

Contrast Filter in Pre-Processing Digital Images Used for Classification

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KEYWORDS: Image classification, Image analysis, pre-processing, filters, locally adaptive contrast enhancement filter

ABSTRACT

Pre-processing digital images, if done accurately and with knowledge, can improve significantly the results of image classification. A locally adaptive contrast filter surely improves the visualization of elements in the image, but probably can also improve the results of classification. This paper's objective is to assess the improvement of classification accuracy of images classified after being pre-processed with a locally adaptive contrast enhancement filter added with the implementation of a new module in the GIS program GRASS, thanks to this software open-source philosophy.

INTRODUCTION

The use of remotely sensed images for automatic or semi-automatic classification has often permitted saving time and money for the people who used them appropriately. Also the presence of sensors which have greater spectral resolution helped increase the accuracy of supervised classification, increasing the definition of the spectral signatures of the different classes which are being identified in the image. The limit of common supervised classifications is the fact that it considers only the spectral dimension of the pixel which it is classifying, and it does not take into consideration the spatial factor, in other words, its neighbors. Human mind, instead, is the best classifier for panchromatic imagery because it considers also shapes, texture, patterns and any association of elements which it can grasp. The so called contextual classification is an example of an algorithm which takes care of some of the elements which are listed above. Keeping into account the context of the element which is being classified can make classification operations more accurate.

In image pre-processing filters are often used. Apart from the fact that there are many people with different opinions on the help that filters give to classification, the objective of this paper is to implement in a free source GIS (G.R.A.S.S.) a locally adaptive enhancement filter; this tool will change the contrast on an image with an intensity which is proportional to the how low the contrast is in the original image. This means that only the areas which need contrast enhancement get filtered. That is why such a filter is called "locally adaptive". This kind of filter might make the following classification more accurate by improving the distinctness of the digital signatures in respect from each other.

STUDY AREA

The image used for this project was acquired by the IKONOS satellite sensor in september 2000. The area represents part of the city of Mestre, just below Venice (figure 1). The image which was used was part of the whole image acquired, and covered a square with the side of four kilometers. We worked with a resolution of four meters per pixel and we used the four common bands, red (R), green (G), blue (B) and near infrared. (NIR). More details are available in the table below:

Map Projection: Universal Transverse Mercator
UTM Specific Parameters
Hemisphere: N
Zone Number: 33
Datum: WGS84
Product Order Pixel Size: 1.00 meters
MTFC Applied: Yes
DRA Applied: No
Media: CD
File Format: GeoTIFF
TIFF Tiled: No
Bits per Pixel per Band: 11 bits per pixel
Multispectral Files: Separate Files

This area was chosen for purely practical reasons; in fact it is easily divided, using visual interpretation, into five distinct classes: urbanized, green agricultural, bare soil, industrialized (cement roofs and roads) and idrological bodies. This helped to visually classify the area, so to have a mean to compare the results from the classification operations. The area is also quite flat, eliminating the classification errors pertaining to shadow

areas. Also cloud cover was less than in other parts of the whole Ikonos acquired image.

There are though some imperfections, as the image was not exactly ideal for this project. For example the atmosphere was not perfectly clear, but there is a presence of cloud cover, very well visible in figure1. This had an effect on the spectral response and on the respecting spectral signature. These effects were taken into account later on, as will be mentioned later.

MATERIALS AND METHODS

The filter which was implemented for this project corresponds to what in literature is called “locally adaptive contrast enhancement filter” or “Wallis filter”. In this particular case the module, which was written in ANSI C computer language as most GRASS modules are, permitted the user to influence four steps of the process, in order to optimize performance and to personalize the filter

the image characteristics. Very many combinations of the four parameters were tried out to see which corresponded to the best. A 1000Mhz processor permitted to have results in some hours time. As mentioned before C language was used, and the code was put in the default directory (\$GISBASE/src/raster) and compiled and linked to the binaries using gmake5 and gmake5links5. The code structure follows the one written by M. Shapiro for module *r.mfilter*.

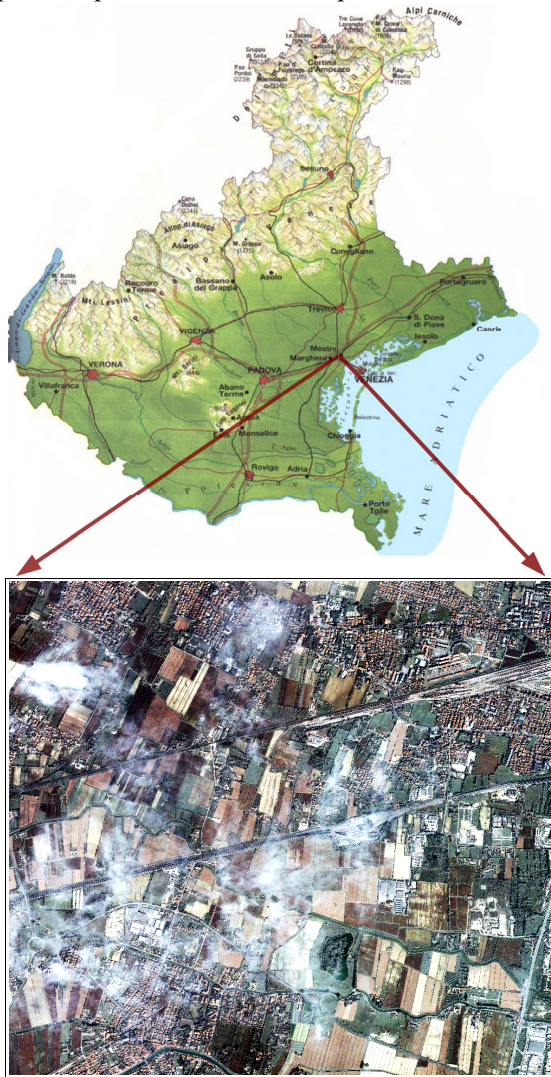
As mentioned before, the image which was used for this project came from a full scene from IKONOS sensor, resampled from one meter resolution to four meter resolution, to increase the processing speed and decrease the space taken up by all the resulting images. Each image had four bands, and each of the four parameters was changed to give around fifty combinations.

– First part: implementing the filter

The first part of the project consisted in putting into code the idea of a locally adaptive contrast filter; this filter had to let the user increase the image quality both for viewing and for classification results. This could be done by letting the user control the key steps of the process, letting him make the algorithm more apt to the image which it has to process. This could be called a semi-automatic control filter.

The spectral response of any image can be represented as a frequency distribution of its grey values. Usually this distribution is similar to a gaussian curve, either uni-, bi-, or tri-modal. To increase contrast and to enhance the visualization of the image a method is to stretch the histogram of the distribution curve in order to make it cover all the grey levels which are available in the screen (usually 256) like in figure 2. This stretching can be linear or equalized. This kind of process though, does not take into account the contrast level which is different in different areas; for example a hill which has one side exposed to the sun and one side in shadow (figure 3a): if a normal contrast stretching was used one side will have improved, but the other did not (figure 3b). Instead, using the locally adaptive enhancement filter we can see that both sides improved visibly (figure 3c) due to the adaptive qualities in the algorithm.

A proportionate change in contrast with different intensity in different areas would act as a sort of small decisional system where the decisional parameters are supplied by the user. The “Wallis Filter” commonly used uses exactly this concept; it lets the user specify the dimension of the filter window and the target contrast level.



to Fig. 1. IKONOS panchromatic image of the study area: the city of Mestre.

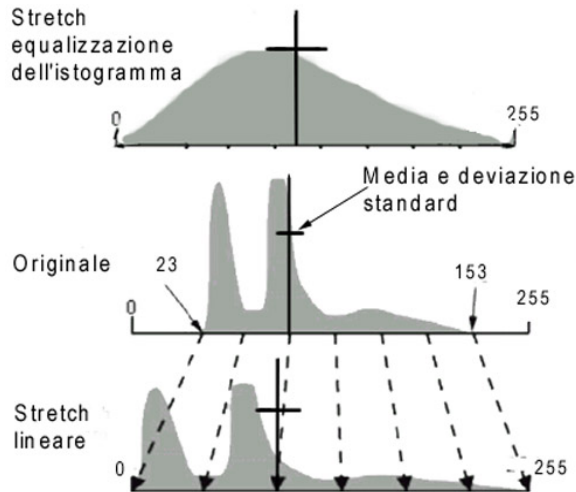


Fig. 2. Distribution of grey values in an image and an example of image stretching, (above and below) in order to cover all the 8 bits ($2^8 = 256$ values) available. Below the original distribution is a linear stretch, above a histogram equalized

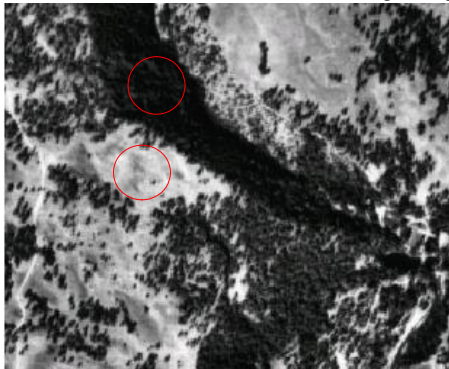


Fig. 3a.

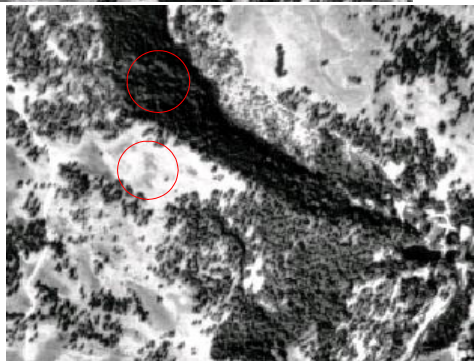


Fig. 3b.

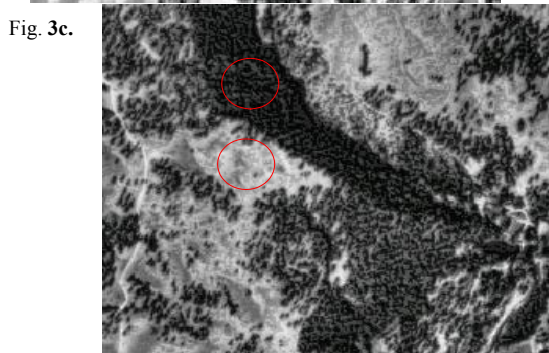


Fig. 3c.

Fig. 3. a – Original image b – normalized stretching c – r.LAfilter module. It must be taken into account that the parts in the red circle the brighter side of the hill becomes darker and viceversa.

This work applies the same principles, but it takes them a little further: it permits the user to specify two more parameters, the contrast intensity and the shrinking of the distribution tails. The latter parameter permits the redistribution of the extreme values in order to equalize the histogram. A comment must be written here: manipulating the grey values of an image brings to loss of information, and this can be damaging to successive operations. It is also true however, that in some cases over abundant information in an image is not likely to improve results, especially when applying a classification algorithm. The nature itself of classification is to turn an image with hundreds of grey values into an image with few grey values each representing a class; in this paper we will try to see if “trimming the edges” of an image will improve this process.

The filter itself has a dialog window (figure 4) which permits the user to insert his parameters. Briefly, the parameters can be thus summarized:

1. *Filter window size:* must be evaluated according to the scale of the elements which we want to see with more contrast. For example if we want to bring to better contrast forests (figure 3) on an image with a resolution of 5 meters (SPOT) a filter window of size 3x3 gives the best results since the canopy of a tree covers that number of pixels.
2. *Threshold of filter use:* the filter will need to make a binary decision: to enhance contrast or not to. To make this decision be more or less selective, the user can enter a value that will be used as threshold. As indicator for contrast the value of the standard deviation is used. Therefore the standard deviation in the filter window is compared to that of the whole image processed. Of course the former for the most part will have a smaller value, but the threshold holds that into account, since it is a multiple of the standard deviation of the whole image. This is more clearly shown in figure 5c.
3. *Contrast intensity:* This parameter is important to get the best result from the filter operation while trying to minimize artifact creation.
4. *Intensity of tail-shrinking of the distribution curve:* this last parameter was added at the very last. It permits to somewhat equalize the histogram, avoiding the presence of extreme values which would eventually make the image unbalanced. As can be noted in figure 5c, the shrinking is proportionate to how far the grey value is from the mean of the whole image.

This proportionality can be controlled by the user.

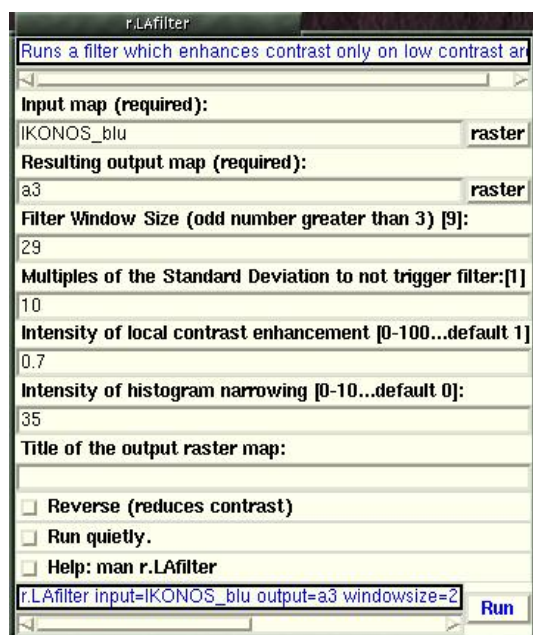


Fig. 4. Dialog window of the module *r.LAfilter*

An image can be interpreted as a sampling with the sampling unit being quadrants the size of the pixel. Maximum likelihood classification is the analysis of the digital signature of every pixel by comparing it the the signature of each of the classes which were previously defined. A locally adaptive contrast enhancement might help by giving more accurate digital signatures both in the training stage and in the successive classification stage. This is what this paper will try to assess in its second part. The first part comes to conclusion with the use of the filter on all of the image's four bands. A lot of different combinations are put under visual examination for choosing some of the best ones.

– Second part: applying the filter as a pre-processing operation to maximum likelihood classification

Supervised classification using the maximum likelihood algorithm makes use of the spectral signatures taken from the training areas representing each class to assign class values to each pixel in the image. In this case the number of bands available for the making of the spectral signature were four, three in the visible spectrum and one in the near infrared zone of the spectrum.

$I(i)$ = Pixel grey value
 $S(t)$ = St. Dev. Filter Window
 $S(img)$ = St. Dev. Image
 T = Threshold I = Intensity
 $M(tot)$ = Mean of image
 $V(i)$ = Error = $[I(i) - M(tot)]$

Fig. 5a

Fig. 5b

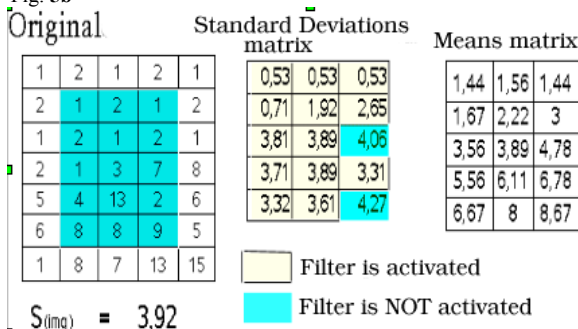


Fig. 5c

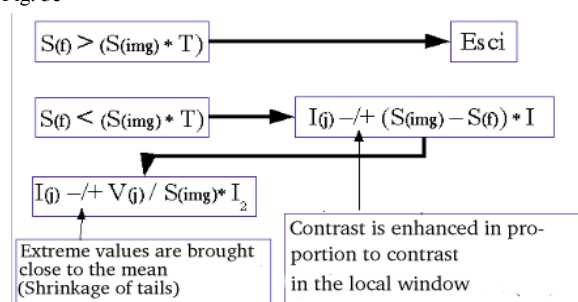


Fig. 5d

RESULT

1	2	1	2	1
2	-2	5	-2	2
1	5	-1	1	1
2	1	3	7	8
5	4	13	1	6
6	9	8	9	5
1	8	7	13	15

Fig. 5. Functional diagram and numerical example of the *r.LAfilter* module: **a** – Key to symbols **b** – In case the threshold for filter application is 1, meaning that the filter will be applied when the standard deviation of the windows is less than the one of the whole image **c** – Functional diagram of the filter **d** - Result

Initially it was decided to use the five classes which are easily interpreted visually. Successively though, after some trials at classifying we saw that it was much better to include another class, namely cloud cover. This improved classification globally. Ultimately six classes were used:

1. urbanized
2. brown soil (bare or ploughed)
3. with vegetation
4. Cement cover (roads and some buildings)
5. Water bodies
6. Cloud cover

The training and the result of the maximum likelihood classification of the original image gave quite good results already (figure 6a and 6b). Successively this kind of classification was applied also to all the filtered images, using, of course, the same training areas. To evaluate if the result was better or worse in terms of accuracy of classification, a confusion matrix between the classification results of the original image and the results of the filtered images. It must be noted the the objective of this paper is to put to light the improvement or not of classification using filtered images as compared to the original, and not the overall classification accuracy. Therefore the matrix results show only the parts pertaining to the

Fig. 6a



Fig. 6b

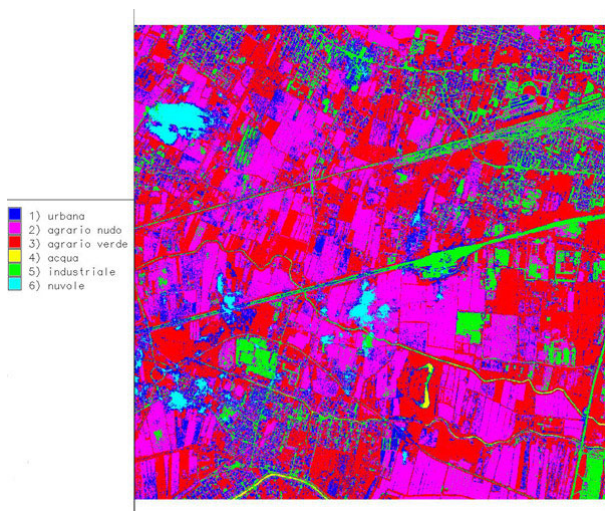


Fig. 6. a- Training areas on a false color image b – result of maximum likelihood classification on the original unfiltered image

discrepancies between the control (classification from original) and the experimental.

RESULTS AND CONCLUSIONS

To find the best combination for the four parameters which can be put in the *L.A.filter* module, forty “educated guesses”-combinations were put to visual test. The ones which obviously made the image worse were discarded, and the four best results were kept. To assess results first the difference image was made: this meant subtracting the results of the control from the results of classification of the filtered image. The pixels which were both equally classified will give a null results, whereas all pixels with a value will be the ones where the classification algorithm gave different results (figure 7). This difference image was overlaid to the panchromatic IKONOS image with full resolution (1 meter) to enable the operator to visually decide which image gave the correct classification, if the control (original) or the filtered one. The confusion matrix (figure 9) represent the result of this operation. It can be seen from these matrices that there was an overall improvement, but not in equal measure for all the classes. This is clearly shown in figure 8, where four windows are visible: the top one is the area seen as the IKONOS panchromatic image, the middle top is the classification result of the original image, the bottom middle is the classification result of the best filtered image, the bottom one is the same as the one before but after the application of a region erosion filter in order to eliminate all the speckles.

Particular care should be taken on the input of the four parameters. An interesting work after this could be a precise account of the effect of the filter in the classification accuracy of each class. Surely this filter improves visualization especially on images which already have a low contrast globally. In cases where contrast is already high the use of this filter could be a waste of time. In figure 3 the filter was applied to a zone of the image *gs13.1* of the set *Imagery* of the *Spearfish*¹ bundle and the result was very good even after trying very few combinations whereas for the IKONOS image used for classification a lot more combinations had to be tried before finding a suitable one. forty combinations were visually tested, and the better ones were with a window of 15x15, a threshold of 0.7, a contrast intensity of 0.8 and a tail shrinking intensity of 25.

In conclusion this paper shows that, if applied with knowledge, and in certain cases, this locally adaptive contrast enhancement filter improves classification. It must also be pointed

¹ *Imagery* is a set of SPOT images available for the *Spearfish* set which is data available as tutorial for GRASS users.

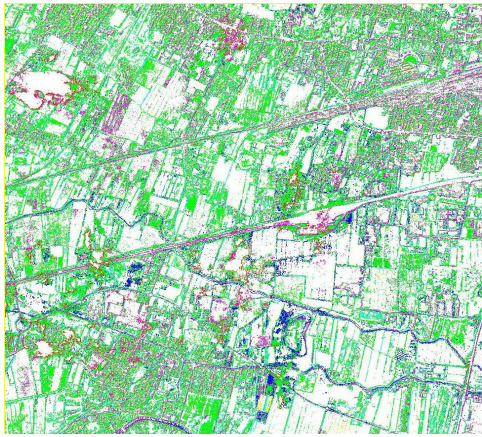


Fig. 7 Image of discrepancies between the classification of the original and the classification results of filtered. The white areas are where both results were the same, the colored areas are where results do not correspond, and represent the classification result of the filtered image.



Fig. 8a

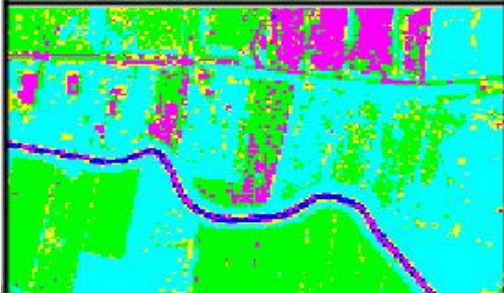


Fig. 8b

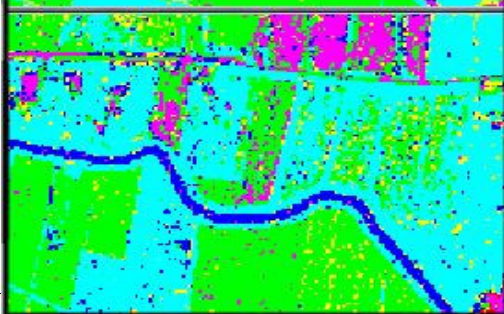


Fig. 8c

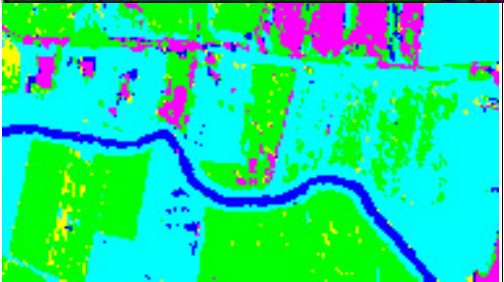


Fig. 8d

Fig. 8 a – IKONOS-pan original image **b** – Classification of the original **c** – Classification of the image filtered with *r.LAfilter* **d** – Post-processing of the latter image with an erosion filter to eliminate speckles.

out though, that different classes respond to the filter in different ways. This must be determined for each case. So this filter can be used when wanting to classify an image in order to find certain elements. In our example (figure 8) the classification of water bodies was certainly improved. So if the operator wants to put into evidence this element then he can certainly find that this filter can give him good results. It must also be noted that the use of this filter increases the presence of speckles, or small two- or three-pixel areas with a different class than the region containing them (figure 8c). That is why an

CONFUSION MATRICES OF DISCREPANCIES

Relative frequency to 100

		11.3.1.10		Discrepancy
		Correct	Incorrect	
Original	Correct	-	78	16% Urban
	Incorrect	22	-	9% Bare soil
Original	Correct	-	43	9% Agricultural
	Incorrect	57	-	1% Water bodies
Original	Correct	-	45	4% Cement
	Incorrect	65	-	1% Cloud cover
Original	Correct	-	29	40% Total
	Incorrect	71	-	

		29.10.07.35		Discrepancy
		Correct	Incorrect	
Original	Correct	-	43	DiscorUrban
	Incorrect	57	-	3% Bare soil
Original	Correct	-	45	28% Agricultural
	Incorrect	65	-	3% Water bodies
Original	Correct	-	29	1% Cement
	Incorrect	71	-	7% Cloud cover
Original	Correct	-	29	1% Total
	Incorrect	71	-	45% Urban

		3.1.07.5		Discrepancy
		Correct	Incorrect	
Original	Correct	-	45	DiscorUrban
	Incorrect	65	-	11% Bare soil
Original	Correct	-	45	12% Agricultural
	Incorrect	65	-	10% Water bodies
Original	Correct	-	45	1% Cement
	Incorrect	65	-	5% Cloud cover
Original	Correct	-	45	1% Total
	Incorrect	65	-	40% Urban

		15.07.08.25		Discordanza
		Correct	Incorrect	
Original	Correct	-	29	7% Urban
	Incorrect	71	-	13% Bare soil
Original	Correct	-	29	9% Agricultural
	Incorrect	71	-	3% Water bodies
Original	Correct	-	29	6% Cement
	Incorrect	71	-	1% Cloud cover
Original	Correct	-	29	39% Total
	Incorrect	71	-	

Fig. 9 Confusion matrices of the results of classification of different images: the filtered ones are compared to the original one. The four parameters used are indicated in the key on top of the matrix.

erosion filter was applied that took care of this. There is however, the risk of losing information, because those small areas could be artifacts of the filter, but also could represent correct classification.

Even if, as can be seen from the confusion matrices, (figure 9), there was a general improvement this does not eliminate the possibility that some areas were classified erroneously after the filtering. Another point is that we could have had a better results if a class was given to shade areas. In fact it seems that

areas of shadow were classified after filtering as water bodies (figure 8c).

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