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Abstract

Today, urban runoff is considered as an important source of environment pollution. Roofing materials, in particular the metallic ones are considered as a major source of urban runoff contamination. An accurate evaluation of contaminant flows from roofs is thus required at the city scale. This paper aims to describe the definition of an appropriate methodology for evaluating the zinc emission at the city scale. This methodology is based on combining two different methods. The first one is an automatic classification and the second one is a theoretical urban study site. In order to obtain representative data, the choice of the study site was based on the diversity of land use and the urban and social context. Finally some results and future works will be presented.

Key words

Urban water; contaminant; methodology; roofing materials; runoff

INTRODUCTION

Roofing materials, in particularly the metallic ones are considered as a major source of urban runoff. This observation was revealed by several research programs conducted since the 1990s (Förster, 1996; Gromaire-Mertz et al., 1999; Odnevall Wallinder, 1998). The OPUR (Observatoire des Polluants URbains en Ile-de-France) program then focused on identifying and quantifying the emission of different contaminant (Zn, Pb…) at the test-bed, roof and small urban catchment scales (Robert-Sainte, 2009). This works have been conducted in the context of TOITEAU project, in which annual metallic runoff rates at different scales (test-bed and roof) have been evaluated, for the different roofing materials commonly used in Paris and suburbs. Then, in other works (Gromaire et al., 2011; Le Bris et al., 2009), the previous results have been extended to larger special scales by using roof surface areas data obtained from aerial photographs and image classification software.

The classification method based on aerial images was applied to an urban catchment with 2.25 km² of surface. The obtained results showed about 75 to 80% of well classified roofing surfaces. Nevertheless, classification method presents some limitations especially in terms of confusion between different classes (eg: zinc and slates at light).

The goal of this paper is to describe the methodology defined to evaluate the zinc emitting surfaces at the city scale. On the one hand, this methodology is based on applying the automatic classification method. In the other hand, we propose to overcome the limitations of the classification method by adding further information. These informations are developed by another work which seeks to understand the key factors leading to the choice of roofing materials on construction projects and defining the related performance indicators.
To validate and apply this methodology in other cities, a complex representative site had to be chosen.

In this paper, we firstly describe the classification method and its limitations. Then, the different criteria of the chosen city will be presented. Finally, we present the proposed solutions and discuss the awaited performances.

METHODS

Our work aims at evaluating the zinc roofing emitting surfaces at the city scale. However, this task seems difficult because of the diversity and the very large number of buildings. So a specific methodology has to be developed to identify and evaluate the different roofing material at the city scale.

Previous studies (Gromaire et al., 2011; Le Bris et al., 2009) have evaluated the surface of zinc at the scale of a small urban catchment by using a classification method based on aerial images. They have shown about 25% of misclassification which is due to some limitations. In fact, some classes have similar radiometry, so it becomes difficult to distinguish between them (eg: zinc and slates at light). Then, roofing materials in shadow are misclassified; this is the case of red tiles in the shadow which are classified as brown tiles. In addition, radiometry greatly varies in the same class.
If we want to apply this method at the city scale, classification errors may be increased because of the larger scale and the different limitations.

As illustrated in Figure 1, we propose to combine the automatic classification method with a theoretical approach based on a study of the site (history, urban land use, social characteristics…). This approach aims to define criteria to interpret the results of the classification method. Therefore we can improve the results by adding further informations, for example in individual habitat we know that zinc as roof material is rarely used. So if the classification result in this area gives zinc, there is an important probability that it is actually slate roof.

To validate and to generalize the methodology we need to apply it to a significant complex urban area which will be chosen according to different criteria which will be described later.

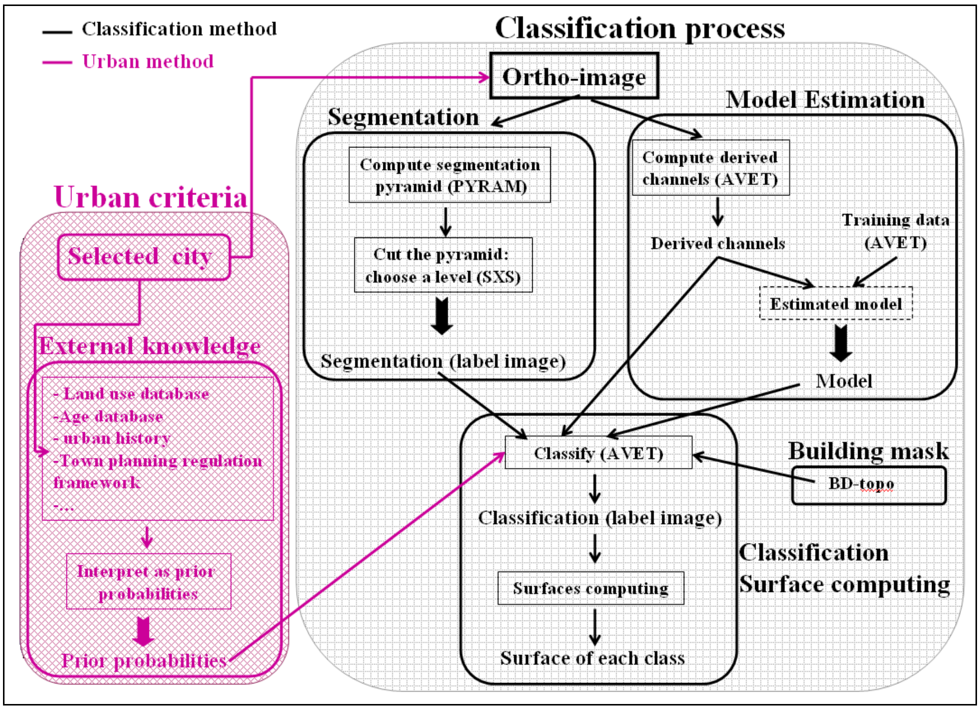

Figure 1 : Methodology to identify and evaluate the different roofing material at the city scale

Classification method

As mentioned earlier, the chosen method is the classification of roofing materials from aerial images using the AVET (Automatic Vegetation Extraction Technique) tool (Trias-Sanz, 2006). This tool was developed to extract information on vegetation areas from aerial images. Then it was adapted by (Le Bris, 2009) for urban roof classification. In fact, six classes corresponding to the following kinds of roofs were defined: *zinc sheetings, slates, red tiles, brown tiles and flat roofs*. Before classification, some treatments are undergone on the images: segmentation and computing building mask.

Data: the ortho-images

The identification of roofing materials will be based on the analysis of aerial photography. These latter, will inform us about the materials used on roofs with their radiometry and their projected surfaces. Aerial images have undergone some treatment to be transformed into orthorectified images. Indeed, in these photos the deformation due to relief and the inclination of the axis of the shooting have been corrected (Lafont et al., 2003).

The images come from IGN's (Institut Géographique National) ortho-image database named BD-ortho, which contains digital colour ortho-photos with three or four (red–green–blue–near infrared) bands and with a 50 cm ground resolution.

Method steps

The classification method consists in the following steps:
- *Segmentation:* First of all, the ortho image is segmented into homogeneous radiometric regions. This is achieved thanks to the multi-scale segmentation method by PYRAM and SXS tools (Guigues et al., 2006; Guigues, 2003).
- *Derived channels:* The classification process is combined with the computing of derived channels. In fact, derived channels have been calculated from the original (red–green–blue–

near infrared) bands of the ortho-image. These channels can be radiometric channels computed as combinations of the original bands (such as channels of another color space or indices as the well known *ndvi* computed from red and near infrared bands to discriminate vegetation) or texture channels.
Therefore, the choice of good associations of channels is important to obtain good classification results. Different tests should be made to get the best association of channels.

- *Building mask:* In this classification method, we focalise only on buildings, so hiding non buildings objects in the ortho-images is needed. In our case, a mask named BD-topo (database for Topographic Information comes from IGN) is used to focalise in buildings. This operation has limitations. In fact, the limits of buildings in BD-topo don't overlap exactly the limits of buildings in BD-ortho (see figure 2). In some cases, the mask didn't include the entire roof, or it includes a small part of roads. This problem is more important for the highest buildings for which the shift between the roof on the ortho-image and the corresponding database building object is sometimes important.

Figure 2 : The building mask don't overlap exactly the limits of buildings in BD-ortho

- *Classification*: The segmented regions are then classified by the AVET classification tool (Trias-Sanz et al., 2005 and Trias-Sanz, 2006). This tool works in tow steps. First model estimation from training data captured by an operator will be computed: for each class of material (zinc, tile…), an n-dimensional histogram of the radiometry of the class is calculated. Then AVET estimate the best statistical distributions (such as gaussian, laplacian laws but also histograms (raw or obtained by kernel density estimation) to fit to the radiometric histogram. Finally, the best model is selected thanks to a Bayes information criterion (Schwarz, 1978) enabling to choose an alternative between fit to data and model complexity. Secondly classification will be applied: the image can then be classified according to the statistical model of the radiometry of the different classes. Several per pixel and per region classification algorithms are proposed (Trias-Sanz, 2006). In the present work, a 'maximum a posteriori' (MAP) classification algorithm is used because it makes possible to take into account external knowledge as prior probabilities (this method will be described in the proposed solution section). 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, $c_0(R)$ is the class c that maximizes the following function:

Equation 1 : $$P_{prior\_knowledge}(c(R)=c).\prod_{pixel\_s\in R} P_{radiometric\_model}(I(s)|c(s)=c)^{1/Card(R)}$$

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*. *Card (R)* the number of pixels in the region.

-*Surfaces computing:* for each class its surface is calculated by computing the number of pixels and multiplying them by the resolution of the image.

All of these steps have been applied for the city selected and figures were illustrated in results paragraph.

Problems and limits

The classification method of roofing materials from aerial image is perturbed by several phenomena causing misclassification (about 20% to 25% of errors at the scale of a small catchment). Indeed, the information provided by the aerial images is not sufficient to classify and separate the different classes of roofing materials at the city scale.

Shadows/Illumination effect

The superstructures of roofs or higher buildings overshadow the lower ones. In this case, red tiles in the shadow are classified as brown tiles and zinc plates in shadow are classified as slate.

Classes with similar radiometry

Some classes have similar radiometry. Therefore it becomes difficult to distinguish between them even by a human operator. These are the case of brown tiles and slates, some red tiles and flats roofs and also zinc sheets and sunny slates.

Radiometric variations within a class

This variation in radiometry is due to several factors:

- *Industrial:* the material could undergo surface treatments which changes the shade of its color.
- *Age:* the material is exposed to the atmosphere (eg: the corrosion for metals) which changes its surface characteristics.
- *Shadow*: shadow could influence the color of the material and then the radiometry in the image.

Resolution of the ortho-images

The resolution of the images is 50 cm. Therefore, it's difficult to use texture channels. Indeed, every roofing material is characterized by a specific texture, for example zinc is used as plates. However tiles are small pieces posed one against the other. These textures cannot be detected in the 50 cm available aerial image.

Age of buildings

The previous studies have shown that the age of the material have an important influence in the emission of contaminants. So it becomes necessary to introduce this information in our work. However, the aerial image cannot or weakly inform us about the age of roofs.

Proposed solution

Shadow/No shadow class

To obtain a correct classification of the image, roofs in shadow must be taken into account. So, we can correct the radiometry in shadows areas after having detected them.
However, this correction is limited by several uncertainties:

- The ortho-images have undergone a process of radiometric treatments as described in the previous section. Therefore there is a loss of information in shadow areas.
- The resolution of the image is taken at 50 cm.
- The accuracy of 3D urban model at the selected city is not available.

In this case, a method was proposed and successfully used in a previous study (Le Men et al., 2002). This method has shown that radiometry of a class will be completely different in the shadow and light. Simpler solution have been proposed (Le Bris et al., 2008) which consist in dividing each class "*c*" into two classes "*c in shadow*" and "*c in light*". So, two distinct radiometric models are obtained for each class of roofing material from the first part of training data in AVET tool.

<u>Introduction of external knowledge in the classification process</u>

The study made by (Le Bris et al., 2008) has shown that it is possible to improve the classification results by taking into account knowledge from external sources.
First, external informations should be identified by studying the urban characteristics of the city which influence the use of roofing materials. In this study many sources are used: urban documents, land use database, planning method, history documents, conducting interviews with actors (master work, architect...)...
Secondly, these informations will be used as prior probabilities in the 'maximum a posteriori' (MAP) classification algorithm. With this classification method, the label $c_o(R)$ given to a region R is the most probable class according to the radiometric model previously estimated and to prior probabilities. Hence, $c_o(R)$ is the class c that maximises the following function:

Equation 2 :
$$\prod_{i\_external\_information\_source} = (P_i(c(R)=c)^{a_i}.(\prod_{pixel\_s\in R} P_{radiometric\_model}(I(s)\,|\,c(s)=c)^{1/Card(R)})$$

With $I(s)$ standing for the radiometry vector of pixel s ($I(s)$ is an n-dimension vector with n standing for the number of channels used for the classification), $c(z)$ meaning class of the region [or pixel] ''z'' and $P(c(z)= c)$ standing for the probability for region [or pixel] z to belong to class c. The a_i terms stand for weight parameters balancing the different prior probability sources.

Study site

To validate our methodology we need to choose a complex site in which we try to have the different aspects of the city. In fact, the city should present a sufficient urban diversity so as to make it possible to apply the methodology to other cities. Therefore our choice will be based on the following criteria:

- *Diversity:* the site should represent urban, functional and social diversity. We should have different type of habitats (houses, collective habitats, and social habitats), different activity areas (economic, industrial, and commercial) and an old downtown.
- *"Sufficient but reasonable" size*: the site should have between 50,000 and 100,000 inhabitants. This makes it easier to identify and study the various aspects of the city during the three year of my thesis.
- *Availability and accessibility of data:* in our work we need different type of data: urban, social, annual contaminant runoff *unit rates*… Therefore it is important to ensure their availability and also their accessibility in the study site. In addition, the site should be easily accessible from our laboratory in order to investigate on it (eg: to make survey).

PRIMARY RESULTS

In this part the different tests that will be applied in our methodology and the selected city are described.

Selected appropriated city

The selected city is Créteil (Department 94) located about 10 km from Paris (France). Créteil has 89 304 inhabitants (www.insee.fr) distributed over 11.5 km² which represents a reasonable size.

This city is presented in figure 2. Créteil is divided into four major historical urban areas: Old center, Mont Mesly, New Creteil I, New Créteil II as illustrated in figure 2.a. Each area presents a specific urban organization which depends especially of the period of construction. The recent zone is number four. Figure 2.b shows the interesting urban and functional diversity of Créteil.

Table 1 : Créteil characteristics

	Area	Population (in 2008)	Location
Créteil	11, 5 km²	89 304 inh	10 km from Paris (France)

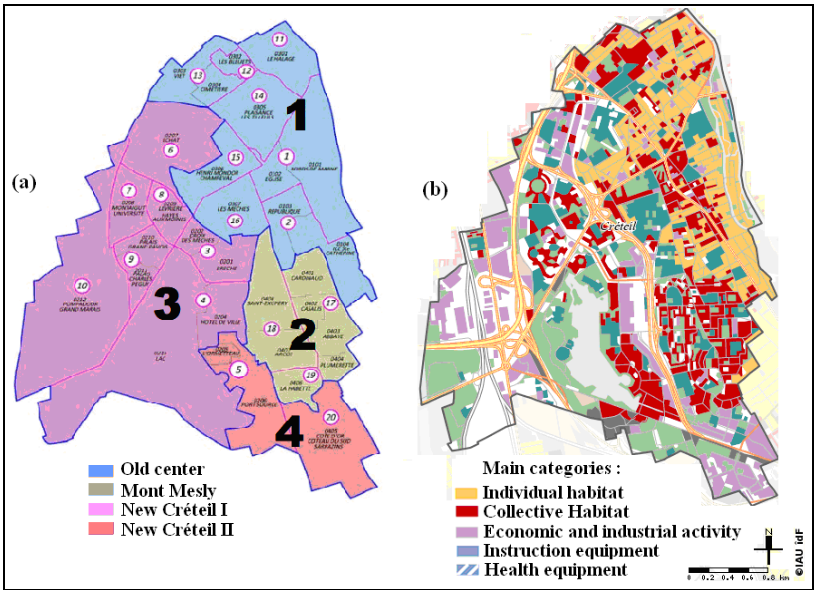

Figure 3: (a): The four urban areas of Créteil (source PLU); (b): The different land uses (source: IAU-IDF)

In fact, we can see different land use represented by different color: industrial activities located nearby (violet color), health equipment (light blue) different types of habitat (collective: red color, individual: yellow color). The land use is not homogeneous in the different urban area of the city. For example the Old center mainly consists of individual habitat. However Mont Mesly is composed of collective habitat. This distribution is mainly due to historical factors. In addition, Créteil is easily accessible from the laboratory. Finally contaminant runoff *unit rates* are available at this site (Robert Sainte, 2009).

Tests

In the classification method, different association of channels will be tested. Then we will apply the classification process to each historical urban area of Créteil (in particularly for each area we get its training data). This operation has double aim. First, we will obtain roofing material classified with their ages with taking into account possible renovation area. Secondly, we can improve results by decreasing the radiometric variations within a class knowing its age. In fact, the age of the material influences its color and then the radiometry in the image. Finally, external informations will be introduced to the classification process by testing different fusion data methods and then their performances will be tested.
The following figures represent the first results of applying only classification method using Créteil city images. In figure 4 we can see the segmentation of roofs in different regions corresponding to the different classes of materials. After segmentation, a building mask was computed as we can see in figure 5: the BD-ortho associated to its BD-topo. Finally, classification was applied and we get the results in figure 6. In this latter, every color represent the material assigned by AVET classification. These first results present misclassification. For example, as we can see in figure 6, a same slate roof was classified into three materials: slate, flat and shadow area. This is due to the shadow problem.

Figure 4 : Example of segmentation

Figure 5: Left: BD-ortho; Right: BD-topo

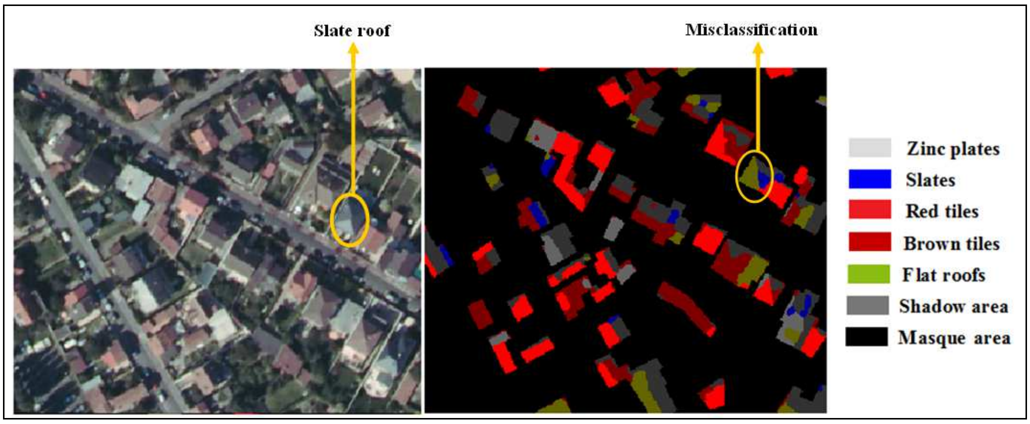

Figure 6: Example of results obtained in Créteil

Introduction of external knowledge in the classification process

In this part, the possible external knowledge to take into account in the classification process is described.
A recent work (which is still under study) aims at understanding the procedure of selecting roofing materials in a given building by studying the history, planning method, land use…at Créteil city. Interviews were conducted with various actors and stakeholders (eg: master of work, contracting authority, architect). This work seeks to identify the decision maker and to understand the key factors leading to the choice of roofing materials on construction projects. The primary results of this study have shown that the choice of roofing materials depends especially on the architect. Nevertheless, this actor is subjected to many constraints: laws constraints, aesthetics, type of building (equipment, house, tower...), the context and the period of the construction, the cost...
In this context, it is proposed to take into account the ages of buildings and the land use in our classification. On the one hand, zinc emission depends on the age of roof. On the other hand, the use of roofing material depends on the land use. In fact, zinc is mostly used in collectives habitats and rarely in individual ones.

Informations related to the land use

For each land use, probability of presence of each class of roofing materials will be calculated: *zinc plates, slates, red tiles, brown tiles and flat roofs*. These probabilities will be integrated in the MAP algorithm. In our classification method a land use database is employed and it comes from IAU_IDF (Institut d'Aménagement et d'Urbanisme de l'Ile-de-France).
These informations will be integrated in AVET tool in addition to the building mask. Indeed, we use a mask of land use.

Informations related to the ages of buildings

Créteil city is divided into four major historical urban areas. The idea is to subdivide the image of Créteil into different areas with their age. Then, we obtain the surfaces of different classes versus their ages.
Once validated, this approach allows us to compute the zinc plates surfaces versus their ages and the land use, and then the zinc runoff rates will be use to obtain the emission of zinc contaminant from zinc plates at Créteil city scale.

CONCLUSION

In conclusion, to quantify zinc emitting surfaces at the city scale, we have defined a methodology based on combining two different methods. The first one is an automatic classification method based on using AVET tool. At a small urban catchment, this automatic classification has shown some limitations. Therefore, to apply this method at the city scale, we have proposed to integrate a second theoretical method based on an urban study of the selected city. Thus, results will be improved. The selection procedure was based on different criteria to validate and generalize the methodology developed in other cities.

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