

CLASSIFICATION OF ROOF MATERIALS FOR RAINWATER POLLUTION MODELIZATION

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KEY WORDS: Supervised classification, Image segmentation, Roofing materials, Roofs, Rainwater pollution

ABSTRACT:

It has been proven that roof runoff water plays an important role in the high metallic concentration levels in urban rainwater since metallic elements are generated by corrosion of roof materials before being swept away by rainwater. The aim of TOITEAU project is therefore to model this phenomenon, evaluating the metallic flows from roofs in rainwater. To achieve this goal, an important work has already been done to model those flows at roof scale. But, it has now to be extrapolated to a whole drainage area, requiring knowledge about the areas concerned by the different kinds of roof coverage, that is to say that a map of roof materials is needed. Such information can be extracted from aerial (ortho-)images owing to (supervised) classification techniques. In the present situation, only six classes corresponding to the following kinds of roofs were defined : zinc plates, slates, red tiles, brown tiles and flat roofs.

Nevertheless, classification results are limited because of several factors that have therefore to be dealt with.

First of all, some distinct classes have very similar radiometric distribution (such as for instance zinc and at light slates), making it hard to distinguish between them. That's why derived channels computed from initial red-green-blue channels of the ortho-image have been used to improve the classification results. Texture channels have also been tested especially to discriminate zinc from other light coloured roof materials. For the same reason and in order not to obtain a too "noisy" result, per region classification algorithms have been used : homogeneous regions will be classified instead of pixels. Secondly, roofs are the only interesting parts of the ortho-image in this study. As a consequence, a building mask is first computed from digital topographic database BDTopo in order to classify only roofs. However, several elements concerning data precision have to be taken into account at this step. For instance, the ortho-image and the topographic database can obviously not have been captured at the same date and, as a consequence, buildings can have been destroyed, modified or built between these two distinct capture times. In addition, as the used ortho-image is not a "true ortho-image", building objects from digital topographic database and ortho-image roofs are not perfectly superposed. However, these topographic database building objects can be registered to the ortho-image. Nevertheless, it must be said that these database objects often remain caricatures of true buildings. Besides, most of the time, homogeneous regions to be classified do not directly correspond to database buildings since those database objects can be groups of buildings or buildings of which the roof is composed of different materials. Therefore, it is necessary to segment building areas (according to the topographic database) of the ortho-image into homogeneous regions that are then classified.

Lastly, shadows can be quite important in roof areas because of the presence of roof superstructures or higher buildings in the neighbourhood. That's why an additional class "shadow" is also defined in order to take into account shadow areas where radiometric information is not sufficient to discriminate between the different kinds of materials.

Tests have been carried out on two distinct study areas with 50cm resolution orthophotos for the first one and 12cm resolution orthoimages for the second one. The first study area was a dense urban centre, whereas the second could be divided into several parts : a residential suburb consisting of houses, a dense urban centre with buildings having up to 4-5 levels and a mixed residential / service area consisting of higher buildings.

1 INTRODUCTION

1.1 TOITEAU project

Zinc-based materials are largely used in urban areas, especially for infrastructure, such as furniture or siding and roofing for buildings. Exposed to atmospheric conditions (environmental pollutants, relative humidity, rain events...), these materials are progressively corroded. During a rain event, a part of the corrosion products formed at their surface will be retained, and the other part will be released and washed off.

Several research programs lead since the 1990's have shown the very high trace metal contamination of runoff from metallic or partly metallic roofs (Forster, 1996), (Gromaire-Mertz et al., 1999). In Paris, experiments conducted on a 42 ha urban catchment have established that atmospheric corrosion of roofing materials could be a major source of zinc, cadmium, lead and copper

during wet weather (Chebbo et al., 2001). Several researches on speciation of metals from roofing materials have been carried out, showing that zinc emissions are mainly in the labile form (Heijerick et al., 2002), which is very bioavailable and therefore harmful to aquatic organisms (both animals and plants).

Thus, in the actual context of the European Water Framework Directive (2000/60 CE), whose aim is to obtain a good ecological state of aquatic environments, it seems necessary to reduce the production of pollutants at their sources. This implies to identify sources and to quantify emissions.

TOITEAU project has begun in 2005, with the aim of developing a methodology for the estimation of annual metallic flows from roofs at the catchment area scale. This work implies on one hand the estimation of metallic runoff rates from different roofing materials, and on the other hand the identification and the quantification of the different roof surface areas, using aerial photographs

and image classification tools.

The first part leads to a large database of runoff rates, concerning 12 materials and 13 metallic species. Complementary experiments - focused on the effect of inclination and length of flow - and carried out both at the test bed scale (see figure 1) and at the roof scale in order to verify the transposition of runoff rates at larger spatial scales, lead to the conclusion that projected areas are sufficient to predict and model metal runoff from materials (Robert-Sainte, 2009).



Figure 1: Experimental evaluation of the effect of inclination on runoff rates

1.2 Measure roof material areas

As previously said in 1.1, work has been done to model metallic runoff rates for roofing materials. To extrapolate these results to whole drainage areas, knowledge about the areas concerned by the different kinds of roof coverage is required : a map of roofing materials is needed. Such information can be extracted from aerial (ortho-)images through classification.

Roofing materials classification from aerial images has already been studied. For instance, an approach using hyperspectral and laser scanning data is presented in (Lemp and Weidner, 2004). The method described in (Martinoty, 2005) uses Bidirectional Reflectance Distribution Function (*BRDF*) of materials computed from red-green-blue-near infrared aerial images and 3D data.

In the present case, only red-green-blue ortho-images (and a 2D topographic database to focus on buildings) are available. Furthermore, as experiments have shown that projected areas are sufficient to predict and model metal runoff from materials, ortho-images can be used directly, without 3D information. Therefore, the chosen method simply consists in classifying them (through a supervised classification method) into the following classes zinc plates, slates, red tiles, brown tiles and flat roofs. This approach is very simple but it will have to face several limits and difficulties.

2 DIFFICULTIES AND LIMITS

2.1 Similar classes and radiometric variations inside classes

Some distinct roofing materials classes have very similar radiometric distributions (as it can be seen on image histogram represented on figure 2), making it often hard to distinguish between them, even for a human operator. For instance, brown tiles and slates often look like each other on the image.

Using associations of derived channels calculated from original red-green-blue spectral bands of the ortho-image is a way to improve classification results. The use of per region classification algorithms can also improve results since it enables to take into account the radiometric distribution of whole regions instead of

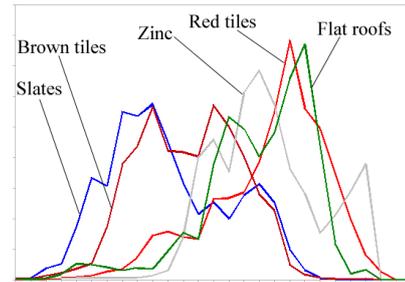


Figure 2: Image histogram for channel "red" for the different classes

isolated pixels.

However, this problem is increased by the fact that the radiometry can greatly vary inside a same class. These variations are caused by several factors and can lead to misclassifications :

- Roof orientation linked to Sun illumination angle is the main reason. Therefore, a same roofing material can appear very different from one side of a roof to an other. This phenomenon is particularly important for slates and zinc plates as shown by figure 3: slates at light can appear as light as zinc plates whereas zinc plates at shadow are sometimes as dark as some slates... Misclassifications occurs also between red and brown tiles because of differences of Sun illumination.



Figure 3: Example of important radiometric variations caused by roof orientation linked to Sun illumination and making it very difficult to distinguish between slates and zinc plates

- The colour of roofing materials obviously depends on their age, because of corrosion.
- Objects of a same class can have different colours for different reasons (painted zinc plates, tiles more red than others...)

2.2 Shadows

Shadow areas can obviously be important in urban areas. They mostly concern streets but roofs can also be partly masked by shadows caused by higher buildings or roof superstructures. If nothing is done to deal with this phenomenon, shadow regions are classified into the two "darkest classes" slates and brown tiles, leading to an over estimation of the areas covered by these materials.

As a consequence, an additional class "shadow" is also defined in order to take into account shadow areas where radiometric information is not sufficient to discriminate between the different kinds of materials.

2.3 Building database

Roofs are the only interesting parts of the image for the classification. As a consequence, a mask is computed from building objects of a topographic database to focus on them. Nevertheless, several elements concerning data precision have to be taken into account at this step.

- First of all, the ortho-image and the topographic database can obviously not have been captured at the same date and, as a consequence, buildings can have been destroyed, modified or built between these two distinct capture times.
- The used ortho-image is not a “true ortho-image”. As a consequence, building objects from the topographic database and roofs on the ortho-image are not perfectly superposed (as it can be seen on figure 4). However, these buildings can be registered to the ortho-image.



Figure 4: Building objects of the topographic database and roofs on the ortho-image are not perfectly superposed

- Nevertheless, it must be said that building objects from the database often remain caricatures of true buildings. Therefore, they can sometimes be wider (containing other parts of the image such as balconies, courtyards or even part of streets) or on the contrary not contain the full roof.
- Besides, most of the time, homogeneous roof coverage regions to be classified do not directly correspond to building objects of the database since those objects can be groups of buildings or even buildings of which the roof is covered by several materials. Therefore, it is necessary to segment building areas (according to the topographic database) of the ortho-image into homogeneous roofing material regions that will then be classified.

2.4 Non roof coverage elements

Roofs can sometimes be partly masked by higher elements such as trees (as it can be seen on figure 5).

Moreover, non roof coverage elements can be present on the roof. For instance, chimneys, glass roofs, balconies and even parts of facades or small courtyards are non roofing materials elements belonging to the roof mask on the orthoimage, as it can be seen on figure 7. In addition, roof coverage can sometimes be covered by vegetation (such as moss) and will therefore be misclassified.



Figure 5: Example of roof partly masked by a tree

3 METHOD

The proposed method consists in the following steps :

1. The image is segmented into homogeneous regions.
2. A building mask is computed from the topographic database and registered to the segmentation of the image computed at previous step.
3. Regions of the segmentation are classified owing to a per region classification algorithm applied to an association of derived channels obtained from initial red-green-blue bands of the ortho-image.

3.1 Segmentation

First of all, the images have to be segmented into homogeneous roofing material regions. This is achieved thanks to the multi-scale segmentation method described in (Guigues et al., 2006) and (Guigues, 2004). It enables to compute a pyramid of segmentations of the image, each level of this pyramid corresponding to an alternative between detail and generalization. This pyramid is then cut at a level empirically chosen in order to obtain a suitable image partition (as for the example shown on figure 6). The choice of this level is a compromise between detail and the size of regions since on one hand, in an over segmentation, some regions will be too small to have “meaning” and will be at risk to be misclassified whereas on the other hand, in a too coarse segmentation, wide regions will contain different roofing materials.

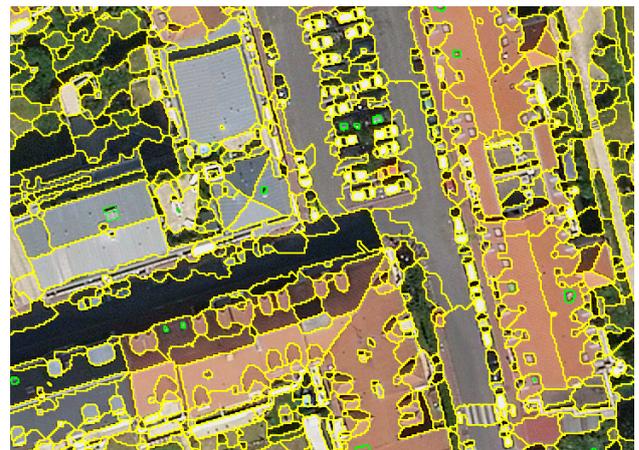


Figure 6: Example of segmentation

3.2 Building mask computation

A building mask is computed from a digital topographic database. (In the present case, IGN’s digital geographic database BDTopo

is used.) Roofs and therefore buildings are indeed the only interesting parts of the image. However, as previously explained in 2.3, database building objects and ortho-image roofs are not perfectly superposed.

Nevertheless, building objects from the topographic database can be registered to the ortho-image. In the present case, building objects are in fact rasterized and then registered to the segmentation (obtained at previous step) : a 2D rigid raster-raster registration of rasterized buildings to the segmentation is processed for each building object of the database using Insight ToolKit Registration tools (Ibanez et al., 2005). It consists in computing the best parameters of a 2D rigid transform (a 2D similitude in this case) minimizing a metric (based on mutual information here) between the two images.

Obtained results are quite good (as it can be seen on figure 7), except for the highest buildings for which the shift between the roof on the orthoimage and the corresponding database building object is sometimes too important.

It must also be said that methods to obtain a finer registration exist (see for example (Trias-Sanz, 2006)), but don't solve the problems described in 2.4.



Figure 7: Example of building mask registration for 3 building objects. (The situation before registration is shown by figure 4.)

3.3 Derived channels

The use of derived channels calculated from original bands of the orthoimage can improve classification results. These channels can be radiometric channels computed as combinations of the original bands (such as channels of an other colour space or indices as the well known *ndvi* computed from red and near infrared bands to discriminate vegetation) or texture channels.

For instance, in the present tests, the following derived channels have been used :

$\logrg = \log(\text{red}) - \log(\text{green})$ (a log-opponent chromaticity channel)

$\logrs = \log(\text{red}) - \log(\text{red} + \text{green} + \text{blue})$

Furthermore, these channels are used in association in the classification process. Therefore, the choice of good associations of channels is important to obtain good classification results.

3.4 Classification

The regions of the segmentation are classified by the classification tool described in (Trias-Sanz, 2006) and (Trias-Sanz and Boldo, 2005). It works in two steps :

1. **Model estimation** from training data captured by an operator : First, for each class, the best parameters of several

statistical distributions (such as gaussian, laplacian laws but also histograms (raw or obtained by kernel density estimation)...) are computed to fit to the radiometric n-dimensional histogram of the class (with n number of channels used for the classification). Then the best model is selected thanks to a Bayes Information Criterion enabling to choose an alternative between fit to data and model complexity.

2. **Classification** : The image can then be classified knowing the statistical model of the radiometry of the different classes. Several per pixel and per region classification algorithms are proposed in (Trias-Sanz, 2006) :

- **Maximum A Posteriori (MAP) and Maximum Likelihood (ML)** per region classification algorithms : The label $c_o(R)$ given to a region R is its most probable class according to the model previously estimated (and to prior probabilities). Hence, with the *MAP* algorithm, $c_o(R)$ is the class c that maximizes the following function : $P_{\text{prior knowledge}}(c(R) = c)$.

$$\left(\prod_{\text{pixel } s \in R} P_{\text{model}}(I(s)|c(s) = c) \right)^{\frac{1}{\text{card } R}}$$

with $I(s)$ standing for the radiometry vector of pixel s , $c(z)$ meaning region or pixel "z's class" and $P(c(z) = c)$ standing for the probability for pixel or region z to belong to class c . Such a method enables to take easily into account external information as prior probability.

- per region classification algorithms based on the comparison of distributions : The label given to a region is the class with the most similar model to the distribution of pixel values in the region to be classified. (Instead of calculating the probability that the pixels in a region come from a certain random variable, distributions of pixels values in the region to be classified are compared to the probability function of the models previously estimated in order to find the class with most similar distribution.) The χ^2 statistic and the Kullback-Leibler divergence (also called relative entropy) are two possible dissimilarity coefficients to use to compare these distributions.

4 TESTS AND RESULTS

The method has been tested on two distinct study areas (Le Marais district in Paris and Noisy-le-Grand) with different urban infrastructures. Image resolution was different for the two study areas. Several classification methods and associations of derived channels from original red-green-blue bands of the ortho-images have been tested.

Results have been evaluated both visually on the whole image and numerically, calculating confusion matrices on smaller parts of the study area. Confusion matrices are computed from test data captured by an operator and enable to calculate user and producer accuracies. Nevertheless it must be said that it was sometimes difficult even for a human operator to identify roofing materials on the image.

4.1 Le Marais - Paris

The first test area is a dense urban centre located in Le Marais district in Paris. 50cm resolution orthophotos (with red-green-blue bands) from the IGN's national orthoimages database were available there (see figure 8).

Results obtained with the different per region classification methods are quite similar. The best results (see figure 9 and table 1) have been obtained for several associations of derived channels. For instance, the associations of channels *red/logrs*, *red/logrg* and



Figure 8: 50cm resolution ortho-image on Paris - Le Marais

even *red/blue* give almost 77 % pixels well classified, which can be considered as a good result taking into account the quality of the processed data. Most misclassifications occur between slates and zinc at shadow and between slates and brown tiles. Misclassifications between red tiles and flat roofs sometimes happen too.

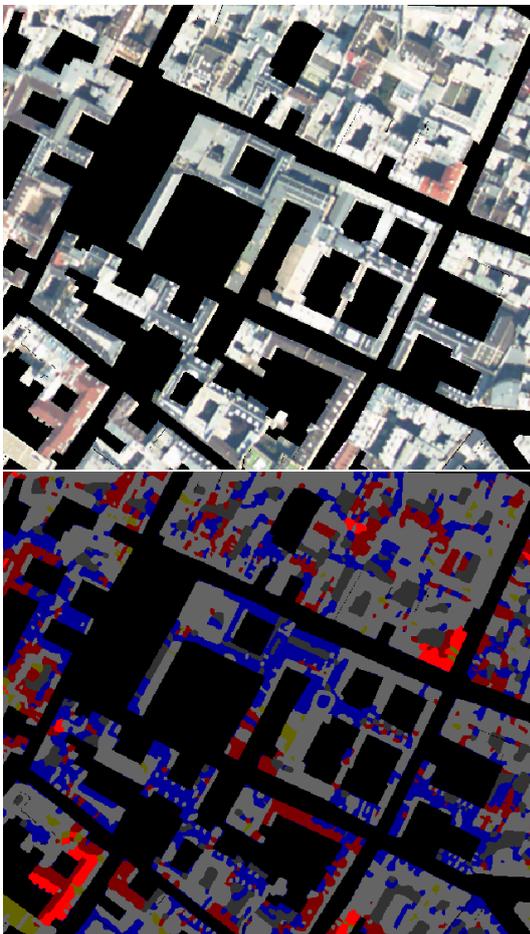


Figure 9: Example of results obtained in Le Marais for *MAP* per region classification algorithm applied to *red/logrg* channels association. (red tiles in light red, brown tiles in dark red, slates in blue, zinc plates in light grey, flat roofs in green, shadows in dark grey)

4.2 Noisy-le-Grand

The second test area is the town of Noisy-le-Grand. It can be divided into several parts :

- a residential suburb consisting of houses,
- a dense urban centre with buildings having up to 4-5 levels
- a mixed residential / service area consisting of higher buildings.

12cm resolution red-green-blue orthoimages have been used (see for example figures 3, 4 or 5). Such resolution could enable the use of texture information especially to distinguish zinc plates from other materials. (Zinc roofing coverage has indeed a particular and regular texture, whereas other materials present a homogeneous texture.) Nevertheless, there has been no real improvements since this texture is often not really visible on the used images because of roof orientation linked to Sun illumination angle. Furthermore, there is no real texture for some small zinc areas on the top of roofs or of roof windows.

As for the first test area, results obtained by the different per region classification algorithms are quite similar. The best results with almost 82% well classified pixels have been obtained for several channels associations as for example *red/logrs* or *red/blue/logrs* (see table 1 and figures 10 and 11).

Misclassifications mostly concern slates and zinc plates, which are sometimes difficult to distinguish from each other even for an operator. Other misclassifications often occur between flat roofs and other themes, but it must be said that those errors could be avoided by the use of information from a 3D city model. Furthermore, some buildings present important roof balconies with plants, leading to misclassification.

Table 1: User (us acc) and producer (pr acc) accuracies (in %) obtained in Le Marais for *MAP* per region classification algorithm applied to *red/logrs* channels association and in Noisy-le-Grand for *chi2* per region classification algorithm applied to *red/blue/logrs* channels association

Class	Paris - Le Marais		Noisy-le-Grand	
	us acc	pr acc	us acc	pr acc
Red tiles	99.3	30.0	95.9	89.4
Brown tiles	62.8	63.7	65.3	77.9
Slates	63.0	63.1	76.3	80.6
Zinc plates	89.8	89.2	64.3	77.3
Flat Roofs	15.8	64.3	90.6	80.4
Well classified pixels	76.7		82.3	

5 CONCLUSION

The method proves to be quite powerful and relatively easy to use for areas where orthophotos are available. The results obtained are promising, with about 75 to 80% of surface areas well classified. The image quality contributes to determine the performance of the classification - shooting limits (shadows, correct contrast, resolution enabling the use of texture channels).

The main source of error is confusion between similar radiometry. Nevertheless, if some (red tiles / brown tiles, brown tiles / slates) remain insignificant in the context of the use made for the evaluation of metal flows from roofs, others are more problematic (slates/zinc).

Such a tool is essential for the evaluation of metal roof surfaces throughout a watershed. Anyway, the use of the described classification method alone does not give a sufficiently detailed estimate of all the metal surfaces implemented: if the performance is good to evaluate the ramp surfaces, the individual little elements can not be taken into account in this review, these elements are generally not visible on the aerial photograph. These metallic elements can be numerous and cumulatively represent important areas, efforts should be made to estimate them too.



Figure 10: Example of result obtained in Noisy-le-Grand for *MAP* per region classification algorithm applied to *red/blue/logrs* channels association. (with the same legend as for figure 9)

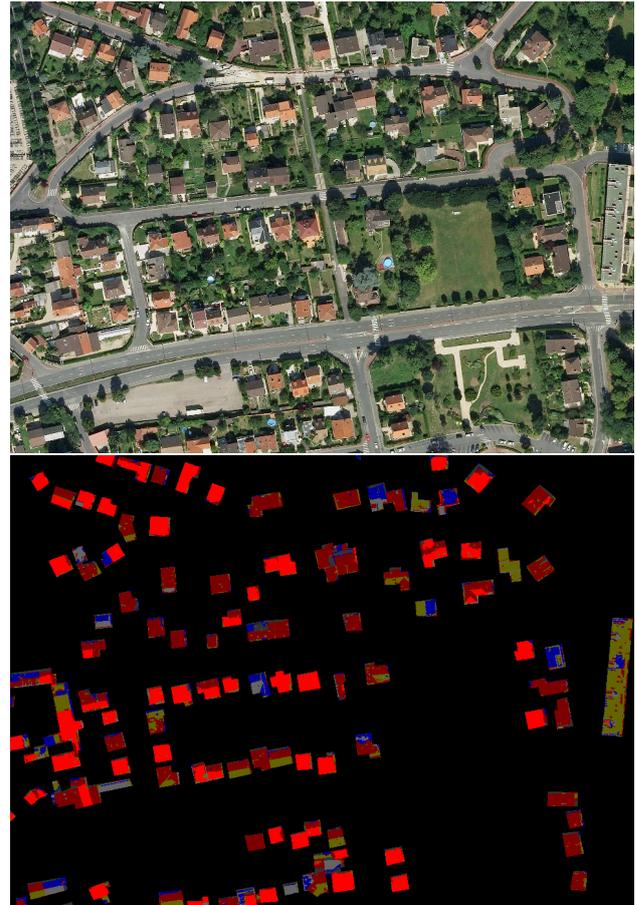


Figure 11: Example of result obtained in Noisy-le-Grand for *MAP* per region classification algorithm applied to *red/blue/logrs* channels association. (with the same legend as for figure 9)

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