were generated in a 1000 m resolution grid. In order to reserve part of the reference data for validation, a suitable number of training pixels was determined by comparing the endmember spectra for a different number of pixels out of the reference geodataset. The lowest percentage for which the endmember spectra were comparable with those generated with all reference data, was selected. A short explanation of the three used endmember estimation techniques is given below.

3.3.1 Reversed Linear Mixture Model (RLMM): Giving the area fractions derived from the reference geodataset, the corresponding endmember spectra were estimated by reversing the linear mixture equation (1) (Verhoeye and De Wulf, 2000):

$$M = \left(F * F^{T}\right)^{-1} * F^{T} * X \tag{3}$$

with
M = Matrix with the endmember spectral values
F = Matrix with the area fractions derived from the reference geodataset
X = Matrix with the MNF values derived from the spectral reflectance values of the original VEGETATION image.

3.3.2 Average of Pure Pixels (APP): Based on the area fractions from the reference geodataset, all pixels with an endmember fraction exceeding 0.95 were selected. The corresponding MNF spectra were averaged for both the sealed and non-sealed class to find the endmember spectra of these “pure” pixels (Quarmby *et al.*, 1992; Foody and Cox, 1994).

3.3.3 Weighted average over all pixels (WA): By multiplying the area fraction for the sealed endmember class, derived from the reference geodataset, with the corresponding values of the MNF bands and averaging these values over the total reference sealed area of the trainings pixels, a weighted average of the MNF values was calculated. The same process was applied for the non-sealed endmember. This WA method, adopted from Genovese *et al.* (2001), can be used as an estimation of the sealed and non-sealed endmembers and is illustrated in Figure 1 for two pixels and two land use classes A and B.

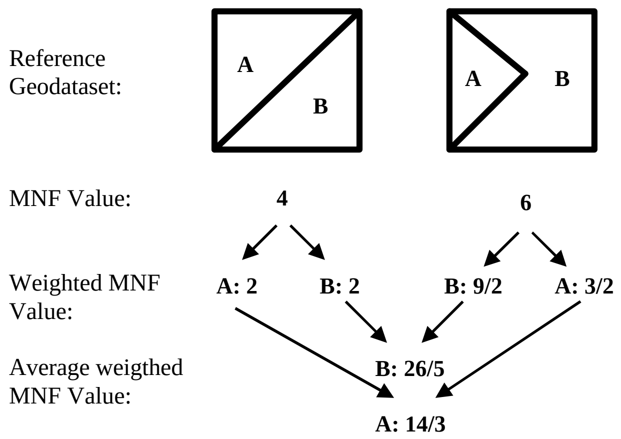
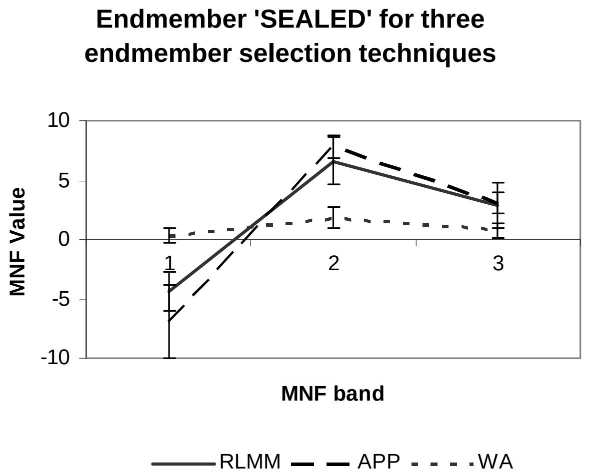


Figure 1. Illustration of the WA endmember selection technique

Hence, three techniques for endmember estimations are used to linearly unmix the MNF-transformed datasets of the three different time periods, with the final aim to generate area fraction indices (AFI’s) for both ‘sealed’ and ‘non-sealed’ land cover over the entire study area.

(a)



(b)

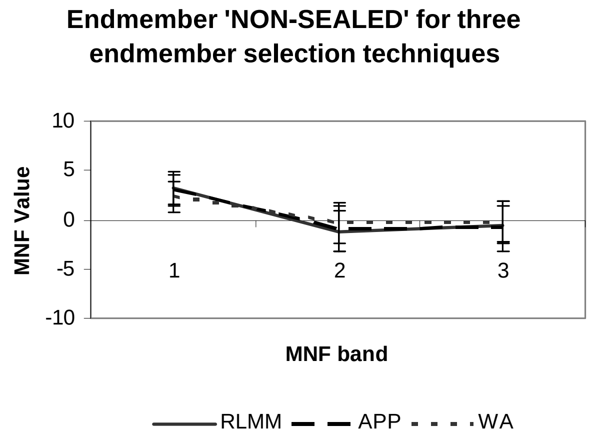


Figure 2. The sealed (a) and non-sealed (b) endmember spectra for the Summer image

4. RESULTS AND DISCUSSION

The first step in the linear unmixing procedure is the estimation of the endmember spectra, expressed in MNF values. A graphical representation of the sealed and non-sealed endmember for the summer image as estimated by the RLMM, APP and WA technique is given together with their calculated standard deviation in Figure 2. It was found that for all techniques, 20% of the total training pixels had to be used for representative endmember spectra estimations. It is apparent when comparing Figure 2a with Figure 2b that the endmembers sealed and non-sealed can be differentiated in all bands with all techniques. While the non-sealed endmember estimations result in similar values for the three techniques, the sealed endmember spectra derived with the WA method differs from the other techniques. This is because the relative large amount of mixed pixels, in comparison to the small number of pure sealed pixels, has mutually a big influence when a simple weighted average is applied.

A linear unmixing procedure was performed to obtain a sub-pixel classification for every endmember selection technique. Before assessing the regional and the individual pixel performance of the sub-pixel classification, a two way ANOVA was executed on the difference between the reference and the

Endmember selection technique	Period of acquisition	Total sealed (km^2)	Difference with reference data (km^2)	Difference with reference data (%)
RLMM	Summer	2850	768	37
APP	Summer	2218	136	7
WA	Summer	4746	2664	128
RLMM	Winter	3063	981	47
APP	Winter	2302	220	11
WA	Winter	5207	3125	150
RLMM	Winter & Summer	2855	773	37
APP	Winter & Summer	2059	-23	-1
WA	Winter & Summer	4914	2832	136

Table 1. The sum of all estimated sealed AFI's and the difference with the total reference sealed area, i.e. 2082 km^2

calculated AFI's with both the endmember selection techniques and the date of image acquisition as independent variables. It was found that both variables have significant influence on the outcome.

A regional analysis of the estimation results is done by calculating the total estimated sealed area fraction and its difference with the total reference sealed area, i.e. 2082 km^2, as shown in Table 1. A first look on Table 1 reveals that the differences between the periods of data acquisition are not as big as the differences between the endmember selection techniques. The APP technique provides a good estimation of the total sealed area while the RLMM and WA methods perform badly, and this for all periods. This can be explained by the location of the sealed endmember spectrum in feature space (Gebbinck, 1998). When the MNF bands are plotted for the whole study area, it is found that the APP derived sealed endmember is situated close to the vertices of the feature space, while the other techniques position the sealed endmember at a distance from these vertices. The variation of the difference between the unmixed and the reference geodataset among the periods of acquisition (summer, winter, winter/summer) indicates a better result for the summer than for the winter

Endmember selection technique	Period of acquisition	Sum of all differences (km^2)	Average difference (km^2)
RLMM	Summer	1915	0.13
APP	Summer	1650	0.12
WA	Summer	3795	0.27
RLMM	Winter	2128	0.15
APP	Winter	1750	0.12
WA	Winter	4234	0.30
RLMM	Winter & Summer	1910	0.13
APP	Winter & Summer	1568	0.11
WA	Winter & Summer	3950	0.28

Table 2. The sum of the absolute and the average differences between the calculated and reference AFI's

period. This and the fact that the best result is generated for the combined winter/summer dataset might be explained by the appearance of bare soil in the study area. More agricultural areas are left under bare soil during wintertime than during the summer, which may explain the larger overestimation of the sealed cover due to the spectral similarity of bare and sealed soil. To the contrary, the combined response of those bare soils over both seasons differs sufficiently from the sealed cover types, having a time-independent response. However, no definitive conclusion should be drawn from Table 1 because individual estimation error is expected to be present in each pixel.

To have a better idea on the individual performance of each pixel on the estimation of the fraction sealed in its area, the calculated AFI's are compared with the reference AFI's for each pixel individually. This is done in an absolute way, so the effect of negative and positive differences compensating for each other is discarded. The sum of all these absolute differences and their average difference are given in Table 2. The average difference calculated here is related to the Mean Absolute Error (MAE) (Swinnen *et al.*, 2001), in the sense that it is the MAE divided by 2. The average difference per fraction of 10 % sealed soil was also calculated and presented in Figure 3 for the APP endmember selection technique. The fact that the sum of all differences in Table 2 is a big number in comparison to the corresponding values of Table 1 indicates that the compensating effect of negative and positive differences over the whole image is important. Figure 3 reveals that this difference depends on the heterogeneity of the pixels. Pixels with small (0-10) and high (90-100) fractions of sealed soil are better estimated for all periods than the severely mixed pixels do. Starting from small percentages of sealed soil cover, the average difference increases in value until the percentage reaches 70-80% and then drops again. The fact that a small value is found when the difference for all pixels is averaged (Table 2), can be explained by the high number of pixels with a low percentage of sealed cover.

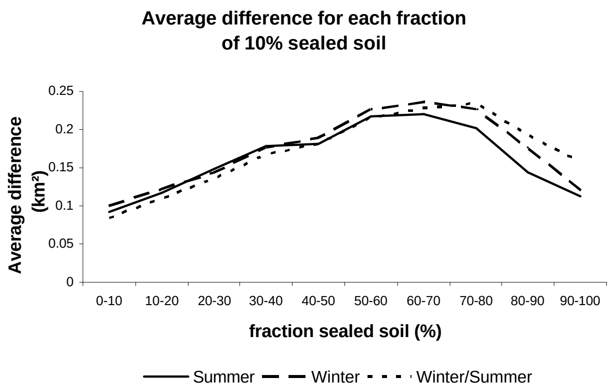


Figure 3. Average difference per fraction of 10 % sealed soil for the APP endmember selection technique

Apart from the numerical validation of the unmixing procedure stands the geographical representation of the final result, i.e. the sealed sub-pixel classification. The reference sealed AFI image (a), together with the sealed AFI image calculated with the APP endmember technique for the winter/summer period combination (b) are given in Figure 4. The calculated area fraction classification of the sealed surface in the study area

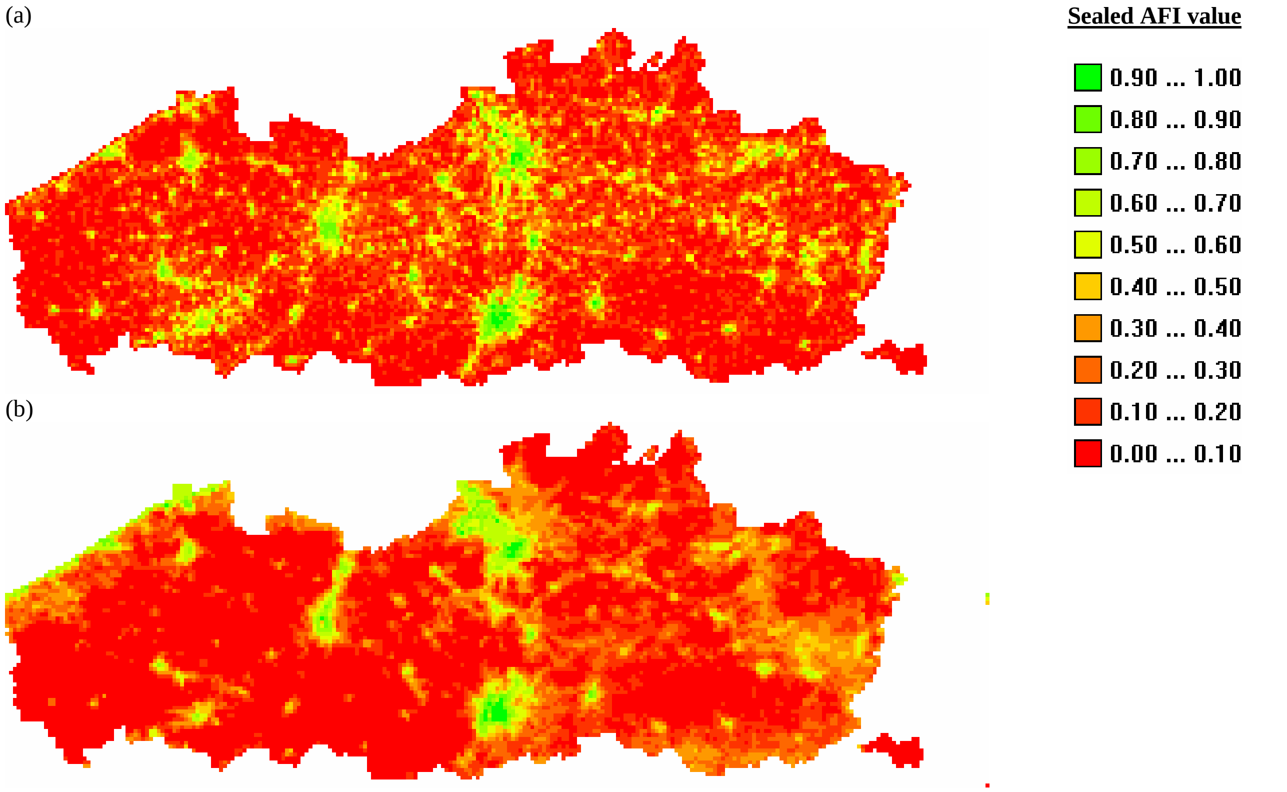


Figure 4. Sub-pixel classification at 1 km^2 resolution: The reference sealed AFI image (a), and the calculated sealed AFI image of the APP endmember technique and summer/winter period combination

does fairly well represent the actual (reference) situation, with a good visualisation of the big urban agglomerations. However, a difference map revealed that there is a clear overestimation of the sealed surface in the south-eastern and western coastal regions, were large areas of agricultural areas and bare soil are present. Also smaller cities scattered around in the study area appear to be underrepresented.

As a final quality assessment of the sub-pixel classification, a cross-comparison was made between the two images of Figure 4. To deal with the fuzzy character of the classification, all differences within a margin of 10% were set to be correctly classified. This resulted in an overall accuracy of 81%, which confirms the visual correspondence between the calculated and reference image.

To compare the results of the sub-pixel classification with a traditional hard classification, a parallelepiped classification was performed on the winter/summer dataset, resulting in sealed surface estimation of 1516 km^2 for the whole regional sealed area. While the big urban agglomerations appear as 100% sealed surface in the hard classification, the smaller cities in the study area are not detected as being sealed. The fact that a great amount of such small cities, interconnected with ribbon development, are present leads to the calculated underestimation of sealed soils in the study area. This analysis shows that a sub-pixel classification of VEGETATION imagery to study sealed surface is more appropriate than a hard classification.

5. CONCLUSION AND FURURE WORK

In order to obtain area statistics of sealed surfaces over a large area, LR satellite imagery (SPOT VEGETATION) was linearly unmixed, and the effect of the period of image acquisition and endmember selection technique was investigated. It was found that the final result was more sensitive to the endmember selection technique than to the period of image acquisition and that the Average of Pure Pixels technique (APP) resulted in the best AFI estimations. The bias with respect to the period of image acquisition may be explained by the presence of bare soils, spectrally similar to sealed surfaces. This problem is more pertinent in winter time but does not disappear during summer. A combination of winter/summer image together with the APP endmember selection technique appeared to be the best alternative. Looking at each pixel individually, the estimations have an average error of ± 0.1 km^2, but increases to a maximum of ± 0.25 km^2 when the heterogeneity of the pixel increases. The calculated area fraction classification of the sealed surface in Flanders and the district of Brussels represents the actual (reference) situation fairly well. This is confirmed with the calculation of the overall accuracy, which is 81 % for the APP endmember selection technique and winter/summer period combination.

Future work should focus on the endmembers present in LR satellite imagery, the parameters involved in their selection and on other, including non-linear, unmixing methods. Also the usability of the calculated endmembers for extension in both the temporal and spatial domain and the use of other LR satellite imagery like MODIS and AVHRR should be investigated.

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