

CREATION OF SOIL PERMEABILITY MAPS THROUGH OBIA CLASSIFICATION OF VERY HIGH-RESOLUTION SATELLITE IMAGES

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ABSTRACT:

In the last few months, we have been working on images acquired by the WorldView3 satellite over the city of Pavia with the final intent to create a soil permeability map. These maps can be particularly useful in various fields, such as water management and public green, for evaluate the correlation between overbuilt areas and pollution, the influence of vegetation on the temperature in within the different areas of the city, for the planning and monitoring of a sustainable transition of cities. To create such maps, it is essential to be able to identify various objects lying in the images, in our case we have done a classification of the image using the software Trimble eCognition™, applying Object-based Image Analysis (OBIA) approach and various classification methods, by applying fuzzy logic and supervised classification. The objects generated through various segmentations have been classified into 7 classes, water, fields, cultivated fields / low vegetation, high vegetation, roads, red roofs, and white roofs. And from the comparison with the manually defined ground truth, an overall accuracy degree of 80% was achieved. Furthermore, by applying various aggregation strategies, by combining the cultivated fields / low vegetation and high vegetation classes, we achieved a better overall accuracy of 91%.

1. INTRODUCTION

In those last years we have seen an increasing connection between geomatics remote sensing and environment sustainability, the improvements made in the field of satellite images allow to have very high-resolution images (VHR) of a certain area with a good frequency. Having this type of data available every few days has attracted a lot of interest and the increase in publications is proof of this. Many studies have been and are done on these images and their application in different fields, from agriculture (Ma et al., 2021) and the survey of related infrastructures (Aguilar et al., 2021), identification and monitoring of urban land use for several purposes (Zhang et al., 2018; Juergens and Meyer-Heß, 2021) to damage estimation in the event of natural disasters and many other purposes. The work conducted involved the classification through different techniques of a portion of the city of Pavia, with the idea of extending the classification to the rest of the city in the future. The portion chosen has a good mix of urban elements and rural areas, with cultivated fields, rivers of different sizes and areas of high vegetation, a good starting point to highlight the criticalities in the classification of both areas. We did Object-based image analysis (OBIA) in the Trimble eCognition™ software, and the tools integrated into it proved to be very useful in the various stages of the work from segmentation to classification and validation of the results obtained. OBIA is a well-established method for classifying high-resolution images of urban areas (Moutinho Duque de Pinho et al., 2012) and thanks to the increase in the computational power of computers compared to the past, this kind of approach is much more accessible. One of the main difficulties encountered, a problem already well known in literature, was to distinguish the shadows generated by buildings with smaller watercourses. The method we propose provides for the growth of objects in adjacent pixels, particularly effective for identifying the edges of elements, not just rivers but the edges of the fields. In the urban

area, on the other hand, buildings with a red or white roof are easily distinguished from the streets, while it is not possible to distinguish the gray roofs of some buildings using only spectral information, and this has been one of the limiting factors, if not the most limiting in achieving a high overall accuracy.

2. MATERIAL USED AND THE STUDY AREA

The images used were acquired by the WorldView3 satellite on March 22, 2021, the first is the panchromatic image of the entire city of Pavia with a ground resolution of thirty centimeters per pixel. The second is a multispectral image composed of eight bands (Table 1), coastal blue, blue, green, yellow, red, red edge, near infrared 1 (nir1) and near infrared 2 (nir2). In this second image the resolution is much lower than the panchromatic, in this case the size of a pixel of 1.2 by 1.2 meters.

WorldView3 multispectral bands	Wavelengths
Coastal Blue	400 – 452 nm
Blue	448 – 510 nm
Green	518 – 586 nm
Yellow	590 – 630 nm
Red	632 – 692 nm
Red edge	706 – 746 nm
Near infrared 1 (Nir1)	772 – 890 nm
Near infrared 2 (Nir 2)	866 – 954 nm

Table 3. Multispectral bands captured by the WorldView3 satellite and their respective wavelengths.

The high ground resolution of the images and the extension of the entire captured area brings with it a high amount of information. To reduce computation times, a relatively small

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area was chosen, but with characterizing elements, both natural and man-made.



Figure 1. Entire area acquired by the WorldView3 satellite.

The complete image shows the whole city of Pavia (Figure 1) but has been divided into 4 smaller pieces. The study area is in the portion highlighted by the red rectangle in the lower right portion of the entire area (Figure 2) and contains both rural and urban elements. The presence of both zones, rural and urban, was specifically chosen to evaluate several types of segmentation and classification in both situations and to choose the most effective for each of them.

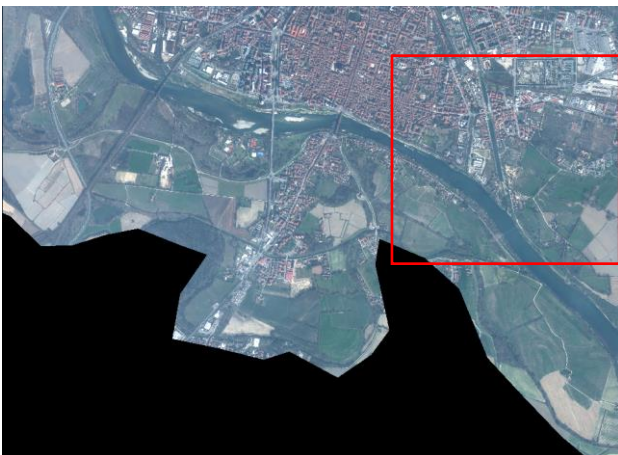


Figure 2. Lower right portion of the entire scene.

Furthermore, the presence of the canal that surrounds this part of the city is an element of great interest to us, to evaluate the effects of various approaches in the attempt to effectively distinguish the shadows from the water even in an urban context (Figure 3). In the future, once we have developed an effective method of classification, we intend to extend this kind of approach to all four pieces that make up the complete picture.



Figure 3. Area of the city of Pavia that has been studied.

The degree of detail of the images is extremely high, in particular in the panchromatic image (Figure 4), the elements that make up the urban area are clearly distinguished. The shapes of the buildings appear clear, as well as the roads and other even more detailed elements, such as the chimneys, it is even possible to distinguish the trees that already have leaves at this time of year and which ones do not.



Figure 4. Degree of detail achieved in the panchromatic image.

In the coming months we aim to exploit this high degree of detail, applying the pansharpener technique to the images of the city of Pavia that we have purchased. This technique is effective but remains an artifice and consequently errors are introduced in the resulting image, for this reason we preferred to develop the technique by working on the "raw data" that have been given to us, without introducing further machinations.

3. METHODOLOGY

On the examined area, the first step was to calculate three indices to better distinguish the different classes. Indices are known to provide several advantages, in addition to being normalized, by combining different bands it is possible to highlight different elements. For this application we decided to rely only on three indices (Table 2), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Soil-Adjusted Vegetation Index (SAVI). These have been calculated in Trimble eCognition™ with the appropriate command called "Index layer calculation", which combines the bands present in the image with the following expressions:

Indices	Formula
NDVI	$(Nir2 - Red) / (Nir2 + Red)$
NDWI	$(Green - Nir2) / (Green + Nir2)$
SAVI	$((Nir2 - Red) / (Nir2 + Red + L)) * (1+L)$

Table 2. Indexes and related formulas.

The results obtained with the Object-based Image Analysis technique (OBIA) are influenced by the quality of the segmentation, for this reason two segmentations with different parameters have been made. The first one using only the information deriving from the indices and the panchromatic image, the second one based only on the bands of Coastal blue, blue, green, yellow, red, Nir2 and again the panchromatic image. The aim is to classify as precisely as possible the "natural elements" first and then the urban area. The algorithm used to segment the image is built in Trimble eCognition™ is a bottom-up segmentation algorithm, it looks for the best fitting with near pixel, if the best fitting is mutual the pixel will be added to the object, otherwise the object will stop growing. This algorithm, called "Multi-resolution segmentation", allows you to segment the image according to certain input layers, as mentioned above, and to attribute a different weight to each of them. In addition to this the segmentation result can be managed by the user according to three parameters, a scale factor, which determines the degree of homogeneity of the resulting objects, a color factor, and a shape factor. Since the sum between colour factor and shape factor is equal to 1, by increasing the value of the shape factor we are choosing to give greater importance to the shape rather than to the spectral information of the pixels. The form factor is composed of compactness and smoothness, in this way it is possible to obtain more or less compact and regular objects according to the needs. To distinguish fields, cultivated fields / low vegetation, high vegetation and water, fuzzy logic was used, different membership functions were defined for the different parameters useful for effectively distinguishing one class from another.

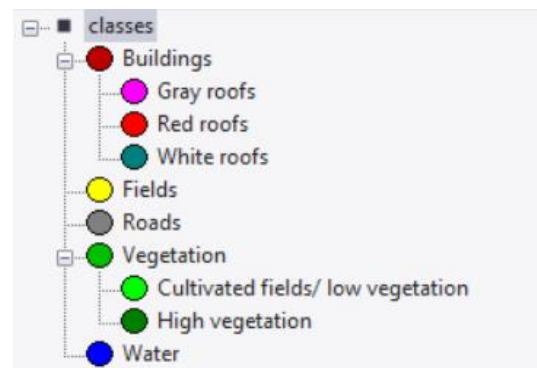


Figure 5. Classes and sub-classes used for classification and validation of results.

The urban area, on the other hand, was classified using a supervised classification algorithm, on the still unclassified image elements after having segmented them. The individual segmentation and classification operations will be explained in detail in the next paragraphs. Finally, a validation of the classification obtained was carried out, comparing the result with objects that represent the ground truth. These objects have been selected and classified manually trying to assign the correct class to the various objects in the image.

4. SEGMENTATION AND CLASSIFICATION OF NATURAL ELEMENTS

4.1 The segmentation

As anticipated, this first segmentation was carried out using the indices and the panchromatic image. After several attempts the most visually satisfying segmentation was achieved using the following parameters scale factor 100, shape factor 0.2 and compactness 0.7. The whole image has been segmented into 8319 different objects, the size and shape of the objects visually separates elements outside the urban area well.



Figure 6. Portion of the image before segmentation.

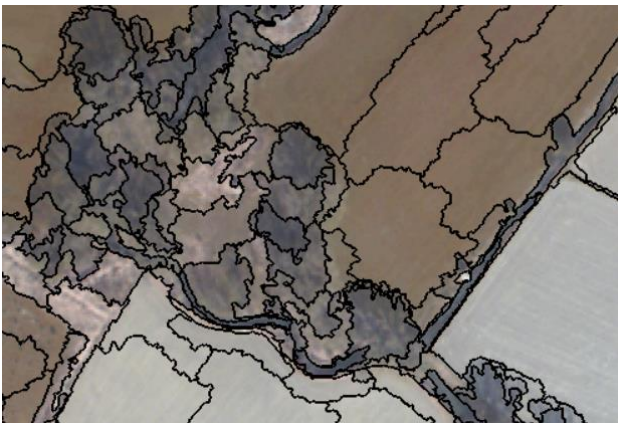


Figure 7. Same portion of the image after segmentation.

4.2 Classification

The classification of these first four classes (Water, Fields, Cultivated fields/ low vegetation, High vegetation) was carried out by applying fuzzy logic, for each class membership functions were defined applied to the parameters considered most significant to identify them correctly. In our case only two types of functions have been used.

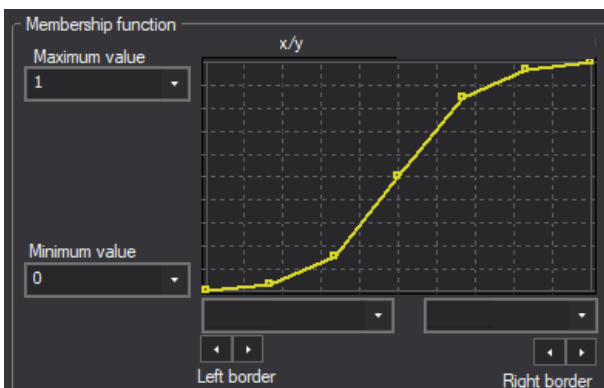


Figure 8. First membership function (F1).

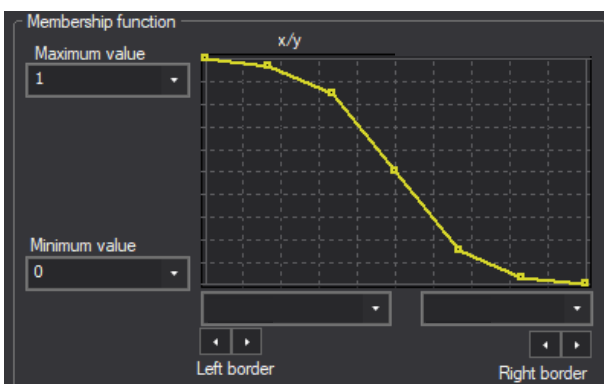


Figure 9. Second membership function (F2).

The membership functions adopted are the opposite of each other (Figure 8, Figure 9), for the first function values of the feature lower than the limit placed on the "Left border" attribute a value of belonging to a class equal to 0, on the contrary, values of the feature higher than the limit placed on the "Right border" attribute a membership value equal to 1, vice versa for

function 2, for values between "Left border" and "Right border" the value of belonging to the class is obtained according to the graph of the function. For each class and feature a different interval has been set (Table 3), calibrate the correct width of the intervals and set the minimum threshold for belonging to a certain class was not easy and particularly time-consuming. After several attempts we have that in our case the best strategy to identify certain classes is to be very selective, for this reason the minimum value of belonging to the classes has been set equal to 0.8, objects with a value lower than this threshold in all four classes are not assigned to any class.

Classes	Feature	Left border	Right border
Water	Mean NDWI (F1)	0.3	0.45
	Area > 2000 pixels		
Fields	Mean Blue (F2)	350	450
	Mean SAVI (F2)	-0.01	0
	Mean Yellow (F1)	200	300
	Area > 40000 pixels		
Cultivated fields/ low vegetation	Mean NDVI (F1)	0.2	0.3
	Mean SAVI (F1)	0.4	0.6
High Vegetation	Mean NDVI (F1)	0.1	0.2
	Mean SAVI (F2)	0.5	0.6

Table 3. Feature used to classify the "natural elements" in the image.

The classification obtained for the vegetation and for the cultivated fields / low vegetation class immediately gave good results and was therefore refined simply by aggregating small objects belonging to the "unclassified" class having at least 80% of the perimeter in common with objects belonging to a class or the other. Unlike the identifiable objects in the water class and field class which required more specific refinement.

4.3 Water classification

Distinguishing shadows from water is a well-known issue (He et al., 2016), for those involved in image classification because from a spectral point of view these two elements are similar. Rivers in this case and in general the water bodies in the images tend to be continuous elements. For this reason, we have decided to make a rough classification of the water elements and subsequently make the objects grow in the adjacent pixels with an NDWI ≥ 0.15 , but with values between $\pm 5\%$ of the average value of the object's NDWI. Using the "pixel-based object resizing" algorithm, integrated in eCognition™ it was possible to insert the expansion criteria to the objects. Once the expansion was completed, the objects were joined, so as to have a single large block composed of many buildings on the edge of the historic center of the city of Pavia. and smaller objects scattered among the vegetation. At this point the macro-object containing the buildings and consequently their shadows, had a much lower average value of the NDWI and therefore by reclassifying in the Water class only the objects with a mean value of the NDWI ≥ 0.26 it was also possible to identify pieces of the small streams immersed in the vegetation (Figure 10).



Figure 10. At the top, the water class before refinement, in the lower part the water class after refinement.

4.4 Fields classification

A similar thought has been made for the field class, from the result of the rough classification only objects with a large extension were classified (Figure 11), due to the parameters set for that class (Table 3). The growth of these large objects has provided excellent results in correctly identifying the fields and their shape.



Figure 11. Classification results for fields-type objects before refinement.



Figure 12. Classification results for fields-type objects before refinement.

In this specific case, growth was only allowed in adjacent pixels with an absolute value of the SAVI index < 0 and an absolute value of the yellow layer ≥ 200 . The result obtained was very satisfactory, the edges of the fields have been identified in a very precise way, even marking the boundaries between one field and another consisting of ditches for irrigation (Figure 12). Unfortunately, the water present inside these ditches has not been classified as such, mainly for two reasons, the degree of detail of the image is not high enough for this and because the depth of the water in those points is not much except in exceptional cases. The final result looks very good and appears to be sufficiently accurate (Figure 13).

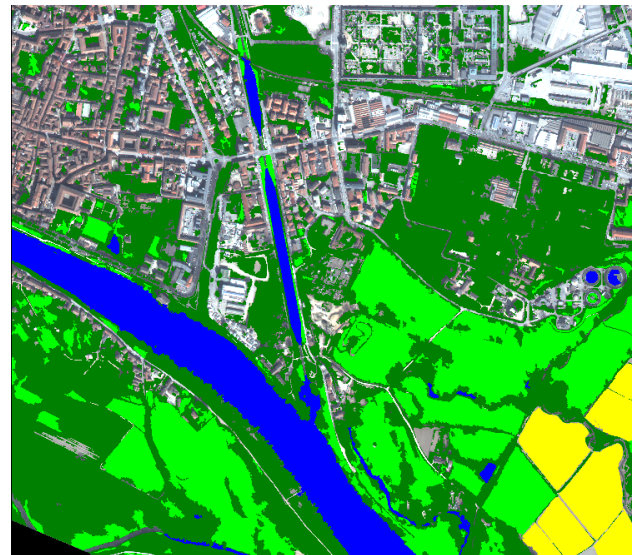


Figure 13. Whole image studied with classified natural elements.

With what we have done so far, we have managed to divide the urban area from the rest of the objects in a fairly good way. There is certainly room for improvement, but this result is adequate for our objective.

4.5 Urban area classification

Once the classification was complete, the resulting objects were joined together, then the portion of the image not belonging to any class was segmented again with different parameters. This second segmentation was performed using the bands in the visible range, the near infrared band, and the panchromatic image, all with the same weights. The segmentation parameters as in the previous case were chosen after numerous visual validations. The most satisfactory result was obtained by applying the values of 150, 0.3 and 0.7 respectively to the scale factor, shape factor and compactness, leading to objects about the same size as the roofs of smaller buildings.



Figure 14. Result of the segmentation on the urban area of the city of Pavia.

Unlike what was done in the classification of natural elements, in the urban area it was not possible to identify a distinctive index or feature for each class. For this reason, a supervised classification was carried out, instructing the algorithms integrated in Trimble eCognition™ (Bayes, KNN, SVM, decision tree and random trees) with samples, and selecting the

one capable of returning the best result. All five algorithms were trained to distinguish between three classes, red roofs, white roofs, and roads based on samples selected. In addition to the mean and standard deviation of the 4 visible bands, near infrared, NDWI and NDVI, we also considered the area of the objects, the roofs of the buildings in comparison to the roads tend to have lower values, but not so uniform as to identify a precise threshold to clearly differentiate them.



Figure 15. Same area that was segmented before being classified.

Without changing the default settings of these algorithms, the best result was obtained with the Bayes algorithm. The other algorithms were not as efficient at capturing the edges of the roofs of buildings, for example, the classification made by the Random trees algorithm, classified many more elements as a road misclassifying completely some buildings (Figure 16).



Figure 16. Same area after the classification with Random trees algorithm with an example of incorrect classification.

The KNN and SVM algorithms gave good results by identifying buildings well, but with frequent errors between the class red roofs and white roofs in similar quantities but in distinct positions. While the SVM algorithm gave a completely misleading result by classifying most of the objects as white roofs. All the algorithms were trained with the same samples and with the same features to be analyzed, Bayes distinguished himself from the others by providing a classification of good quality without the need for excessive refinement of the result obtained (Figure 17).

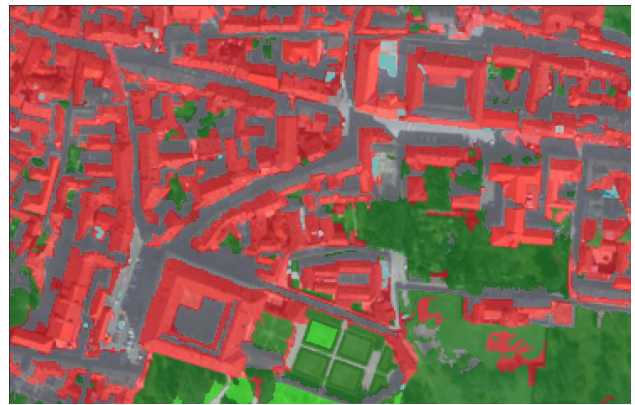


Figure 17. Same area after the classification with Bayes algorithm.

Finally, a slight refinement was done to better define the contours of the buildings and regularize their shapes, but without substantially changing the result obtained from the supervised classification.



Figure 18. Final result, complete classification of the entire study area after refinement of the objects in the urban area.

The final result (Figure 18) shows how there is a concentration of buildings with red roofs, typical of historic buildings, in the left portion of the image towards the historic center. While the white roofs, typical of industrial buildings, are located in the upper right corner of the study area, where in fact there is a small industrial area. This result at least visually seems to encourage the use of a supervised classification in urban areas if only the spectral information is available as in our case.

5. VALIDATION OF RESULT

The quality of the classification can be obtained by comparing the result obtained with objects of which you are sure of their class. To do this, the result obtained was segmented only based on the panchromatic image, for greater detail, respecting the limits of the objects obtained from the classification.

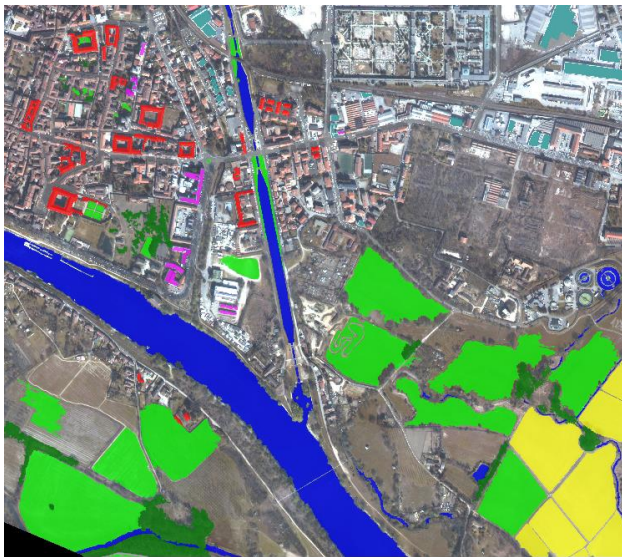


Figure 19. Ground truth used to validate the classification obtained.

A perfect validation would consist in manually classifying the whole image but given the extension of the scene it was not possible, it would have been too time consuming, but 6968 objects were manually selected, in the most critical areas, trying to represent reality (Figure 19). As you may have noticed, the "gray roofs" class was not used for the classification, due to the high similarity with the roads class, however these buildings were considered in the generation of the confusion matrix. Observing the results, we can see how an overall accuracy of 0.8 is achieved (Table 4).

CONFUSION MATRIX

User Class\ Sample	Wa..	Hig..	Fie..	Cul..	Bui..	Roa..	Sum
Water	488	13	0	4	0	0	505
High vegetation	30	688	11	686	8	58	1481
Fields	0	0	344	0	0	0	344
Cultivated fields\low vegetation	4	43	0	1654	1	5	1707
Buildings	8	3	0	26	1191	110	1338
Roads	71	21	13	15	167	830	1117
Sum	601	768	368	2385	1367	1003	

Accuracy

	Wa..	Hig..	Fie..	Cul..	Bui..	Roa..
Producer	0.812	0.8958	0.9348	0.6935	0.8713	0.8275
User	0.9663	0.4646	1	0.969	0.8901	0.7431
Hellden	0.8825	0.6118	0.9663	0.8084	0.8806	0.783
Short	0.7896	0.4407	0.9348	0.6784	0.7867	0.6434
Kappa Per Class	0.7961	0.865	0.9311	0.5842	0.8378	0.7917

Totals

Overall Accuracy	0.8002
Kappa	0.7491

Table 4. Confusion matrix, accuracy and totals obtained by comparing the ground truth with the result of the classification.

From the reported values we note that many Cultivated fields/ low vegetation objects have been erroneously classified as high vegetation and how difficult it is to identify water, in many cases small rivers could not be identified, because they have a spectral response similar to the shadows generated by buildings in the urban area. As previously mentioned, we do not have an effective way to distinguish buildings with a gray roof from asphalt and this greatly lowers the quality of the result obtained on the building and road classes.

CONFUSION MATRIX

User Class\ Sample	Water	Fields	Buil...	Roads	Veg...	Sum
Water	488	0	0	0	17	505
Fields	0	344	0	0	0	344
Buildings	8	0	1191	110	29	1338
Roads	71	13	167	830	36	1117
Vegetation	34	11	9	63	3071	3188
Sum	601	368	1367	1003	3153	

Accuracy

	Water	Fields	Buil...	Roads	Veg...
Producer	0.812	0.9348	0.8713	0.8275	0.974
User	0.9663	1	0.8901	0.7431	0.9633
Hellden	0.8852	0.9663	0.8806	0.783	0.9686
Short	0.7896	0.9348	0.7867	0.6434	0.9391
Kappa Per Class	0.7961	0.9311	0.8378	0.7917	0.9489

Totals

Overall Accuracy	0.9125
Kappa	0.8716

Table 5. Confusion matrix, accuracy and totals combining high vegetation classes with cultivated fields / low vegetation.

If we consider combining the high vegetation and cultivated fields / low vegetation classes, a situation for which the soil permeability can be considered similar if not identical, the overall accuracy of the classification carried out increases dramatically reaching a value of 0.91 (Table 5).

6. CONCLUSIONS

The results obtained are encouraging. We aim at reaching higher accuracy levels. Therefore, in future activities, we will experiment with other approaches, based on the same principle, applied on the same area but combining the 8-band image with the panchromatic image using the pansharpening technique. More detail can improve the identification of the various classes, but the ideal would be to have a different type of information and for this reason a great addition would be the integration of height information through a (Digital Terrain Model) DTM and a (Digital Surface Model) DSM. It would allow to clearly distinguish buildings from roads, even those with gray roofs, and would make it easier to distinguish between high and low vegetation. There is certainly room for improvement and on the work carried out it must be considered that in the period of the year in which the satellite photo was acquired, several plants did not yet have leaves and this probably contributed to the incorrect classification of classes related to vegetation. In the future the objectives we set ourselves are to improve the quality of the classification and extend it to a wider area of the city of Pavia. And then evaluate

the criteria with which to attribute permeability values to the various identified classes.

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