Use of Land Cover Fractions Obtained from Multiple Endmember Unmixing of CHRIS/Proba Imagery for Distributed Runoff Estimation

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Abstract. In the last decades RS and GIS technology have been increasingly used for hydrological applications. Hydrological parameters estimation is strongly related to land cover composition. This study examines the impact of different approaches to estimate land cover distribution on the prediction and the spatial pattern of surface runoff. Land cover fractions are derived at sub-pixel scale from CHRIS/Proba data by applying Multiple Endmember Spectral Mixture Analysis (MESMA). These are used as input for a spatially distributed hydrological model (Wetspass). A fully distributed approach, where land cover fractions are specific for each cell and obtained through MESMA is compared to a semi distributed approach, where the land cover fractions for each cell are fixed a priori, based on the land-use type of the specific cell. The fully distributed approach, based on RS derived land cover estimation, proves to have a strong impact on the spatial distribution of runoff when compared to the results obtained with the more traditional, semi-distributed approach. Using MESMA in combination with the Wetspass model allows making full use of the potential distributed hydrological modelling, leading to a spatially more detailed characterization of hydrological processes.

Keywords. Hydrological modelling, CHRIS/Proba imagery, multiple endmember unmixing, landcover mapping, runoff, evapotranspiration.

1. Introduction

The use of remote sensing and GIS technology in hydrological modelling has strongly increased in the last decades. This allows the mapping of the spatial variability of various parameters which are important for runoff estimation (land cover, soil texture, slope). Several studies have focused on the use of multispectral satellite imagery from medium and high resolution sensors to improve hydrological modelling results [1], [2]. Recently, spaceborne hyperspectral sensors such as Hyperion and CHRIS/Proba (Compact High Resolution Imaging Spectrometer/Project for On Board Autonomy) have opened up new possibilities for land cover mapping, thanks to their increased spectral resolution. Recent work has focused on the potential of CHRIS/Proba data for deriving land cover fractions at sub-pixel scale [3]. A technique which has proved very effective for estimating sub-pixel land cover fractions in urban areas is Multiple Endmember Spectral Mixture Analysis (MESMA) [4]. Compared to standard Linear Spectral Mixture Analysis (LSMA), MESMA allows endmembers to vary on a per-pixel basis and therefore allows taking full account of the heterogeneous composition of land cover in urbanized areas.

The objective of this work is to integrate the results of MESMA applied on CHRIS/Proba data in the Wetspass model, a spatially distributed model to estimate the main water balance components: evapotranspiration, surface runoff and groundwater recharge [5]. In Wetspass, the water balance is calculated at the level of raster cells. For each raster cell, the water balance is split into independent water balances for the vegetated (V), bare soil (B), impervious surfaces (I) and open water (W) fractions, which are present within the cell. Sub-pixel estimates of these land cover components obtained from hyperspectral CHRIS/Proba imagery by applying the MESMA approach, are used in this study to improve runoff mapping with Wetspass for the Woluwe, a strongly urbanized catchment in the Brussels Capital Region.

In this study we compare the effects of different land cover input scenarios on the spatial distribution of surface runoff, going from a semi distributed to a fully distributed approach. For the semi distributed approach, sub-pixel fractions of the four major land cover components (V-B-I-W) are fixed a priori based on the land use type of each pixel, using fractional values specific for each type of land use as implemented in WetSpass or as obtained from remote sensing. For the fully distributed approach, land cover fraction values for V, B and I for each cell are derived directly from the MESMA results. Mean and standard deviation values of runoff are calculated for each land use type in the study area and are compared for the different input scenarios.

2. Study area and data

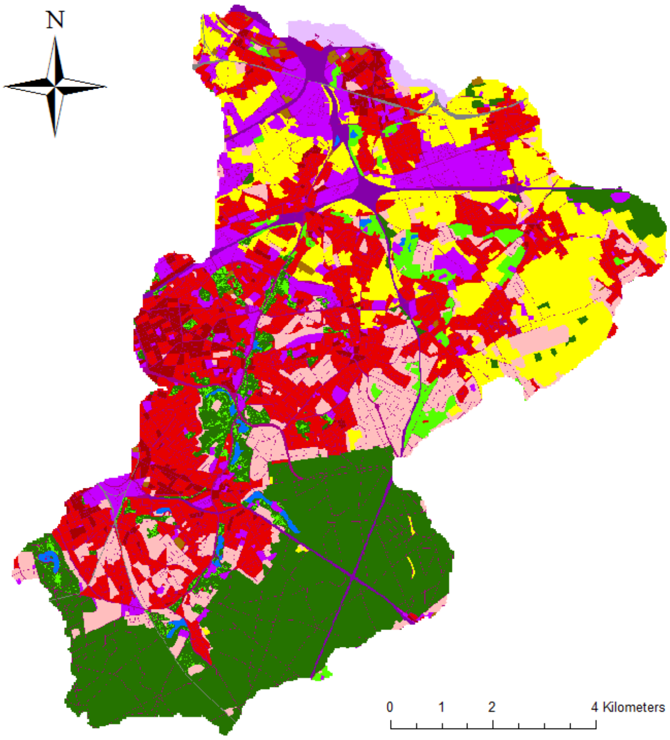
The test area for this study is the catchment of the Woluwe, a small river crossing the eastern part of the Brussels Capital Region (Belgium). The catchment is characterized by a complex mixture of urban and non-urban land cover types. The catchment topography decreases from 129m above sea level in the south to 15m above sea level in the northern part at the confluence with the Zenne river, with slopes varying between 0 and 22%. The soil cover is loam (94%) and sandy loam (6%). Mean monthly temperatures range from 5.0°C in winter to 14.1°C in summer. The mean annual precipitation in the region is approximately 780 mm/year.

2.1. Remote sensing data

A cloud free CHRIS/Proba image covering an area of 14 km by 14 km was acquired in MODE 3 on August 19th, 2009. It includes 18 spectral bands at 18 meter pixel resolution. The BEAM Toolbox software was used to remove drop-outs and vertical striping generated during the image formation process and to transform at-sensor radiance into surface reflectance [6]. The image was geo-referenced in the Belgian Lambert coordinate system using 0.25 m orthophotos obtained from AGIV (Agentschap voor Geografische Informatie Vlaanderen) as a reference. To reduce within-class spectral heterogeneity the brightness normalization method proposed by Wu [7] was applied. The method removes differences between spectra caused by overall brightness thus emphasizing the shape information of each spectrum.

2.2. Input data for the Wetspass model

A land use map covering the study area was downloaded from the GMES “Urban Atlas” project issued by the European Environmental Agency and subsequently rasterized at a spatial resolution of 3 meters (Figure 1). Land use was spatially aggregated to 18 m, corresponding to the resolution of the CHRIS/Proba data. A DEM at a scale of 1:10,000 was acquired from the NGI (Nationaal Geografisch Instituut) of Belgium and subsequently rasterized at 18 m resolution.



Code	Land-use class	Area [%]
1	Continuous urban fabric (S.L.>80%)	3.1
2	Discontinuous dense urban fabric (S.L. 30-80%)	23.0
10	Discontinuous low density urban fabric (S.L.<30%)	11.1
4	Infrastructure	0.5
6	Airport	0.9
3	Industrial, commercial, public units	9.0
201	Fast roads and assoc. lands	2.5
202	Other roads	6.9
7	Bare soil fields	0.5
21	Agricultural, semi-natural and wetland areas	14.2
33	Mixed forest	24.5
307	Grass	3.2
52	Water	0.6

Figure 1: Land use map of the Woluwe catchment based on data from the European Environmental Agency – GMES "Urban Atlas" project.

3. Methods

3.1. MESMA: Estimating land cover fractions from CHRIS/Proba data

Multiple Endmember Spectral Mixture Analysis (MESMA) is an unmixing approach which has been reported effective in increasing the accuracy of land cover fractions in cases where the spatial and spectral heterogeneity of land cover is high [3], [4], [8]. It is an extension of standard Linear Spectral Mixture Analysis (LSMA), where the reflectance of a pixel is modelled as the sum of the reflectance of each material (endmember) occurring within the sensor's field of view, weighted by its respective fractional cover:

$$r_b = \sum_{i=1}^{N} f_i * r_{ib} + \varepsilon_b \tag{1}$$

where r_{ib} is the reflectance of endmember i for a specific band b, f_i is the fraction of endmember i, N is the total number of endmembers, and ε_b is the residual for band b. By letting endmembers vary on a per pixel basis, MESMA takes account of spatial and spectral heterogeneity and thus makes better use of the potential of RS data for discriminating between different land cover types. The reader is referred to [3] for a detailed explanation on the methodology applied for deriving land cover fractions from CHRIS/Proba data, using the MESMA approach. Sub-pixel land cover fractions for the Woluwe catchment were estimated for vegetation (V), bare soil (B) and impervious surfaces (I) (Figure 2). The water fraction was not estimated at sub-pixel level. The presence of water (rivers, canals, ponds) was directly taken from the GMES land use map resulting in a binary image indicating water fractions of 1.0 (presence) or 0.0 (absence). Land cover fractions for V, B and I were validated using a sub-pixel groundtruth dataset obtained through visual interpretation of 25 cm orthophotos, resulting in an overall mean proportional error of around 12%. For more details on the results of the validation, the reader is referred to [8].

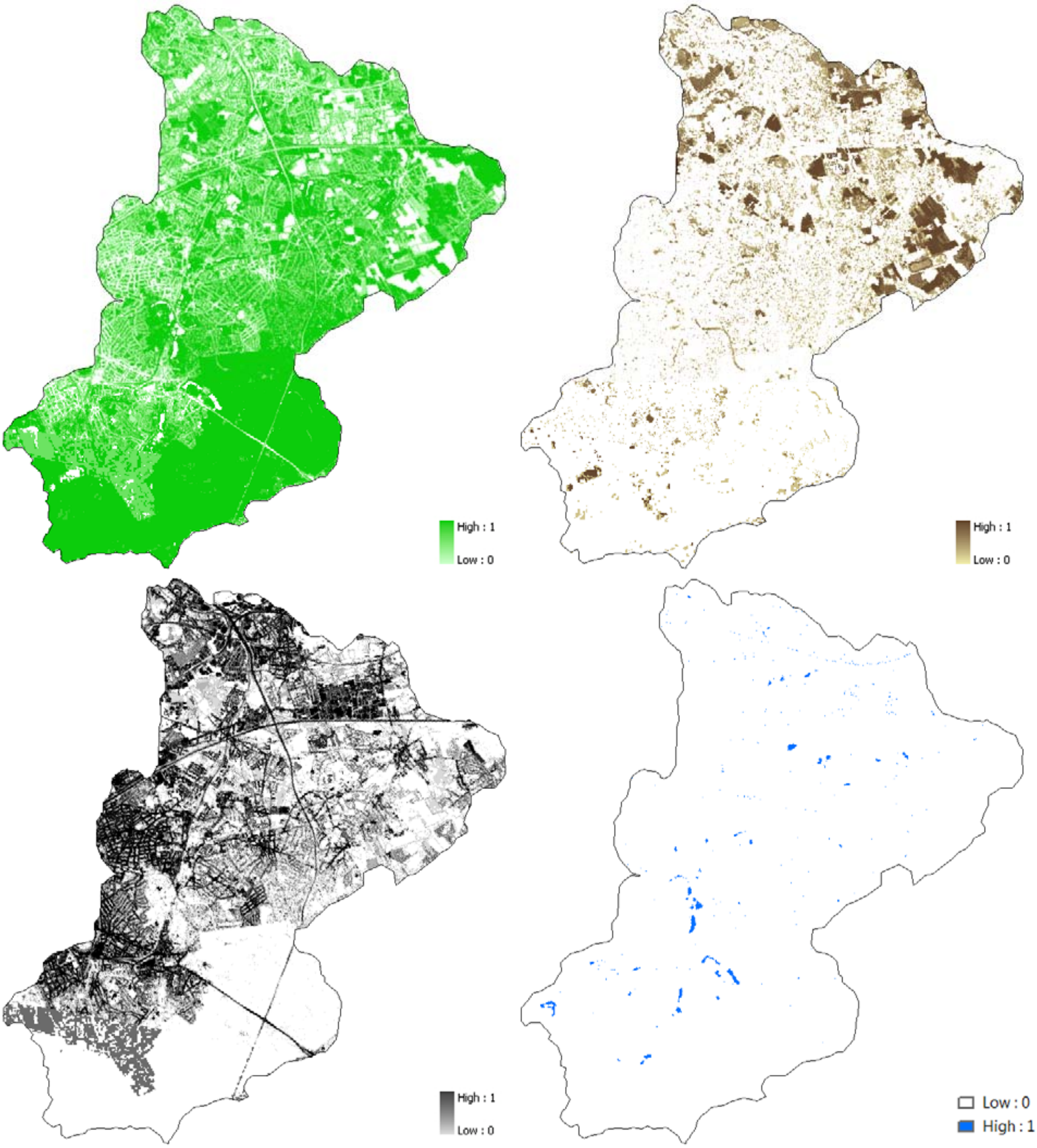


Figure 2: Land cover fractions for the Woluwe catchment. Vegetation fraction (upper left), bare soil fraction (upper right), impervious surfaces fraction (lower left) and open water fraction (lower right).

3.2. Wetspass: A spatially distributed hydrological model for runoff estimation

WetSpass stands for *W*ater and *E*nergy *T*ransfer between *S*oil, *P*lants and *A*tmosphere under quasi-*S*teady *S*tate [5]. It is a physically based model able to simulate long-term average spatial patterns of groundwater recharge, surface runoff and evapotranspiration. It is fully integrated in a geographical information system as a raster model and is able to handle spatially distributed input data, such as soil type, land use type, slope, and groundwater depth, as well as long-term average climatic data. The water balance computations are performed at cell level. For each cell, the water balance is split into independent water balances for the vegetated, bare soil, open water and impervious surfaces fractions present within the cell. By summing up these independent water balances, the total water balance at cell level is obtained. The basic equations used in the model are:

$$ET_{raster} = a_v ET_v + a_b E_b + a_i E_i + a_w E_w \quad (2)$$
$$S_{raster} = a_v S_v + a_b S_b + a_i S_i + a_w S_w \quad (3)$$
$$R_{raster} = a_v R_v + a_b R_b + a_i R_i + a_w R_w \quad (4)$$

where ET_{raster}, S_{raster}, R_{raster} are the total evapotranspiration, surface runoff and groundwater recharge of a raster cell respectively, each having a V, B, I and W area component denoted by a_v, a_b, a_i and a_w respectively. The reader is referred to [9] for a more detailed explanation on how the computations of each component's water balance is performed.

3.3. Improving Wetspass runoff estimation using land cover fractions obtained from MESMA

In order to solve equations (2), (3) and (4) at pixel level, knowledge about the four land cover area components (a_v, a_b, a_i and a_w) is necessary. The Wetspass model defines default proportions of the four land cover components for each land use type (Table 1) [10]. As an alternative for the use of default values, sub-pixel estimates of the fraction of the four major land cover components (V-B-I-W), obtained from CHRIS/Proba imagery by applying the MESMA approach, were used in this study to improve runoff mapping with Wetspass. To test the effect of using RS derived data instead of default values per land use type, three different scenarios have been defined, corresponding to a gradual increase of information on the spatial distribution of the four major land cover fractions (V-B-I-W), going from a semi-distributed to a fully-distributed approach.

3.3.1 Scenario 1: Semi-distributed approach based on default Wetspass land cover fractions

In this scenario, the four major land cover components (a_v, a_b, a_i and a_w) are fixed a priori. For each type of land use, a particular land-cover composition corresponding to the fractions of V, B, I and W specific for that land use class was assigned. The fraction values used are those defined by default in the Wetspass model [10], as shown in table 1. For each pixel the land-cover composition relies on its land-use type.

3.3.2 Scenario 2: Semi-distributed approach based on MESMA derived land-cover fractions

This scenario is similar to scenario 1, in the sense that it is also a land use related approach. For each pixel, the four major land cover fractions depend on the land use type, just as in the previous scenario. The difference is that in this case the land cover composition specific for each land use type is obtained from the CHRIS/Proba unmixing results. Average fraction values of V, I, B and W were calculated for each of the thirteen land-use classes present in the Woluwe catchment (Figure 1) from the pixel-based fractions obtained by applying MESMA (Figure 2). The values obtained and used in scenario 2 are shown in table 1.

Table 1. Land cover fraction estimates for each land-use class (see fig. 1) as used in Wetspass (left) compared to land-cover fraction estimates obtained by applying MESMA on the CHRIS/Proba dataset for the Woluwe catchment (right).

Code	Wetspass defalut fractions:				MESMA/CHRIS fractions:			
	Vegetation (a_v)	Bare soil (a_b)	Impervious (a_i)	Open Water (a_w)	Vegetation (a_v)	Bare soil (a_b)	Impervious (a_i)	Open Water (a_w)
1	0.200	0.000	0.800	0.000	0.267	0.022	0.711	0.000
2	0.500	0.000	0.500	0.000	0.536	0.059	0.405	0.000
10	0.600	0.100	0.300	0.000	0.695	0.098	0.207	0.000
4	0.600	0.100	0.300	0.000	0.412	0.159	0.429	0.000
6	0.200	0.000	0.800	0.000	0.391	0.308	0.301	0.000
3	0.400	0.000	0.600	0.000	0.335	0.094	0.571	0.000
201	0.600	0.100	0.300	0.000	0.444	0.040	0.517	0.000
202	0.600	0.100	0.300	0.000	0.479	0.053	0.468	0.000
7	0.000	1.000	0.000	0.000	0.478	0.157	0.365	0.000
21	0.800	0.200	0.000	0.000	0.499	0.372	0.129	0.000
33	1.000	0.000	0.000	0.000	0.959	0.010	0.031	0.000
307	1.000	0.000	0.000	0.000	0.816	0.062	0.122	0.000
52	0.000	0.000	0.000	1.000	0.000	0.000	0.000	1.000

3.3.3 Scenario 3: Fully-distributed approach based on cell-specific land cover fractions derived from MESMA

Finally, in this scenario fractions for the four major land cover components (a_v, a_b, a_i and a_w) were assigned at pixel level and were obtained directly from MESMA. This way, the local variability of land cover composition within each land use type is taken into account and the capabilities of the spatially distributed Wetspass model are fully exploited.

In each scenario the mean and standard deviation values for runoff have been calculated per land use class, in order to assess the impact of using a fully-distributed instead of a semi-distributed approach for runoff estimation.

4. Results and discussion

The objective of this study was to analyze the impact of using remote sensing based estimates of land cover fractions obtained through MESMA in the modelling of runoff with Wetspass, compared to the use of fixed, a priori defined fractions per land use type.

4.1 Land cover fractions for different land uses

As explained in section 3.3., in scenario 2, average land cover fractions for each land use type present in the Woluwe catchment were calculated based on per-pixel estimates of these fractions obtained through MESMA (Table 1). A comparison with the default fraction values for different land use types defined in Wetspass, and used in scenario 1, shows some clear differences in fraction value estimates. For the three major “urban fabric” classes (code 1, 2, 10) estimates of the impervious surface fraction obtained through remote sensing prove to be about 10% lower than the default fractions used in Wetspass. For the “Infrastructure” class (code 4) the opposite is observed, with the impervious surface fraction estimate obtained from remote sensing about 13% higher than the default value and the vegetation fraction almost 20% lower. Also for the “road” classes (201, 202) remote sensing estimates of the I-fraction prove to be substantially higher than the default values used in Wetspass. This systematic under- and over-estimation of impervious surface cover for the different urban classes is likely to have an impact on local runoff estimation. Vegetation fractions for the “Agricultural, semi-natural and wetland areas” (code 21) and “Grass” (code 307) prove to be substantially lower than the Wetspass default values (30% and nearly 20% respectively), which may be explained by the fact that the area covered by these two classes includes fields that are temporarily left fallow. This is clear from the map showing bare soil fraction estimates in Figure 2. The presence of an impervious surface fraction above 10% in these two classes is partly caused by spectral confusion between specific types of bare soil and impervious surface cover.

4.2 Runoff estimation

When comparing the mean runoff values per land use class for the three input scenarios, some clear differences are observed (Figure 3). Except for the transportation related land use classes (code 201, 202 and 4), urban land uses produce smaller average runoff values when using remotely sensed data for estimating land cover composition (scenario 2-3) then when using default land cover parameters incorporated in the Wetspass model (scenario 1). This is due to the fact that the impervious surface cover in most urban classes proves to be lower than assumed in the default land cover parameterization of the Wetspass model. For the “Fast roads and assoc. Lands”, “Other roads” and “Infrastructure” classes (codes 201, 202 and 4 respectively) the imperviousness level is underestimated in the Wetspass model, while the vegetation fraction is overestimated. Therefore, making use of the unmixing results obtained from hyperspectral CHRIS/Proba data (scenario 2 and 3) increases the runoff estimate for these specific classes. The highest runoff value in the three scenarios (close to 400 mm/year) is obtained for the land use class “Continuous Urban Fabric (S.L.>80%)” (code 1), which corresponds to the most dense urban class. For the “Airport” class (code 6) the mean runoff value in scenario 1 is much higher than in the other two scenarios. This is because, using its standard parameter estimates, the Wetspass model assumes a much higher level of imperviousness for this specific class, ignoring the presence of vegetation and bare soil in the airport area, the way it is delineated in the GMES urban atlas. This illustrates the benefits of using remotely sensed data for obtaining more realistic estimates of land cover fractions for each land use class, and consequently more realistic hydrological parameter estimates.

In general, mean runoff values are in line with results obtained for other catchments in Belgium in previous work [9], and show the strong link between runoff and level of imperviousness within each land use type. Mean values are very similar when comparing scenarios 2 and 3, as both make use of the same remotely sensed derived input. The difference between scenarios 2 and 3 lies in the standard deviation values for runoff calculated over all cells that are part of the same land use class. Using the unmixing results from CHRIS/Proba obtained for each cell directly as input for the model (scenario 3) strongly increases the variance in runoff within the urban land use classes. In scenario 2, the unmixing results derived from CHRIS/Proba are used only for obtaining a more realistic overall estimate of land cover composition for each land use class. The land cover composition of each cell depends on the land use class it belongs to, and therefore per-class standard deviations for runoff are very similar to the values obtained for scenario 1. In scenario 3, local variations in land cover composition within each land use type are taken fully into account. As a result, standard deviation values for runoff strongly increase for this scenario.

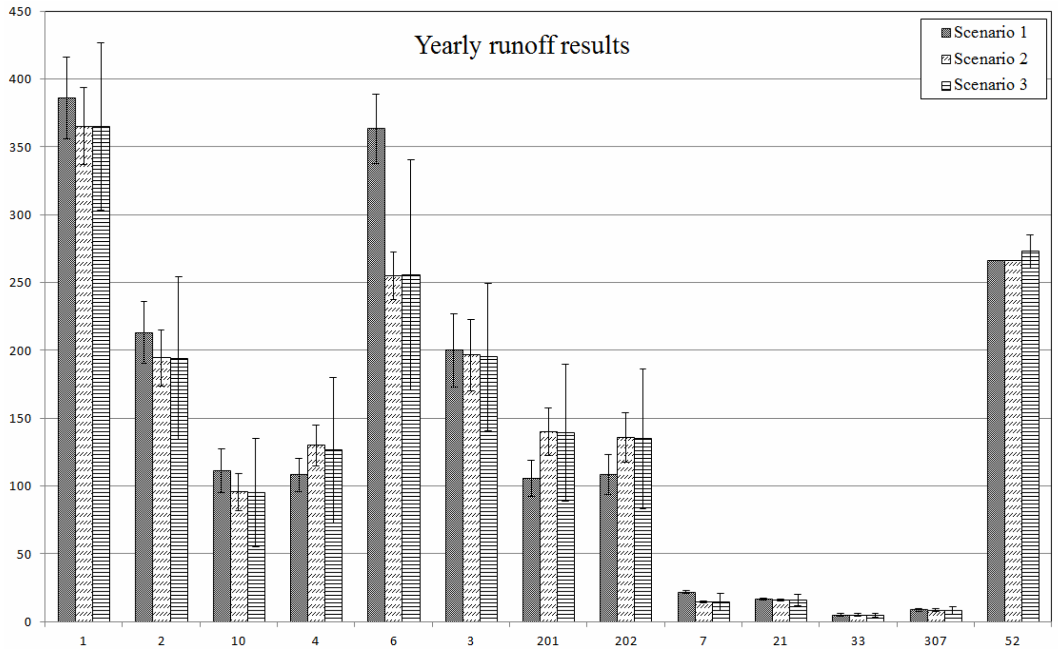


Figure 3: Mean and standard deviation of runoff estimates for the three scenarios and for each land use class.

Figure 4 shows the spatial distribution of runoff in the Woluwe catchment produced by the Wetspass model. For scenario 1 and 2, the spatial pattern of runoff is very similar and clearly linked to the pattern of land use for the catchment (Figure 1), showing that land use knowledge plays an important role for defining the spatial distribution of runoff when using a distributed hydrological model such as Wetspass. Variations in runoff value within each land use class are limited, confirming the small standard deviation values obtained (Figure 3). In scenario 3, a strong local variation in the runoff pattern is noticed within the urban area, confirming the high standard deviation values obtained for this scenario (Figure 3), and indicating the importance of the land cover component in runoff estimation. For each pixel, the runoff estimate is not derived mainly from its specific land use class membership, but also from its real land cover class composition, yielding to a more realistic final result.

5. Conclusions

In this study land cover fraction estimates obtained by multiple endmember unmixing (MESMA) of a hyperspectral CHRIS/Proba image are used to improve the estimation of runoff for the Woluwe catchment (Brussels), using the Wetspass model. In Wetspass, water balances are calculated at the raster cell level, independently for the vegetated, bare soil, open water and impervious surface fractions present within the cell. The objective of this study was to assess the impact of using remote sensing based estimates of per-pixel land cover composition on runoff estimation, compared to the use of a priori defined land cover fractions for each land use type, included in the model. Also the impact of using cell-specific land cover fraction estimates instead of land use specific, spatially invariant land cover fractions was examined.

Results show that, for most urban land use classes, land cover fraction values included in the model substantially differ from values obtained through remote sensing, with impervious surface levels being systematically overestimated. These land use classes produce smaller runoff values when remotely sensed data are used as an input in the hydrological model, showing the strong link between runoff and the level of imperviousness present within each land-use type.

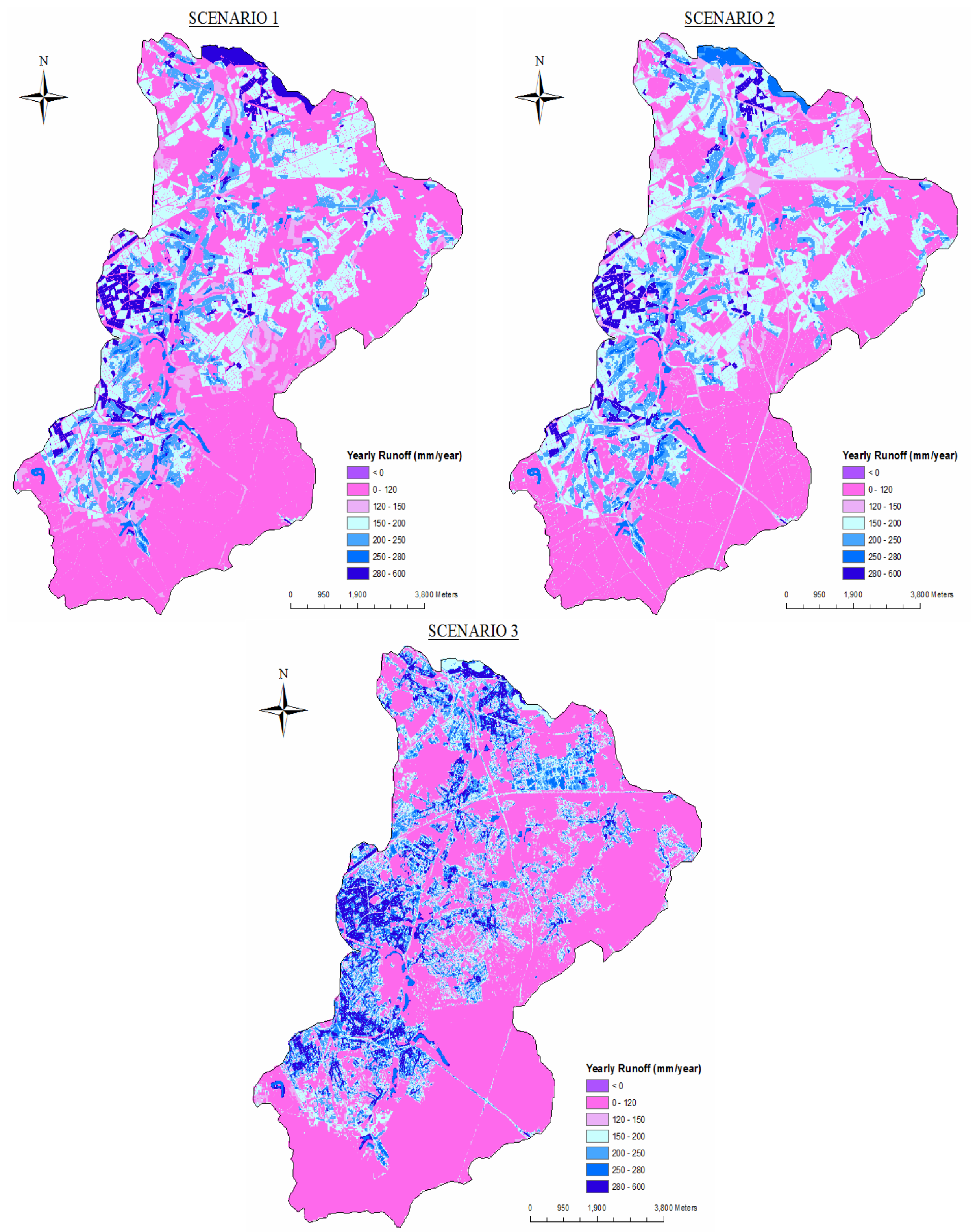


Figure 4: Yearly runoff estimation for the three scenarios.

When subpixel estimates derived from MESMA are directly used for the estimation of runoff values at cell level, the local variation of land cover composition is fully taken into account in the modelling. In this scenario, a strong local variation is observed in the spatial distribution of runoff values, proving the benefits of using remotely sensed data for obtaining more detailed information on the spatial pattern of runoff.

Combining MESMA, a per-pixel basis unmixing approach, with Wetspass, a spatially distributed hydrological model, allows one to fully benefit from spatially detailed mapping of land cover in the modelling of runoff. On the other hand, our work also pointed out the limitations of the CHRIS/Proba sensor for land cover mapping in urbanized areas, due to the spectral similarity between specific types of impervious surfaces and bare soil [3], [8], which may negatively affect the quality of runoff estimation in some locations. Hyperspectral data with a higher spectral resolution and covering a larger spectral range may enhance the distinction between spectrally similar land cover classes leading to a further improvement in runoff estimation.

Acknowledgements

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