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Land cover mapping using aerial and VHR satellite images

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for distributed hydrological modelling of periurban catchments:

5

application to the Yzeron catchment (Lyon, France)

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Jacqueminet C. ⁽¹⁾, Kermadi S. ⁽¹⁾, Michel K. ⁽¹⁾, Béal D. ⁽¹⁾, Gagnage M. ⁽¹⁾,

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Branger F. ⁽²⁾, Jankowsky S. ^(2,3), Braud I. ⁽²⁾

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13 ⁽¹⁾ Université de Lyon, UMR CNRS EVS, 18 Rue Chevreul, 69363 Lyon Cedex 7,

14 France

15 ⁽²⁾ Irstea, UR HHLY, CP 220, 3bis Quai Chauveau, 69336 Lyon Cedex 9, France

16 ⁽³⁾ LUNAM Université, IFSTTAR, GER, 44340 Bouguenais, France

17

18 **Corresponding author:** Christine JACQUEMINET, Université de Lyon, UMR CNRS

19 EVS-ISTHME, 6, rue basse des rives, 42023 Saint-Etienne, France,

20 christine.jacqueminet@univ-st-etienne.fr

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1 **Abstract**

2

3 The rapid progression of urbanization in periurban areas affects the hydrological cycle
4 of periurban rivers. To quantify these changes, distributed hydrological modelling tools
5 able to simulate the hydrology of periurban catchments are being developed. Land cover
6 information is one of the data sources used to define the model mesh and parameters.
7 The land cover in periurban catchments is characterized by a very large heterogeneity,
8 where the vegetated and the artificial surfaces are finely overlapping. The study is
9 conducted in the Yzeron catchment (150 km²), close to the city of Lyon, France. We
10 explore the potential of very high-resolution (VHR) optical images (0.50 to 2.50 m) for
11 retrieving information useful for those distributed hydrological models at two scales.
12 For detailed object-oriented models, applicable to catchments of a few km², where
13 hydrological units are based on the cadastral units, manual digitizing based on the 0.5 m
14 resolution image, was found to be the most accurate to provide the required information.
15 For larger catchments of about 100 km², three semi-automated mapping procedures
16 (pixel based and object-oriented classifications), applied to aerial images (BD-
17 Ortho@IGN), and two satellite images (Quickbird and Spot 5) were compared. We
18 showed that each image/processing provided some interesting and accurate information
19 about some of the land cover classes. We proposed to combine them into a synthesis
20 map, taking profit of the strength of each image/processing in identifying the land cover
21 classes and their physical properties. This synthesis map was shown to be more accurate
22 than each map separately. We illustrate the interest of the derived maps in terms of
23 distributed hydrological modelling. The maps were used to propose a classification of
24 the Yzeron sub-catchments in terms of dominant vegetation cover and imperviousness.
25 We showed that according to the image processing and images characteristics, the

1 calculated imperviousness rates were different. This can lead to significant differences
2 in the hydrological response.

3

4 **Key-words:** distributed hydrological model, land cover mapping, impervious surface,
5 very high resolution images, image processing methods

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7 **1. Introduction**

8

9 The increase of urbanization associated with population growth is one of the major
10 changes affecting land use around big cities. The UN 2009 world urbanization prospect
11 predicts that about 68.7% of the worldwide population (94.1% in France) will live in
12 urban areas by 2050. This phenomenon mostly affects periurban areas, where natural or
13 agricultural areas are being progressively replaced by built-up areas (e.g. Meija and
14 Moglen, 2010). These changes have an impact on the water cycle through the increase
15 and acceleration of surface runoff or decrease of groundwater recharge (e.g. Chocat et
16 al, 2001; Booth et al, 2002; Matteo et al, 2006; Marsalek et al, 2007; Jacobson, 2011)
17 and an impact on water quality and bank erosion (e.g. Walsh et al. 2005; Lafont et al.,
18 2006). Water pathways are also modified by the building of networks such as drinking
19 water, sewer systems or roads (Jankowsky et al., 2012).

20 To better understand how these land use modifications affect the hydrological cycle in
21 periurban catchments, distributed hydrological models, able to take into account the
22 complexity of those areas, are very useful (e.g. Ott and Uhlenbrook, 2004; Praskievicz
23 and Chang, 2009). Land cover maps can provide useful information to set up these
24 models, both in terms of model spatial discretization and model parameters

1 specification. The requirements regarding the accuracy of the land cover maps will
2 depend on the scale of interest, as detailed below (Dehotin and Braud, 2008).

3

4 In terms of catchment discretization, a first generation of distributed hydrological
5 models was based on the Digital Elevation Model (DTM), leading to model meshes
6 corresponding directly to the DTM grid (Abbott et al., 1986a, b), isocontours of
7 altitudes (Vertessy et al., 1993) or Triangular Irregular Networks (TINs – Ivanov et al.,
8 2004). In order to take into account landscape characteristics, and define modelling
9 units which could be considered as homogeneous with regards to the hydrological
10 processes, the concept of Hydrological Response Units (HRU) was introduced by
11 Fluegel (1995). The HRUs are obtained by intersection and combination of raster and
12 vector maps such as topography, land cover, soil properties, or geology, assuming that
13 the association of these factors controls the main hydrological processes in a catchment.
14 Landscape information is of particular importance for the delineation of HRUs. The
15 nature of land use / land cover maps (vector or raster) and their exact use in the HRU
16 delineation process and model parameterization is scale dependent (Dehotin and Braud,
17 2008). In the remaining of the paper, land use will refer to the function of the land
18 surface (agriculture, residential, industrial, etc.) and land cover to the physical
19 properties of those surfaces (woody vegetation, herbaceous vegetation, bare soil,
20 building, road, etc).

21

22 For small catchments of a few km², object-oriented modelling approaches can be used.
23 In this case, HRUs are derived from the intersection of polygon layers representing
24 information such as land cover, soil type, sub-catchments and geology. Information on
25 natural and artificial drainage networks can also be taken into account. The resulting

1 hydrological mesh is formed by simple polygons with irregular shapes. They are able to
2 better represent man-made features, which significantly affect hydrological processes in
3 a catchment (Carluer and De Marsily, 2004; Lagacherie et al., 2010). This is particularly
4 relevant for periurban or urban catchments, where the urban and rural elements have
5 different response times (Braud et al., 2012) and where artificial networks can affect the
6 flow direction (Gironás et al, 2009). Examples of such object-oriented models, adapted
7 to small catchments, are the URBS (Rodriguez et al., 2003) and MHYDAS (Moussa et
8 al., 2002) models; and models built within the LIQUID modelling framework (Branger
9 et al., 2010) such as the BVFT model (Branger et al., 2010) designed to study the
10 impact of agricultural drainage and hedgerows on the hydrological cycle of small rural
11 catchments; and the PUMMA model specifically designed for periurban catchments
12 (Jankowsky, 2011; Jankowsky et al., 2010, 2011). Those models are useful to test the
13 impact of the various objects present in the catchment on the hydrological response
14 (Clark et al., 2011).

15 For larger catchments of about 50 km² to more than 10000 km², used for assessing the
16 impact of land use or climate change on the water balance, less detail on the land cover
17 will be required. Typically, raster format data, aggregated or averaged over large
18 surfaces are used in the HRUs delineation (Fluegel, 1995; Tolson and Shoemaker, 2007;
19 Krause and Hanisch, 2009; Viviroli et al., 2009).

20

21 Parameters, representing the properties of the identified HRUs must be specified and
22 land cover data is one of the data sources that can document two main hydrological
23 processes: the partition of rainfall between soil infiltration and surface runoff, and
24 evapotranspiration. For soil infiltration, especially in periurban areas, it is important to
25 distinguish between pervious and impervious surfaces as it directly impacts infiltration

1 capacity. For rural areas, vegetation type can also impact significantly soil infiltration as
2 shown by Gonzalez-Sosa et al (2010), who suggest a spatialization method of soil
3 hydraulic properties based on land cover. Vegetation cover has also a significant impact
4 on evapotranspiration according to the vegetation type (forest / herbaceous / crops,
5 deciduous / evergreen...) and the vegetation development. The latter can be described
6 using the leaf area index (LAI), which is often derived from remote sensing images,
7 based on the calculation of a vegetation index (NDVI) (Boegh et al, 2004).

8

9 Periurban catchments form a particularly complex system. They are composed of a
10 mixture of agricultural, forested and more or less densely urbanized areas in complex
11 interactions (Santo Domingo et al., 2010; Braud et al., 2012). The spatial organization
12 of these various land covers is often fragmented and the size of urban parcels is
13 generally much less than that of the agricultural or forested ones. The distinction of
14 pervious and impervious areas, and of various vegetation types is also important as they
15 correspond to surfaces with different response times. To address all these points at the
16 two scales highlighted before, specific image processing can be necessary to get the
17 required accuracy.

18

19 There exists numerous data on land use / land cover such as the US Geological survey
20 land cover map or the EU CORINE land cover map. CORINE land cover map only
21 provides information on land use (residential, industrial...) about the artificialised areas
22 but do not provide information on the distribution of developed surfaces and pervious
23 surfaces within different urbanization forms.

24 Remote sensing data are more appropriate to map biophysical surface properties.

25 Several land use mapping studies, based on remote sensing images were developed for

1 hydrology. Weng (2012) provides a review of the use of aerial and remote sensing
2 images for the mapping of impervious surfaces in urban areas. He underlines the limits
3 related to the spatial resolution of the image sensors. In periurban areas, dominated by
4 individual housing, land cover is characterized by a large diversity and a very strong
5 spatial heterogeneity where the impervious surfaces (built-up areas, roads) and the
6 pervious surfaces (vegetation, bare soils) can overlap. For this reason, mixed pixels are
7 common for coarse resolution images. The identification of built-up areas is obtained
8 by mapping the vegetation first. The remaining areas are then considered as built-up
9 areas (Bauer et al, 2004, Carlson, 2004, Gillies et al, 2003). Several studies tried to
10 decompose the mixed pixel in order to extract the vegetated, mineral and impervious
11 areas. An example is the Vegetation-Impervious surface Soil (VIS) approach proposed
12 by Ridd in 1995 (Jacobson, 2011; Small and Lu, 2006).

13

14 The increase of the number of very high-resolution sensors is a real opportunity to
15 identify the components of urban and periurban areas: "the fine spatial resolution
16 images contain rich spatial information and greatly reduce the mixed pixel problem,
17 providing a greater potential to extract much more detailed thematic information (e.g.
18 land use and land cover) and cartographic feature (building and roads)" (Weng, 2012).
19 A spatial resolution of 0.25 m to maximum 5 m is generally thought to be sufficient to
20 detect or distinguish types of buildings and individuals buildings (Jensen and Cowen,
21 1999, Puissant and Weber, 2002). Since the end of the 20th century, several maps of
22 urban areas have been derived using optical sensors with a resolution lower than 5 m
23 (IKONOS, Quickbird, ORBview...), using newly developed segmentations procedures.
24 They show the potential of those sensors and techniques to delineate buildings, roads,
25 mineral surfaces and vegetated surfaces (Lhomme et al, 2004; Karsenty et al, 2006;

1 Yuan and Bauer, 2006; Chormanski et al, 2008; Lu and Weng, 2008). However, the
2 improved spatial resolution does not always lead to easier land cover mapping, due to
3 the high spectral variation within the same land cover class (Herold and Scepán, 2003;
4 Van der Sande et al, 2003) and shadows caused by topography, tall buildings and trees
5 (Hyun-Ok et al, 2005). The use of those data derived from VHR images into distributed
6 hydrological models shows that a more accurate identification of settlement areas in a
7 catchment together with an improved estimation of the actual imperviousness of these
8 areas is beneficial for accurate calculations of surface runoff and flood peaks
9 (Wegehenkel et al., 2006; Chormanski et al, 2008; Zou and Wang, 2008).

10 However, the use of VHR imagery for the land cover mapping of complex landscapes
11 such as those encountered in periurban areas is less common (Moran, 2010). This
12 requires the identification of land cover corresponding to the various agricultural,
13 forested and urban uses. The object size is also different from one land use to the other.
14 Those studies generally address small catchments ($< 10 \text{ km}^2$) (Chormanski et al, 2008;
15 Van der Sande et al, 2003) or large catchments ($> 10 \text{ km}^2$) with a weak detailed
16 typology of land cover (Jacquin et al, 2008).

17

18 In this paper, we address the following question: in the specific context of peri-urban
19 areas characterized by a heterogeneous, contrasted and changing land use, which useful
20 information can be extracted from Very High Resolution (VHR) images for use in
21 distributed hydrological models? We propose 1/ to compare the respective inputs of
22 three types of VHR optical images and various manual and semi-automated processing
23 methods and 2/ to study the gain of combining the information from various images
24 recorded at different dates, to provide land cover information suitable for the spatial
25 discretization of distributed hydrological models adapted to periurban catchments at

1 various scales: small catchment and larger catchment. We also address the question of
2 the physical properties, relevant for distributed hydrological models, that can be
3 extracted from those images. We particularly explore the relevance of VHR images in
4 deriving impervious and pervious surfaces, as well as the characterization of various
5 vegetation types throughout the growing season in periurban areas.

6 The methodology is applied to a periurban catchment, the Yzeron catchment (147 km²),
7 located close to the city of Lyon, France. Two scales are considered: the scale of small
8 subcatchments of a few km² and the scale of larger catchments of about 100 km².

9

10 **2. Material and methods**

11

12 **2.1. Study area**

13

14 The study was carried out in the Yzeron catchment (147 km², see Figure 1), close to the
15 city of Lyon in France (483,181 inhabitants in 2008). It is located in the Monts du
16 Lyonnais, culminating at an altitude of 917 m in the western part of the catchment. The
17 catchment has a contrasted land use, with wooded and cultivated areas upstream and a
18 densely urbanized area downstream in the outskirts of Lyon city. In the catchment
19 center, individual habitats and industrial areas are mixed with agricultural fields. The
20 catchment urbanization has constantly increased since the 1960's with a population of
21 75,600 inhabitants in 1962 and 164,000 inhabitants in 2006 (Kermadi et al, 2010). The
22 large difference in altitude of about 700 m, slopes exceeding 10% in more than half of
23 the catchment (Gnouma, 2006), as well as a pedogeological and geological structure
24 (clay and granite) of low permeability, provides conditions favoring a rapid rise of river
25 discharge and flooding. Over the last few decades, the number of damaging floods has

1 increased from 3 in the 1970-1989 period to 9 in the 1989-2009 period, especially
2 downstream of the basin where human pressure is the highest (Radojevic et al, 2010;
3 Kermadi et al, 2010).

4 The catchment was studied in the framework of the AVuPUR (Assessing the
5 Vulnerability of Peri-Urban Rivers) research project (Braud et al., 2010). The objective
6 was to enhance the understanding and modelling of hydrological processes in periurban
7 catchments. In terms of modelling, one of the objective was to better represent the
8 specific features of periurban areas within distributed hydrological models, and in
9 particular the impact of impervious surfaces.

10

11 FIGURE 1 AROUND HERE – Location of study area: the Yzeron catchment (Lyon,
12 France). The figure also shows the pilot catchments (Mercier and Chaudanne) where
13 detailed land cover mapping was conducted.

14

15

16 **2.2. Building of the data set**

17

18 The land cover mapping has two objectives. First, we must restore the heterogeneity of
19 the periurban landscape and in particular the diversity of pervious and impervious
20 components and their spatial fragmentation. Second, we want to characterize the
21 different types of vegetation cover (trees, herbaceous, permanent or temporary). For this
22 purpose, we compared and combined the potential of different sensors.

23 The periurban space is composed of small objects, with small areas such as individual
24 houses, narrow roads, hedges... Their identification requires the use of VHR (Very High

1 Resolution) images. This spatial constraint led us to choose images taken from optical
2 sensors which presently offer the highest resolutions.

3 In order to be able to distinguish the various land covers (roads, buildings, water,
4 herbaceous vegetation, woody vegetation...), we favored the VHR optical sensors
5 offering large spectral information (visible and near infrared).

6 The identification of temporary vegetation can be obtained using several images,
7 recorded at different dates within the vegetation growing season, to capture the
8 plowing/crop rotation. However, in the optical domain, cloud cover often limits the
9 number of usable images. Year 2008, was a very rainy year, which limited the
10 availability of cloud free images, for use in this study.

11 Finally, as our objective was to develop automated mapping procedures, applicable to
12 large catchment areas, the method had to be based on homogenous and readily
13 accessible information. So we used satellite sensors and not airborne ones, with the
14 exception of the aerial imagery (BD-Ortho®IGN) which covers the whole French
15 territory and which is available to all research centers in France. However, the spectral
16 information from the latter data base was limited to the visible wavelength, at the time
17 the study was carried out.

18 Therefore three aerial and satellite images were acquired, covering the whole Yzeron
19 catchment: (1) the aerial images BD-Ortho®IGN, 0.50 m resolution, visible bands, from
20 May 5th 2008; (2) one QuickBird satellite image, 2.44 m resolution, visible and near-
21 infrared bands, from August 29th 2008; (3) one Spot 5 satellite image, 2.50 m resolution,
22 visible and near-infrared bands, from September 22nd 2008. More precisely, Spot 5
23 satellite imagery has an initial resolution of 5 m and is re-sampled by the data provider
24 at 2.5 m resolution (Rosak et al, 2004).

1 In addition to the images, we also used information about cadastral units, managed by
2 the Central Tax Office in France, provided by the corresponding authorities. We also
3 acquired the RPG (2008) (Registre Parcellaire Graphique) data from the ASP (Agence
4 de Service des Paiements), which provides information on the crop types on various
5 cadastral units, for the farms concerned by the common agricultural policy of the
6 European Union.

7

8

9 **3. Methods used for land cover mapping**

10

11 Specific mapping methods were proposed for the two hydrological modelling scales.
12 For small catchments, where the land use is directly used as modelling units in object-
13 oriented approaches, we extracted a photo-interpretation from the highest resolution
14 image (BD-Ortho®IGN) to get the best accuracy.

15 For large catchments, for which coarser land use classes are sufficient, we propose to
16 assess the inputs of the three types of VHR optical images presented in section 2.2. In
17 addition, as periurban areas are evolving quite quickly, we have explored reproducible
18 and automated mapping methods able to document large areas.

19

20 **3.1. Small catchment**

21

22 At the scale of small catchments, the modelling objective is to understand the impact of
23 the different landscape components on the hydrological response. For this purpose,
24 object-oriented modelling approaches, representing explicitly the landscape objects,
25 used as basic modelling units (see section 1), are very useful. The following

1 developments are adapted to models where the cadastral unit is used as a basis for the
2 model mesh such as in the MHYDAS (Moussa et al., 2002), UBRS (Rodriguez et al.,
3 2003), BVFT (Branger et al., 2010) or PUMMA (Jankowfsky et al., 2011) models. Land
4 cover information must therefore be extracted at this scale.

5 The information which must be retrieved depends on the dominant land use and aims at
6 documenting infiltration and evapotranspiration properties of the corresponding objects.
7 For the forested areas, we tried to identify the dominant vegetation type: the
8 broadleaved populations, the coniferous populations and clearings. For the agricultural
9 areas, we documented the presence or absence of vegetation and its type (orchards,
10 gardens, crops and grasslands). In the rural areas, several landscape objects, such as
11 hedges, paths and roads, ditches, lakes, can influence water pathways by diverting the
12 natural flow path derived from the topography or retaining water. For the built-up areas,
13 two types of land cover were distinguished: the pervious surfaces (vegetation, bare
14 soils) and the impervious surfaces (buildings, car parks, terraces, roads).

15 The BD-Ortho®IGN aerial image with the highest resolution (0.50 m) was the most
16 suitable image to provide all this information. The cadastral units digital layer was
17 directly superimposed to the orthorectified aerial cover. The cadastre provides
18 information on the hydrological objects boundaries (parcels, roads....) and the image
19 information about the land cover within these units. The mapping method relies mainly
20 on manual digitizing. An automated extraction of land cover classes, using aerial
21 imagery is performed in section 4 of the paper. We extracted five land cover types from
22 this automatized processing. One of them, the areas covered with trees or bushes which
23 can be distinguished by their specific spectral values, is also considered in this
24 application. The asphalt roads were directly taken from the BD-Topo®IGN (IGN-
25 France) database.

1

2 **3.2. Large catchment**

3

4 The method can be divided into two steps. In the first step, we produce a land cover
5 map using one of the three images and a given semi-automatized mapping method. The
6 quality of each map produced in step one is assessed. At the end of step one, three
7 maps, derived from images with different spatial and spectral resolutions and/or
8 obtained at different dates in 2008, are available. In the second step, we combine these
9 three maps using an intersection procedure. This combination provides a synthesis map,
10 where the land cover classes produced in the first step are improved and where new
11 classes, related to the seasonal evolution of vegetated surfaces can be extracted.

12 From the three images, we developed three semi-automated image processing methods
13 (Beal et al, 2009). We generally distinguished two types of approaches for image
14 analysis: the first one, called traditional, is a pixel oriented analysis (POA), while the
15 second one, which appeared at the beginning of the 21st century, is an object oriented
16 analysis (OOA). In the first case (POA), pixels are directly labeled (e.g. classified)
17 without considering (apart from adjacent pixels) their position within the image.
18 Afterwards, objects are defined as sets of connected pixels with the same label using
19 post-classification methods (Lillesand and Kiefer, 2007). In the second case (OOA), a
20 multi-level segmentation (e.g. a partitioning into non-overlapping segments, or regions)
21 of the image is carried out as one of the first step in the analysis. Then, classifications
22 affect objects to a unique land cover class (Neubert and Meinel, 2003, Blaschke, 2010).
23 The POA was led with the aid of the ENVI software on the Spot image. We compared
24 two methods based on OOA, which was considered the most appropriate for processing
25 very high-resolution images. The first one used the eCognition software and was led on

1 the Quickbird image. The second one is based on the Matlab software and was led on
2 the BD-Ortho®IGN. The eCognition software provided all integrated solutions while
3 the Matlab software required the complete development of the processing chain (Béal et
4 al., 2009). On Quickbird ou Spot image, we applied a different mapping method
5 without a priori on the choice of the most suitable method according to the image type.
6 The BD-Ortho®IGN imagery is composed of a 217 rectified aerial images of 1 km²
7 mosaic. The interest of using Matlab software in this study is that it allows a
8 customization of the processing for an application to a large number of images, as BD-
9 Ortho®IGN data. The processing chains applied to the three images are detailed in
10 Table 1.

11

12 TABLE 1 AROUND HERE – Algorithms of image processes applied to aerial images
13 (BD-Ortho®IGN, 0.50 m resolution) and to satellite images (Quickbird, 2.44 m, Spot,
14 2.50 m).

15

16 **4. Results**

17

18 **4.1. Small catchments**

19

20 The mapping method was applied to two small catchments (the Mercier and Chaudanne
21 sub-catchments) with a large landscape diversity. The results are presented in Figure 2.
22 We distinguished forested areas to the west and in the center, agricultural areas and
23 dispersed settlements in the center, and a densely urbanized zone to the east.

24

1 FIGURE 2 AROUND HERE – Digitizing of land cover objects from aerial images
2 (BD-Ortho®IGN) in the Mercier and Chaudanne catchments.
3
4 The following difficulties were encountered during the digitizing of the landscape
5 objects based on the cadastral map. First, the overlay of the aerial images and the
6 cadastral map, although geo-referenced in the same map projection, did not perfectly
7 match at all places of the catchment. Second, the delineation of parcels from the land
8 registry is sometimes complex due to numerous land subdivisions which can exist in
9 small areas. In these two cases, we relied on the aerial image to fix the boundaries of
10 these parcels (hedgerows, enclosures, and change in land use). The visual identification
11 of some surfaces proved to be difficult: the porous mineral surfaces and the impervious
12 mineral surfaces in urbanized areas appeared in similar clear colors, and were difficult
13 to distinguish visually.
14 Furthermore, we were not able to retrieve all the information useful for hydrological
15 modelling, especially information related to water pathways. For instance, ditches were
16 difficult to identify because the color and the linear shape were confused with the
17 vegetation. Obviously also, aerial images were not able to provide information about
18 underground networks, such as sewer networks, which must be added to the model
19 using other sources of information (for instance from the local authorities in charge of
20 their management).
21 However, this manual mapping was able to identify a large number of objects due to a
22 visual analysis. It contained a rich information at a high resolution but was very time
23 consuming. Valid for small catchments, it could not be reproduced for the larger areas
24 (whole Yzeron catchment).

1 The time necessary to get the map could be reduced by including more external data to
2 the aerial imagery. We could add several vector data on land use, if they exist at the
3 target scale, to the cadastral data, and then perform the manual mapping to extract the
4 objects used in the modelling. Up to now, there is no comprehensive data inventory
5 mapping all the components (private roads, terraces) that can be found in urbanized
6 areas. Therefore, manual digitizing remains unavoidable to map objects, relevant for
7 distributed hydrological models at this scale.

8

9 **4.2. Large catchment**

10

11 Three land cover maps were produced from the three VHR images. Five land cover
12 classes were extracted from the BD-Ortho®IGN image. Eight land cover classes were
13 extracted from the satellite images (Fig. 3). The physical properties of the surface, and
14 consequently the land cover classes that were derived, were directly linked with the
15 spectral signal measured by the sensors, and the sensors resolution. The very high
16 resolution image allowed a better object spatial delineation. However, the intra class
17 spectral variability was increased (Weng, 2012). This strong intra class variability
18 restricted the number of distinguished classes to surfaces having very distinct spectral
19 signatures. This constraint is enhanced due to the large catchment area and the
20 heterogeneity of the land cover.

21

22 FIGURE 3 AROUND HERE – Land cover semi-automated mapping from aerial images
23 (BD-Ortho®IGN, 0.50 m resolution) and satellite images (Quickbird, 2.44 m, Spot, 2.50
24 m).

25

1 Water bodies (ponds, dams) were distinguished on the satellite images but not on the
2 BD-Ortho®IGN image. In this visible canal, the identification of land cover greatly
3 relies on one parameter, which is the color. Water, which has the same green color as
4 the herbaceous vegetation, could not be distinguished. The Yzeron hydrographic
5 network, deep and narrow, was not directly perceptible on the images. It was detected
6 thanks to the river-border vegetation. For the hydrological modelling, the information
7 on the hydrographic network was extracted from the BD CARTHAGE®database (IGN-
8 France) or from a digital elevation model (DTM).

9 The BD-Ortho®IGN spectral information, limited to the visible wavelength, allowed
10 the extraction of only two vegetation classes: the woody vegetation and the herbaceous
11 vegetation. The input of near infrared wavelength allowed us to better define these two
12 vegetation classes from satellite images. For the herbaceous vegetation, two classes
13 were highlighted: the low chlorophyll content vegetation and the high chlorophyll
14 content vegetation. We used this latter information to analyze the seasonal variations of
15 herbaceous vegetation.

16

17 **4.3. Large catchment: validation of the three land cover maps**

18

19 The visual examination (Figure 3) and statistics (Table IV) of the three maps highlight
20 differences between the results of the different classifications. We used standard
21 confusion matrices (Congalton and Green, 1999) to assess the quality of the produced
22 classifications. For this purpose, we compared a classified image with a reference data
23 set, called ground truth. In numerous studies, this ground truth is collected from aerial
24 photographs (Prasada Mohapatra and Wu, 2008; Lu and Weng, 2008) and we also used
25 the aerial image as ground truth.

1 The confusion matrix is a double-entry table. Each line refers to one thematic classe of
2 the classified image. The columns correspond to the classes of the ground truth image.
3 The diagonal shows the percentage of well classified pixels. The commission errors
4 indicate the percentage of pixels attributed to another class than the one they belong to.
5 The omission errors represent the percentage of ground truth pixels no affected to the
6 class that they belong to. The Kappa index, between 0 and 1, provides a global
7 evaluation of the classification accuracy (Caloz and Collet, 2001).

8 In our study, we used the available aerial imagery, i.e the BD-Ortho@IGN recorded on
9 the 5th May 2008 as ground truth. Although this image has been used for classification,
10 it has the advantage to have been recorded the same year as our satellite images.
11 However, the recording date of the ground truth data impacted the confusion matrix
12 calculation (Tables II to V), when applied to classified images with recording dates
13 varying from May to September. Between these three dates, the vegetation phenology
14 evolved and the vegetation coverage of agricultural land also changed. Considering
15 these temporal variations between classified and reference images, we proposed two
16 Kappa index calculations, the first one taking into account all the identified classes, and
17 the second one where the two classes: "herbaceous vegetation" and "bare soil" were
18 gathered in only one class. 146 test polygons, corresponding to the 7 following classes:
19 broadleaved, coniferous, herbaceous, bare soil, building, roads and water were selected
20 using a random sampling in all the Yzeron catchment area. The Kappa indexes
21 measured by the confusion matrix on the three classifications varied from 0.73 to 0.92
22 (Table II).

23

1 TABLE II AROUND HERE – Matrices confusion results by class and image. (*): the
2 two classes "herbaceous vegetation" and "bare soils" have been assembled into only one
3 class

4

5 The classification accuracy depends on the classes. The two forest classes (broadleaved
6 and coniferous) were better extracted from the two satellite images rather than from the
7 aerial images. On the aerial image, the "forest" class tended to be under-estimated (an
8 omission error of 21.0) to the profit of the herbaceous vegetation class. The latter was
9 therefore over-estimated (commission error of 19.8) (Table III).

10 The herbaceous class result varied from one image to another. The classification
11 accuracy depends mainly on the acquisition date of the classified image. When
12 gathering the two classes "herbaceous vegetation" and "bare soils", better validation
13 results are obtained.

14 The results were much most contrasted for the "buildings" and "roads" classes. These
15 two classes were respectively identified with 95.1% and 94.6% accuracy respectively,
16 on the Quickbird image; 62.3% and 77.6% accuracy respectively on the Spot image;
17 and with 48.8% and 51% accuracy respectively on the BD-Ortho@IGN (Table II).

18 The confusion matrices analysis of the BD-Ortho@IGN and Spot images (Table III and
19 V) indicated a confusion between these two classes (buildings and roads) and the "bare
20 soil" class. These three classes equally had high omission and commission errors, which
21 revealed close spectral signatures.

22

23 TABLE III AROUND HERE – BD-Ortho@IGN confusion matrix (F: Forest, HV:
24 Herbaceous Vegetation, BS: Bare Soils, B: Buildings, R: Roads, Err. Com.: Errors of Commission, Err.
25 Omis.: Errors of Omission).

26

1 TABLE IV AROUND HERE – Quickbird image confusion matrix (BF: Broadleaved Forest,
2 CF: Coniferous Forest, HV: Herbaceous Vegetation, BS: Bare Soils, B: Buildings, R: Roads, W: Water,
3 Err. Com.: Errors of Commission, Err. Omis.: Errors of Omission).

4

5 TABLE V AROUND HERE – Spot image confusion matrix (BF: Broadleaved Forest, CF:
6 Coniferous Forest, HV: Herbaceous Vegetation, BS: Bare Soils, B: Buildings, R: Roads, W: Water, Err.
7 Com.: Errors of Commission, Err. Omis.: Errors of Omission).

8

9 **5. Land cover mapping synthesis and discussion**

10

11 We have produced three land cover maps in the same year. The Kappa indexes
12 calculated from the confusion matrices show a better global result for the classification
13 extracted from the Quickbird image. However, the classes "broadleaved" and
14 "herbaceous" are respectively better extracted from the Spot and BD-Ortho®IGN
15 images (Table II). In order to improve the information on land cover, we built a
16 synthesis map from these three classifications. This improvement included (1) a better
17 identification of stationary land cover classes from the three dates and (2) the
18 exploitation of the change in vegetation cover from May to September 2008 to identify
19 the permanent vegetation and the temporary vegetation in agricultural areas.

20 The three images were geo-referenced in the same projection system (Lambert II
21 stretched). We re-sampled the three images at the Spot spatial resolution: 2.50 meters. It
22 is the lowest resolution amongst the three available images.

23

24

25 **5.1. Derivation of a synthesis map of stationary land cover**

26

1 We performed an intersection of the three classifications and analyzed the stability of
2 classified pixel values from these three dates. The data fusion method relies on a local
3 statistical analysis. Each single combination of values extracted from the three classified
4 images takes a singular value in the resulting fusion image (with a total of up to 320
5 combinations). The pixels having the same class value on the three classifications (or
6 two) kept this value (dominant). For the pixels having different class values in the three
7 classifications, we performed a photo-interpretation. We analyzed each combination by
8 taking into account: the potential confusion between classes revealed by the confusion
9 matrices, the image characteristics, and the images processing method. Finally, 7 major
10 combinations were created: coniferous, broadleaved, permanent and temporary
11 herbaceous, permanent bare soils, water bodies, buildings, roads. The particular
12 processing of the herbaceous class is described more in details in the next section.

13

14 TABLE VI AROUND HERE – Percentage of classified pixels in each class for the
15 three classified images and for the synthesis map.

16

17 This synthesis operation provides information on the various factors, affecting the
18 classification results, such as: the spectral resolution, the spatial resolution, the image
19 recording date, the processing method and their combinations. Their effects varied
20 according to the mapped land cover.

21 In the case of forest, classification information extracted from the Quickbird and Spot
22 images compensated the weak representation of this class extracted from the BD-
23 Ortho@IGN. This weak representation could be explained by the highest spatial
24 resolution which highlighted the discontinuity of tree cover where the gaps are occupied
25 by herbaceous vegetation. The intersection of two classifications extracted from the

1 satellite images allows the delineation of the two classes "broadleaved" and
2 "coniferous", thanks to the information from the near infrared canal.

3 The percentage of the "building" class is highly variable according to the classification
4 (Table VI). The coarser the spatial resolution of the image is, the more the urban objects
5 (buildings, roads – car parks) came back more or less grouped and numerous. On the
6 other hand, the 0.50 m resolution of the aerial image allowed the extraction of these
7 objects in an individual manner (Fig. 3). However, the limited visible information of the
8 BD-Ortho@IGN did not allow the extraction of all of the urban objects because of the
9 diversity of human-made materials and their various colors. The input of near infrared,
10 classically known to help discriminating vegetation, contributed to a better distinction
11 of urban objects because of the radiometric contrast between the vegetation surfaces and
12 the artificial surfaces increased. In addition to the spatial resolution, this also explained
13 the low number of pixels classified as buildings and roads in the classification extracted
14 from the BD-Ortho@IGN.

15 Two types of images processing methods were developed on satellite images. The
16 object-oriented approach (OOA) applied to the Quickbird image had a more accurate
17 reproduction of the geometry of small sized objects, as compared to the Spot image.
18 The multi-scale object-oriented approach of the eCognition software, offered the
19 advantage to take into account spectral information but also textural, morphological and
20 multi-scale nesting of the various objects. The use of these attributes allowed solving
21 the spectral confusions between for example, porous mineral areas (plowed) and
22 impervious mineral areas (artificial areas), the urban objects being generally of smaller
23 size as compared to farming land.

24 The recording date of the image played an important role. It impacted the development
25 stage of the vegetation and especially the cover fraction of herbaceous vegetation,

1 which grows from bare soil to low and then high chlorophyll content vegetation. For
2 these reasons, the herbaceous class corresponded to a large number of combinations,
3 which are described in more details in the next section. We decided to keep a
4 "permanent bare soil" class which represents the bare mineral surfaces at the three dates.
5 The choice of the acquisition dates was important for a good representation of the
6 different vegetation types. We also took into account the rainfall season. The rainfall
7 during the eight decades before the Spot image acquisition (September 22nd 2008) were
8 two times the average; 410 mm against 219 mm. These high rainfall rates were spread
9 out over three months. The rainfall amount was just above the average in August (86.2
10 mm / 69 mm), but it was three to two times the average for July and September (176.8
11 mm / 62 mm and 146.6 mm / 88 mm respectively) (Kermadi et al, 2010). This very
12 humid summer favored the development of permanent herbaceous. The permanent bare
13 soil parcels were not numerous. The identification of built-up areas and temporary
14 vegetation was also facilitated.

15

16 Finally, the synthesis operation contributed to an improvement in the classes definition.
17 The combination of the three classifications provided a more accurate delineation of the
18 "building" class subjected to confusions with the roads and bare soils (Table VI). The
19 road network was identified as 9.4 % of the surface on the synthesis map, whereas it
20 was only 8.1% on the classified Quickbird image, and 4.4 to 5.4 % on the two other
21 classified images. The road object is a thin and straight object, more or less well
22 identified according to the sensor spatial resolution and the image processing method.
23 This land cover can locally present spectral confusion with other classes (bare soils,
24 buildings, water). According to the image recording date, it can be more or less masked
25 by the bordered tree vegetation. As a result, it is retrieved only partially for each

1 classification. The combination of the three images allows an increase in "roads" class
2 retrieval.

3

4 **5.2. Derivation of a synthesis map of temporary and permanent vegetation**

5

6 Agricultural use is characterized by intra-seasonal variations or inter-annual variations
7 of its vegetation cover. From sowing until harvesting, each production has its own
8 calendar. The spectral information provided by the sensors, especially in the near
9 infrared canal, allowed the mapping of different vegetation types according to the
10 dominant species and their chlorophyll content at different times during the year.

11 We manually digitized a mask including the agricultural areas and applied it to the three
12 classified images before further processing. Within this area, we analyzed the following
13 class combinations: low chlorophyll content herbaceous, high chlorophyll content
14 herbaceous, and bare soils.

15 The identification of temporary or permanent vegetation relies on the following
16 information: the presence or absence of vegetation and its state, revealed by the images
17 classified at the three dates; the *Recensement Parcellaire Graphique* (RPG 2008) and
18 the agricultural calendar of the Yzeron catchment main productions (Cottet, 2005; Table
19 VII). The RPG is a non-exhaustive spatial survey of crops, carried out each year by the
20 French government (see section 2.2). From the RPG data, the main crops in the Yzeron
21 catchment are, by order of importance: permanent grassland (61.5%), temporary
22 grassland (25.9%), winter cereals (7.9%), corn (1.4%), and various other crops. The
23 agricultural calendar provides information on the temporal evolution of vegetation
24 cover for the agricultural production (Table VII). The winter cereals (wheat, barley...)
25 and the corn have an annual cycle alternating between plowing and cultivating. The

1 temporary grassland has an inter-annual cycle from 2 to 5 years. For this reason, in the
2 studied year 2008, one part (not identified) of the temporary grassland had been plowed.
3
4 TABLE VII AROUND HERE – Agricultural calendar of the main agricultural
5 productions in the Yzeron catchment (Cottet, 2005) (image acquisition periods in grey).
6
7 The synthesis of the three classes extracted from the three classifications, highlighted 6
8 major combinations in the agricultural area. These 6 combinations were compared with
9 the RPG data. Table VIII shows, for each class combination, the pixel percentage
10 corresponding to each main crop from the RPG inventory. With our method, cereals,
11 winter crops correspond at 93.4% to the following class combination (herbaceous on the
12 5th May – bare soils on 31st August and 22nd September). The permanent and temporary
13 grassland correspond, respectively at 88.2% and 70.8%, to a class combination
14 revealing a vegetation cover present at the three dates. Therefore, the vegetation
15 development, as described by the three classifications, is consistent with the RPG data.
16 In the case of the grassland, being recognized as bare soil at one or two dates out of the
17 three classifications could indicate plowing (temporary grassland), mowing or pasture,
18 leading to a weaker chlorophyll content. The corn, a springtime crop, is represented at
19 51.6% by the combination class: bare soils in May and vegetation in August and
20 September. Two reasons could explain this weak result: the image recording dates were
21 not appropriate enough to capture the annual cycle of this crop and/or the RPG
22 information was not accurate enough. This latter was collected by crop islands, where
23 one or several crops can be present. The corn, a minor crop in the Yzeron catchment
24 area, could be associated with other crops in the same island. This could alter the RPG
25 information.

1

2 TABLE VIII AROUND HERE – Table crossing the class combinations extracted from
3 aerial and satellite images at the three dates and the crops identified from RPG shown in
4 percentages (H: herbaceous vegetation; LCH: low chlorophyll content herbaceous;
5 HCH: high chlorophyll content herbaceous; BS: bare soils).

6

7 At the end of these processing, the stationary landscape components and the temporary
8 and permanent vegetation cover were gathered into one unique map (Fig. 4).

9

10 FIGURE 4 AROUND HERE – Synthesis map resulting from the combination of the
11 classifications of three aerial and satellite images recorded on the May 5th 2008 (BD-
12 Ortho@IGN), August 29th 2008 (QuickBird image) and September 22nd 2008 (Spot
13 image).

14

15

16 **6. Use for distributed hydrological modelling**

17

18 As a result of our study, several land cover maps were produced at two scales: one map
19 of two small sub-catchments of a few km², and four maps for the whole Yzeron
20 catchment (150 km²).

21 In this section, we will illustrate how this land cover information was exploited within
22 two distributed hydrological models run at the two scales highlighted before, within the
23 framework of the AVuPUR research project (Braud et al., 2010 Braud et al., 2011) to
24 which this study contributed (Fig. 5). However, the possible use of the produced land
25 cover maps is not restricted to those two models, as explained in the following sections.

1

2 FIGURE 5 AROUND HERE – Flow chart of operations carried out since the extraction
3 of land cover data from the hydrological modelling. The bottom of the figure mentions
4 hydrological models used during the AVuPUR project (Braud et al., 2011), but other
5 models could be used.

6

7 **6.1. Exploitation for small scale models**

8

9 At the scale of small catchments, the exploitation of the land cover map described in
10 section 4.1 (Fig. 2), is illustrated using the PUMMA model (Jankowsky, 2011;
11 Jankowsky et al., 2011), specifically designed for periurban catchments. However, the
12 results presented below are also relevant to other object-oriented models such as the
13 MHYDAS, URBS and BVFT presented in section 1. Note also the PUMMA model
14 integrates both the BVFT and URBS models for the description of the hydrological
15 functioning of rural and urban units respectively.

16

17 In the PUMMA model (Jankowsky, 2011) urban cadastral units, hedgerows,
18 agricultural fields or retention basins are modelled with different process modules. The
19 land cover map (Fig. 2) is thus the criteria for the choice of the process module. It is
20 also the main component of the model mesh, which consists of HRUs in the rural part
21 and Urban Hydrological Elements (UHEs, Rodriguez et al., 2003) in the urban part.
22 UHEs are composed of an urban cadastral unit and part of the adjoining street, which
23 are derived from the land cover map. In the rural part, HRUs are composed of
24 agricultural fields, forested parcels and hedgerows, directly derived from the land cover
25 map of Figure 2. The polygon boundaries are used in the model to estimate the

1 exchange length for the computation of lateral flow (surface and sub-surface) and must
2 therefore be realistic. The shape of the polygons should also be as convex as possible.
3 Additional processing chains were developed within GRASS GIS to fulfil all the
4 geometric constraints of the hydrological mesh, while keeping as much as possible the
5 information about the land surface objects derived from the land use map. The
6 interested reader can refer to Jankowsky (2011) and Branger et al. (2012a) for more
7 details.

8

9 The land cover information was also used to derive some of the model parameters. For
10 each UHE, the built-up area, the road area and the natural area were calculated based on
11 the land cover map. Furthermore, in each UHE, the percentage covered by trees for each
12 of these three parts was obtained by intersection of the vegetation cover automatically
13 extracted from the BD-Ortho@IGN image with the manually digitized land cover map.

14 In the rural part, the different land cover classes (grassland, bare soils, coniferous forest,
15 etc.) induce different crop coefficients and leaf area index time series influencing thus
16 the simulated evapotranspiration. Look up tables based on the FAO (1998) were
17 therefore associated to each vegetation class to describe the annual course of those
18 parameters.

19 In addition, Gonzalez-Sosa et al. (2010) showed that the soil infiltration capacity within
20 the Mercier and Chaudanne catchments was related to the land cover. They proposed a
21 method for the spatialization of the soil hydraulic parameters which was based on a re-
22 classified version of the land cover map shown in Figure 2 (see Figure 9 in Gonzalez-
23 Sosa et al., 2010). This method was used to specify the soil surface parameters of the
24 PUMMA model.

25

1 It is beyond the scope of this paper to show the results of the PUMMA hydrological
2 model. Details can be found in Jankowfsky (2011) and Jankowfsky et al. (2011). They
3 show that the model results were very satisfactory, without any specific calibration,
4 justifying a posteriori the time consuming task of manual digitizing of the land use map
5 in the Mercier and Chaudanne catchments. The results also pointed out the importance
6 of the connection between the runoff generated on the impervious surfaces and the river
7 network. This degree of connectivity greatly influenced the model results, but this
8 information is not accessible from the aerial or satellite images. Jankowfsky et al.
9 (2012) solve this question by combining GIS based terrain analysis, in situ field work
10 and sewer system data.

11

12 **6.2. Exploitation for larger scale models**

13

14 At the scale of the whole catchment, the interest of the four land cover maps described
15 before is illustrated using the J2000 distributed hydrological model (Krause, 2002;
16 Krause et al., 2006). But the presentation would also be valid for other models using
17 HRUs as modelling units or for models based on a grid mesh (see examples in Braud et
18 al., 2011 in the context of the AVuPUR project).

19

20 The application of the J2000 model to the Yzeron catchment and the discussion in terms
21 of hydrological processes is detailed in Branger et al. (2012b). Here we only discuss the
22 part of the application related to the processing of the four land cover maps discussed in
23 this paper. In the present case study, the HRUs were defined as sub-catchments
24 corresponding to a reference network, corrected from the influence of sewer networks.
25 But the HRUs could have been defined as the intersection of various GIS layers as

1 described in section 1. The land cover maps were mainly used as input information for
2 the specification of the model parameters.

3 The J2000 model is based on a reservoir type approach. It represents rainfall
4 interception, infiltration, evapotranspiration. Within the soil surface runoff, sub-surface
5 flow and groundwater flow are also represented. The produced runoff is routed from
6 one HRU to the other, following topography and then routed in the river network, using
7 a simple kinematic wave equation.

8 The model requires, for the various land cover classes, information about the soil
9 permeability and the vegetation type, for which crop coefficient and leaf area index
10 values are associated. To provide this information, the land cover maps were simplified
11 into three dominant classes: wooded, farmland, and urban. For each sub-catchment, the
12 percentage of imperviousness and the dominant vegetation type were extracted (see the
13 following sections). This information was used to specify the model parameters within
14 each sub-catchment (Branger et al, 2012b).

15

16 **6.2.1. Characterization of vegetation coverage within the subcatchments**

17

18 Several classes of vegetation were recognized with the help of the three aerial and
19 satellite images: broadleaved, coniferous, permanent and temporary herbaceous
20 vegetation. We carried out a statistical analysis to quantify the respective fraction of
21 three vegetation components: woody vegetation, permanent herbaceous vegetation and
22 temporary herbaceous vegetation within each subcatchment. The temporary herbaceous
23 vegetation, as indicated by the RPG, is little represented: the percentage of areas
24 occupied varies from less than 1% to 19% in the sub-catchments, whereas that of the
25 forest varied from 1% to 88%, and that of the permanent herbaceous vegetation from

1 less than 1% to 82%. A subcatchment classification according to their dominant
2 vegetation is presented in Figure 6. It reveals a strong topography influence on the
3 vegetation cover: grasslands and crops occupy the flat areas whereas the forest is mainly
4 located in the steep sloped areas, westwards of the Yzeron catchment.

5

6 **FIGURE 6 AROUND HERE** – Distribution of main types of vegetation within the
7 various Yzeron sub-catchments. "Very sparse vegetation" corresponds to less than 15% vegetation
8 cover; "Sparse vegetation" to 15-45 % vegetation cover; "Dominant forest" to 50-88% forested areas;
9 "Permanent herbaceous vegetation and forest" to 49-91% of those to classes; "Permanent herbaceous
10 vegetation" to 35-82% of this class; "Permanent and temporary herbaceous vegetation" to 43-80%
11 herbaceous including 10-19% temporary herbaceous.

12

13 **6.2.2. Comparative quantification of impervious surfaces from the various land** 14 **cover maps**

15

16 The quantification of impervious areas requires the translation of the land cover types,
17 in terms of imperviousness. The available information about land cover was used as
18 follows. We proposed two classes: the class of pervious areas which included forest,
19 herbaceous, water and bare soils; and the class of impervious surfaces which grouped
20 together buildings and roads.

21 We quantified the rate of impervious surfaces within the various subcatchments for the
22 four available maps and compared the results in Table IX. Table IX shows the
23 percentage of imperviousness, of 112 subcatchments, classified into 10 classes with
24 equal counts. The percentages calculated from the synthesis map were very close to
25 those calculated from the satellite images (Spot and QuickBird), which have similar
26 spatial resolution. These percentages differ from those calculated using the

1 classification retrieved from the BD-Ortho@IGN. The largest percentage for this
2 classification is less than 25% for the more urbanized subcatchments, whereas it reaches
3 more than 68% for the three other classifications. The weak amount of impervious
4 surfaces on the map retrieved from BD-Ortho@IGN is explained by the very high
5 spatial resolution which contributes to a more accurate rendering and less spread
6 identification of built-up areas (see § 5.1.).

7

8 TABLE IX AROUND HERE – Classification of the subcatchment percentages of
9 impervious surfaces into 10 classes, with equal counts, for the four processed images.

10

11 FIGURE 7 AROUND HERE – Percentage of imperviousness within the subcatchments
12 from the three land cover maps extracted from BD-Ortho@IGN, Quickbird image, Spot
13 image and the synthesis map of the three classifications.

14

15 Figure 7 provides a map of the subcatchment percentage of imperviousness using the
16 same color scale for the four maps. The imperviousness rate is different from one land
17 cover map to the other, however, Figure 7 shows that they all provide the same
18 hierarchy of subcatchments. The percentage of the subcatchments imperviousness
19 decreases from the east towards the west. This can be related to the urbanization rates
20 which decreases from the town of Lyon, located eastwards of the catchment area,
21 towards the western part of the Yzeron catchment. However, the estimated values differ
22 from one map to another. Therefore, the absolute values must be used with care within
23 hydrological models, as imperviousness is a sensitive parameter of hydrological models
24 in periurban areas. As an example, Branger et al. (2012b) applied the J2000 model
25 without calibration to the Yzeron catchment, using the parameters derived from the

1 simplified classification shown in Figures 6 and 7. They show that the total discharge is
2 slightly affected, but that the components of the discharge (base flow, sub-surface flow,
3 surface runoff) are sensitive to the choice of the image. BD-Ortho@IGN classification,
4 which leads to the lowest imperviousness has a lower surface runoff and a higher base
5 flow than the three other maps.

6

7 **7. Discussion and conclusions**

8

9 In this study, we used three VHR remote sensing images (BD-Ortho@IGN, Quickbird
10 and Spot 5) to map land cover and derive physical properties of the surface relevant for
11 distributed hydrological modelling in periurban catchments. Two scales were
12 considered: the scale of catchments of a few km² and of catchments of about 100 km².

13 As a whole, the optical sensors, with spatial resolution from 0.50 m to 2.50 m, were
14 found appropriate for the mapping of the heterogeneous land cover of periurban
15 catchments. The retrieved maps restored the large land cover fragmentation with
16 numerous vegetal and artificial components.

17

18 For the small scale catchments, where object-oriented distributed hydrological
19 modelling approaches are used, the method based on photo-interpretation offers the
20 advantage of being able to select accurately the information useful at the scale of the
21 modelling units, although it is time consuming and quite slow. Compared to the
22 information available on cadastral maps, the 0.5 m resolution BD-Ortho@IGN image
23 allowed the retrieval of valuable information about natural and impervious areas inside
24 urban cadastral units, hedgerows, vegetation type and rotation and bare soils. It greatly
25 improved the model parameterization. At this scale, given the average size of cadastral

1 units and of the objects we want to represent in the modelling, the 0.50 m resolution of
2 the aerial image appeared satisfactory. However, as shown with the analysis at the
3 whole Yzeron scale, the low spectral resolution (absence of near-infrared canal) of BD-
4 Ortho@IGN, at the time of our study, prevented the use of automatic methods due to the
5 poor retrieval of land cover. Since then, a near-infrared canal has been added to BD-
6 Ortho@IGN, which could solve partly this problem.

7

8 For larger scale catchments (of about 100 km²), where the surface properties are
9 aggregated over larger areas (HRUs), currently used hydrological models do not
10 represent explicitly the various landscape objects but generally use percentage areas of
11 various land cover types within the modelling units. For these models, the spectral
12 resolution of VHR sensors has a greater impact on the quality of the derived land cover
13 map than the spatial resolution. Thanks to the near-infrared canal, it was possible to
14 retrieve a larger number of land cover types using the Quickbird and Spot images than
15 using the BD-Ortho@IGN. The comparison of the results obtained using the object-
16 oriented classification and the pixel based analysis (comparison of Quickbird and Spot
17 mapping) showed the interest of object-oriented segmentation. They were better able to
18 delineate the small artificialized objects encountered in periurban areas. Indeed, the
19 results of the two maps were quite comparable in the rural areas (see Figure 3) where
20 the object size was much larger than the image resolution. On the other hand,
21 differences were more important in urbanized areas where the size of the objects was
22 smaller.

23 In addition, when moving from a 0.5 m to a 2.5 m resolution, there is a change of scale
24 and definition of the retrieved land covers. For instance at 2.50 m, the mapping
25 procedure identified the built-up areas associated with one or several buildings and

1 adjacent terraces, a part of a forest, while at 0.50 m we distinguished each building or
2 woody component. The spatial resolution choice should therefore be done according to
3 the hydrological model requirements, for example the delineation of built-up areas or
4 those of each building.

5 The comparison of the land cover maps, obtained from the different images and by
6 different processing methods, highlighted their variability and complementarity. The
7 combination of several images, such as the three classifications used in our study into a
8 synthesis map proved to increase the land cover reliability. First, the comparison of
9 extracted maps from the three classifications allowed a cross-validation of the retrieved
10 land cover classes. Second, the multi-temporal character of aerial and satellite images
11 provided information on the variations of vegetation cover and increased the retrieved
12 information by distinguishing the permanent vegetation from the temporary vegetation.
13 Therefore, the synthesis map, which was built using images at various resolutions and
14 recorded at various dates within the vegetation growing cycle provided the most
15 accurate land cover mapping.

16 The land cover information extracted using VHR resolution images improved the
17 delineation and identification of the areas occupied by each type of land cover or
18 hydrological object. This also led to a better quantification of the hydrological model
19 parameters, in particular the imperviousness rate. The synthesis map, which is the best
20 compromise between the three compared approaches should provide the most reliable
21 estimation of this parameter.

22 Hydrological models also require information about the impervious surfaces connected
23 to the river network. Obviously, this information cannot be provided by the land cover
24 mapping and must be obtained using other sources of information.

25

1 The final land cover classification and requirements in terms of the various modelling
2 spatial scales are the results of a constant discussion between geographers and
3 hydrologists. This experience highlights the interest of a shared work where the
4 exploration of the potential of remote sensing images could help in the development of
5 hydrological models and vice versa. The current increase in the availability of sensors
6 with resolution lower than 1 m provides to remote sensing imagery users, and in
7 particular to hydrologists, an accurate information about land cover and its physical
8 properties. This multiplication of the sensors promotes the production of “land cover”
9 data bases, which must be chosen according to the input data (spatial and spectral
10 resolution), the mapping method (manual or automatic), the nomenclature, the date of
11 the images and finally the validity of the produced maps. Although the spectral
12 information brought by the new sensors is often restricted to the visible and near-
13 infrared wave lengths, which restrain the number of classes which can be retrieved, the
14 spatial accuracy of the provided maps is consistent with the requirements in terms of
15 hydrological modelling of periurban catchments.

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7

8 **References**

9 Abbott, M., Bathurst, J., Cunge, J., O'Connell, P., Rasmussen, J., 1986a. An introduction
10 to the european hydrological system, "SHE". 1: History and philosophy of a
11 physically-based, distributed modelling system. *Journal of hydrology*, 87, 45-59.

12 Abbott, M., Bathurst, J., Cunge, J., O'Connell, P., Rasmussen, J., 1986b. An introduction
13 to the european hydrological system, "SHE". 2: Structure of a physically-based,
14 distributed modelling system. *Journal of hydrology*, 87, 61-7.

15 Bauer, M. E., Heinert, N. J., Doyle, J. K., Yuan, F., 2004. Impervious surface mapping
16 and change monitoring using Landsat remote sensing. ASPRS Annual Conference
17 Proceedings, Denver, Colorado, May 2004 (Unpaginated CD ROM).

18 Beal, D., Gagnage, M., Jacqueminet, C., Kermadi, S., Michel, K., Jankowsky, S.,
19 Branger, F., Braud, I., 2009. Cartographie de l'occupation du sol pour la
20 modélisation hydrologique spatialisée du cycle de l'eau en zone périurbaine.
21 Actes du XXVII^e congrès INFORSID, Atelier SIDE2009 " Systèmes
22 d'Informations et de Décision pour l'Environnement ", Toulouse, France, 26 mai
23 2009, 23-32. Available at <http://eric.univ-lyon2.fr/~sbimonte/side2009.html>

24 Blaschke, T., 2010. Object based image analysis for remote sensing. *ISPRS Journal of*
25 *Photogrammetry and Remote Sensing*, 65, 2-16.

1 Boegh, E., Thorsen, M., Butts, M.B., Hansen, S., Christiansen, J.S., Abrahamsen, P.,
2 Hasager, C.B., Jensen, N.O., van der Keur, P., Refsgaard, J.C., Schelded, K.,
3 Soegaard, H., Thomsen, A., 2004. Incorporating remote sensing data in physically
4 based distributed agro-hydrological modelling. *Journal of Hydrology*, 287, 279–
5 299

6 Booth, B.D., Hartley, D., Jackson, R., 2002. Forest cover, impervious-surface area, and
7 the mitigation of stormwater impacts. *Journal of the American water resources*
8 *association*, 38 (38), 835-845.

9 Branger, F., Braud, I., Debionne, S., Viallet, P., Dehotin, J., Hénine, H., Nédélec, Y.,
10 Anquetin, S., 2010. Towards multi-scale integrated hydrological models using the
11 LIQUID framework. Overview of the concepts and first application examples,
12 *Environmental Modeling & Software*, 25, 1672-1681,
13 doi:10.1016/j.envsoft.2010.06.005.

14 Branger, F., Jankowsky, S., Vannier, O., Viallet, P., Debionne, S., Braud, I., 2012a.
15 Use of open-source GIS for the pre-processing of distributed hydrological models,
16 *Geospatial free and open source software in the 21rst century*, Bocher, E., Neteler,
17 M. (Eds), *Lecture notes in Geoinformation and Cartography*, Chapter 3, 35-48.

18 Branger, F., Kermadi, S., Jacqueminet, C., Michel, K., Labbas, M., Krause, P., Kralisch,
19 S., Braud, I., 2012b. Assessment of the influence of land use on the hydrology of
20 a periurban catchment using a distributed modelling approach. *Journal of*
21 *Hydrology*, special issue 'Hydrology of periurban catchments: processes and
22 modelling", in revision.

23 Braud, I., Chancibault, K., Debionne, S., Lipeme Kouyi, G., Sarrazin, B, Jacqueminet,
24 C., Andrieu, H., Béal, D., Bocher, E., Boutaghane, H., Branger, F., Breil, P.,
25 Chocat, B., Comby, J., Dehotin, J., Dramais, G., Furusho, C., Gagnage, M.,

1 Gonzalez-Sosa, E., Grosprêtre, L., Honegger, A., Jankowsky, S., Joliveau, T.,
2 Kermadi, S., Lagouy, M., Leblois, E., Martin, J.Y., Mazagol, P.O., Michell, K.,
3 Molines, N., Mosini, M.L., Puech, C., Renard, F., Rodriguez, F., Schmitt, L.,
4 Thollet, F., Viallet, P., 2010. The AVuPUR project (Assessing the Vulnerability of
5 Peri-Urbans Rivers) : experimental set up, modelling strategy and first results.
6 Proceedings of the 7th Novatech 2010 Conference, June 28-July 1 2010, Lyon,
7 France, 10 pp, http://hal.archives-ouvertes.fr/hal-00527564_v1/

8 Braud, I., Branger, F., Chancibault, K., Jacqueminet, C., Breil, P., Chocat, B.,
9 Debionne, S., Dodane, C., Honegger, A., Joliveau, T., Kermadi, S., Leblois, E.,
10 Lipeme Kouyi, G., Michel, K., Mosini, M.L., Renard, F., Rodriguez, F., Sarrazin,
11 B., Schmitt, L., Andrieu, H., Bocher, E., Comby, J., Viallet, P., 2011. Assessing
12 the Vulnerability of PeriUrban Rivers. Rapport scientifique final du projet
13 AVuPUR (ANR-07-VULN-01), 96 pp. In French, available at
14 <http://cemadoc.cemagref.fr/cemoa/PUB00034642>

15 Braud, I., Breil, P., Thollet, F., Lagouy, M., Branger, F., Jacqueminet, C., Kermadi, S.,
16 Michel, K., 2012. Evidence of the impact of urbanization on the hydrological
17 regime of a medium-sized periurban catchment in France, Journal of Hydrology,
18 special issue on periurban catchments, 10.1016/j.jhydrol.2012.04.049.

19 Caloz, R. Collet, C., 2001. Précis de télédétection; vol. 3: Traitements numériques
20 d'images de télédétection. Presses de l'Université de Québec et Agence
21 universitaire de la Francophonie, Sainte-Foy (Québec), 386 p.

22 Carlson, T. N., 2004. Analysis and prediction of surface runoff in an urbanizing
23 watershed using satellite imagery. Journal of the American Water Resources
24 Association, 40(4), 1087–1098.

- 1 Carluer, N., De Marsily, G., 2004. Assessment and modelling of the influence of man-
2 made networks on the hydrology of a small watershed: implications for fast flow
3 components, water quality and landscape management. *Journal of Hydrology*,
4 285(1-4): 76-95.
- 5 Chocat, B., Krebs, P., Marsalek, J., Rauch, W., Schilling, W., 2001. Urban drainage
6 redefined: from stormwater removal to integrated management. *Water and
7 Science Technology* , 43, 61-68.
- 8 Chormanski, J., Van de Voorde, T., De Roeck, T., Batelaan, O., Canters, F., 2008.
9 Improving Distributed Runoff Prediction in Urbanized Catchments with Remote
10 Sensing based Estimates of Impervious Surface Cover. *Sensors*, 8, 910-932.
- 11 Clark, M.P., Kavetski, D., Fenicia, F., 2011. Pursuing the method of multiple working
12 hypotheses for hydrological modeling. *Water Resources Research*, 47 p.
- 13 Congalton, R.G., Green, K., 1999. *Assessing the Accuracy of Remotely Sensed Data:
14 Principles and Practices*, Lewis publishers.
- 15 Cottet, M., 2005. Evolution de l'occupation du sol dans le bassin versant de l'Yzeron au
16 20^{ème} siècle : premiers éléments pour un diagnostic hydrologique. *Mémoire de
17 Master 1, Université Lyon III*, 105 p.
- 18 Dehotin, J., Braud, I., 2008. Which spatial discretization for distributed hydrological
19 models? Proposition of a methodology and illustration for medium to large scale
20 catchments. *Hydrology and Earth System Sciences*, 12, 769-796.
- 21 FAO, 1998. *Crop Evaporation - Guidelines for computing crop water requirements*,
22 FAO, Irrigation Paper n° 56, Rome.
- 23 Fluegel, W., 1995. Delineating hydrological response units by geographical information
24 system analyses for regional hydrological modelling using PRMS/MMS in the

- 1 drainage basin of the River Brol, Germany. *Hydrological Processes*, 9 (3-4), 423-
2 436.
- 3 Gillies, R. R., Box, J. B., Symanzik, J., Rodemaker, E. J., 2003. Effects of urbanization
4 on the aquatic fauna of the Line Creek watershed, Atlanta — A satellite
5 perspective. *Remote Sensing of Environment*, 86, 411–422.
- 6 Gironás, J., Niemann, J.D., Roesner, L.A., Rodriguez, F., Andrieu, H., 2009. A morpho-
7 climatic instantaneous unit hydrograph model for urban catchments based on the
8 kinematic wave approximation. *Journal of Hydrology* 377, 317-334.
- 9 Gnouma, R, 2006. Aide à la calibration d'un modèle hydrologique distribué au moyen
10 d'une analyse des processus hydrologiques : application au bassin versant de
11 l'Yzeron. Thèse de l'Institut National des Sciences Appliquées de Lyon, France,
12 412 p. Available at [http://theses-search.insa-lyon.fr/thematic-
13 search.html?menuKey=theses_insa&submenuKey=authors&id=gnouma_raouf](http://theses-search.insa-lyon.fr/thematic-search.html?menuKey=theses_insa&submenuKey=authors&id=gnouma_raouf)
- 14 Gonzalez-Sosa, E., Braud, I., Dehotin, J., Lassabatère, L., Angulo-Jaramillo, R.,
15 Lagouy, M., Branger, F., Jacqueminet, C., Kermadi, S., Michell, K., 2010. Impact
16 of land use on the hydraulic properties of the topsoil in a small French catchment.
17 *Hydrological Processes*, 24(17), 2382-2399.
- 18 Herold, M., Scepan, J., 2003. Object-oriented mapping and analysis of urban land
19 use/cover using IKONOS data. *in* *Geoinformation for European-wide Integration*,
20 Benes (ed.), Millpress, Rotterdam, 531-538.
- 21 Hyun-Ok, K., Kleinschmit, B., Kenneweg, H., 2005. High resolution satellite imagery
22 for the analysis of sealing in the metropolitan area Seoul. *Göttinger
23 Geographische Abhandlungen*, Vol. 113, 281-286.

- 1 Ivanov, V., Vivoni, E., Bras, R., Entekhabi, D., 2004. Preserving high-resolution
2 surface and rainfall data in operational-scale basin hydrology: a fully-distributed
3 physically-based approach. *Journal of Hydrology*, 298, 80-111
- 4 Jacobson, C.R., 2011. Identification and quantification of the hydrological impacts of
5 imperviousness in urban catchments: a review. *Journal of Environmental*
6 *Management*, 92, 1438-1448.
- 7 Jacqueminet, C., Kermadi, S., Michel, K., Chocat, B., 2011. Méthodes de cartographie
8 de l'occupation du sol et de son évolution pour le suivi des phénomènes
9 hydrologiques de bassins versants périurbains, Fiche technique OTHU n°24, 4 p.
10 <http://www.irstea.fr/sites/default/files/ckfinder/userfiles/files/FTOTHU11.pdf>
- 11 Jacquin, A., Misakova, L., Gay, M., 2008. A hybrid object-based classification
12 approach for mapping urban sprawl in periurban environment. *Landscape and*
13 *Urban Planning*, 84, 152–165.
- 14 Jankowsky, S., Branger, F., Braud, I., Debionne, S., Viallet, P., Rodriguez, F., 2010.
15 Development of a suburban catchment model within the LIQUID® framework,
16 Proceedings of the International congress on Environmental Modelling and
17 Software, iEMSs 2010, 5-8 July 2010, Ontario, Ottawa, Canada, 9 pp. Available
18 in session S10 “Integrated modelling Technologies” at
19 <http://www.iemss.org/iemss2010/index.php?n=Main.Proceedings>
- 20 Jankowfsky, S., 2011. Distributed hydrological modelling of small peri-urban
21 catchments. Application to the Chaudanne and Mercier sub-basins (Yzeron). PhD
22 thesis. University of Grenoble, France, 351 pp, available at , available at
23 <http://tel.archives-ouvertes.fr/tel-00721988>
- 24 Jankowfsky, S., Branger, F., Braud, I., Gironas, J., Rodriguez, F., 2012. Comparison of
25 catchment and network delineation approaches in complex suburban

1 environments. Application to the Chaudanne catchment, France, Hydrological
2 Processes, in press, doi: 10.1002/hyp.9506

3 Jensen, J.R., Cowen, D.C., 1999. Remote sensing of urban/suburban infrastructure and
4 socio-economic attributes. Photogrammetric Engineering and Remote Sensing,
5 65, 611-622.

6 Karsenty, A., Alzir Felipe, B., Silva Centeno, A.J., 2006. Classification orientée objet
7 de la perméabilité des sols en zone urbaine à l'aide d'imagerie très haute
8 résolution et de données laser scanner à Curitiba (Brésil). Anais XIII Simpósio
9 Brasileiro de Sensoriamento Remoto, Florianópolis, Brasil, 21-26 abril 2007,
10 INPE, 565-572.

11 [http://www.researchgate.net/publication/228864171](http://www.researchgate.net/publication/228864171_Classification_orientee_objet) Classification orientee objet
12 de la perméabilité des sols en zone urbaine à l'aide d'imagerie très haute résolu
13 tion et de données laser scanner Curitiba (Brésil)

14 Kermadi, S., Florent, R., Jacqueminet, C., Michel, K., 2010. Inondations et occupation
15 du sol dans un bassin versant périurbain : l'Yzeron (ouest lyonnais). Publications
16 de l'Association Internationale de Climatologie, 23, 313-318.

17 Krause, P., 2002. Quantifying the impact of land use changes on the water balance of
18 large catchments using the J2000 model. Physics and Chemistry of the Earth, 27,
19 663-673.

20 Krause, P., Bäse, F., Bende-Michl, U., Fink, M.; Flügel, W., Pfenning, B., 2006.
21 Multiscale investigations in a mesoscale catchment - hydrological modelling in
22 the Gera catchment, Advances in Geosciences, 9, 53-61, 2006.

23 Krause, P., Hanisch, S., 2009. Simulation and analysis of the impact of projected
24 climate change on the spatially distributed water balance in Thuringia, Germany.
25 Advances in Geosciences, 21, 33-48

- 1 Lafont, M., Vivier, A., Nogueira, S., Namour, P., Breil, P., 2006. Surface and hyporheic
2 oligochaete assemblages in a French suburban stream. *Hydrobiologia*, 564, 183-
3 193.
- 4 Lagacherie, P., Rabotin, M., Colin, F., Moussa, R., Voltz, M., 2010. Geo-MHYDAS: a
5 landscape discretization tool for distributed hydrological modeling of cultivated
6 areas. *Computers & Geosciences* 36, 1021-1032.
- 7 Lhomme, S., Weber, C., He, D., 2004. L'extraction du bâti à partir d'images satellitaires
8 THRS. *Revue internationale de Géomatique*, Vol. 14, (3-4/2004), 465-484.
- 9 Lillesand, T.M., Kiefer, R.W., 2007. *Remote Sensing And Image Interpretation*, 5th Ed.,
10 Wiley India Pvt. Limited, 820 p.
- 11 Lu, D., Weng, Q., 2008. Mapping Urban Impervious Surfaces from Medium and High
12 Spatial Resolution Multispectral Imagery, *in*: Weng Q. (Editor), *Remote sensing
13 of impervious surfaces*, CRC Press, Taylor&Francis Series in Remote Sensing
14 Applications, pp. 59-73.
- 15 Marsalek, J., Jiménez-Cisneros, B.E., Karamouz, M., Malmquist, P.A., Goldenfum, J.
16 and Chocat, B., 2007. *Urban water processes and interactions*. UNESCO IHP-VI
17 program, UNESCO, Paris, 239 pp.
18 www.bvsde.paho.org/bvsacd/cd63/149460E.pdf
- 19 Matteo, M., Randhir, T., Bloniarz, D., 2006. Watershed-scale impacts of forest buffers
20 on water quality and runoff in urbanizing environment. *Journal of the American
21 Water Resources Association* 132, 144-152.
- 22 Meija, A.I., Moglen, G.E., 2010. Spatial distribution of imperviousness and the space-
23 time variability of rainfall, runoff generation, and routing. *Water Resources
24 research*, 46: W07509, doi:10.1029/2009WR008568.

- 1 Moran, 2010. Land Cover Classification in a Complex Urban-Rural Landscape with
2 Quickbird Imagery. *Photogrammetric Engineering and Remote Sensing*, 76(10):
3 1159–1168.
- 4 Moussa, R., Voltz, M., Andrieux, P., 2002. Effects of the spatial organization of
5 agricultural management on the hydrological behaviour of a farmed catchment
6 during flood events. *Hydrological Processes*, 16(2), 393-412.
- 7 Neubert, M., Meinel, G., 2003. Evaluation of segmentation programs for high resolution
8 remote sensing applications, in: Schroeder, M., Jacobsen, K., Heipke, C. (Eds.),
9 Proceedings Joint ISPRS/EARSel Workshop "High Resolution Mapping from
10 Space 2003", Hannover, Germany, October 6-8, 2003 (8 p., CD-
11 ROM).<http://www.ipi.uni-hannover.de/fileadmin/institut/pdf/neubert.pdf>
- 12 Ott, B., Uhlenbrook, S., 2004. Quantifying the impact of land-use changes at the event
13 and seasonal time scale using a process-oriented catchment model. *Hydrology and
14 Earth System Sciences*, 8(1), 62-78.
- 15 Prasada Mhapatra, R., Wu, C., 2008. Subpixel impervious estimation with IKONOS
16 imagery: an artificial neural network approach, in: Weng Q. (Editor), *Remote
17 sensing of impervious surfaces*, CRC Press, Taylor&Francis Series in Remote
18 Sensing Applications, 21-37.
- 19 Praskievicz, S., Chang, H., 2009. A review of hydrological modelling of basin-scale
20 climate change and urban development impacts. *Progress in Physical Geography*,
21 33(5), 650-671.
- 22 Puissant, A., Weber, C., 2002. The utility of Very High Spatial Resolution images to
23 identify urban objects. *Geocarto International*, vol. 17, 1, 31-41.

- 1 Radojevic, B., Breil, P., Chocat, B., 2010. Assessing impact of global change on flood
2 regimes. *International Journal of Climate Change Strategies and Management*,
3 2(2), 167-179.
- 4 Ridd, M. K., 1995. Exploring a V-I-S (Vegetation-Impervious Surface-Soil) model for
5 urban ecosystem analysis through remote sensing: Comparative anatomy for
6 cities. *International Journal of Remote Sensing*, 16(12), 2165-2185.
- 7 Rodriguez, F., Andrieu, H., Creutin, J.-D., 2003. Surface runoff in urban catchments:
8 morphological identification of unit hydrographs from urban databanks. *Journal of*
9 *Hydrology*, 283(1-4), 146-168.
- 10 Rosak A., Latry C., Pascal V., Laubier D., 2004. From Spot 5 to Pleiades HR: evolution
11 of the instrumental specifications. *Proceedings of the 5^{ème} International*
12 *Conference on Space Optics (ISCO 2004)*, 30 March - 2 April 2004, Toulouse,
13 France, 141-148. www.congrexprojects.com/icso/2004-proceedings
- 14 Santo Domingo, N., Refsgaard, A., Mark, O., Paludan, B., 2010. Flood analysis in
15 mixed-urban areas reflecting interactions with the complete water cycle through
16 coupled hydrologic-hydraulic modelling. *Water Science and Technology*, 62,
17 1386-1392.
- 18 Small, C., Lu, J.W.T., 2006. Estimation and vicarious validation of urban vegetation
19 abundance by spectral mixture analysis. *Remote Sensing of Environment*, vol.
20 100, Issue 4, 441-456.
- 21 Tolson, B., Shoemaker, C., 2007. Cannonsville Reservoir Watershed SWAT2000 model
22 development, calibration and validation. *Journal of Hydrology*, 337, 68-86.
- 23 Tucker, C.,J., 1979. Red and photographic infrared linear combinations for monitoring
24 vegetation. *Remote Sensing of Environment*, 8, 127-150.

- 1 Van der Sande, C.J., de Jong, S.M., de Roo, A.P.J., 2003. A segmentation and
2 classification approach of IKONOS-2 imagery for land cover mapping to assist
3 flood risk and flood damage assessment. *International Journal of Applied Earth
4 Observation and Geoinformation*, 4, 217-229.
- 5 Vertessy, R. A., Hatton, T., O'Shaughnessy, P., Jayasuriya, M., 1993. Predicting water
6 yield from a mountain ash forest catchment using a terrain analysis based
7 catchment model. *Journal of Hydrology*, 150, 665-700.
- 8 Viviroli, D., Zappa, M., Gurtz, J., Weingartner, R., 2009. An introduction to the
9 hydrological modelling system PREVAH and its pre- and post-processing tools.
10 *Environmental Modelling & Software*, 24, 1209-1222.
- 11 Walsh, C.J., Fletcher, T.D., Ladson, A.R., 2005. Stream restoration in urban catchments
12 through redesigning stormwater systems: looking to the catchment to save the
13 stream. *Journal of the North American Benthological Society*, 24(3), 690-705.
- 14 Wegehenkel, M., Heinrich, U., Uhlemann, S., Dunger, V., Matschullat, J., 2006. The
15 impact of different spatial land cover data sets on the outputs of a hydrological
16 model: a modelling exercise in the Ucker catchment, North-East Germany.
17 *Physics and Chemistry of the Earth*, 31(17), 1075-1088.
- 18 Weng, Q., Hu, X., Lu, D., 2008. Extracting impervious surface from medium spatial
19 resolution multispectral and hyperspectral imagery: a comparison. *International
20 Journal of Remote Sensing*, 29(11), 3209–3232.
- 21 Weng, Q., 2012. Remote sensing of impervious surfaces in the urban areas:
22 requirements, methods and trends. *Remote sensing of environment*, 117, 34-49.
- 23 Yuan, F., Bauer, M.E., 2006. Mapping impervious surface using high resolution
24 imagery: a comparison of object-based and per pixel classification. *ASPRS 2006
25 Annual Conference*, Reno, Nevada, May 1-5, 8 p.

- 1 <http://www.asprs.org/a/publications/proceedings/reno2006/0178.pdf>
- 2 Zhou, Y., Wang, Y.Q., 2008. Remote sensing of impervious surface area for improved
- 3 hydrologic modeling. The International Archives of the Photogrammetry, Remote
- 4 Sensing and Spatial Information Sciences. Vol. XXXVII. Part B8. Beijing 2008,
- 5 73-78.
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10 Figure 3: Land cover semi-automated mapping from aerial images (BD-Ortho®IGN,
11 0.50 m resolution) and satellite images (Quickbird, 2.44 m, Spot, 2.50 m).

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13 Figure 4: Synthesis map resulting from the combinaison of the classifications of three
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22 Figure 6: Distribution of main types of vegetation within the various Yzeron sub-
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24 vegetation" to 15-45 % vegetation cover; "Dominant forest" to 50-88% forested areas; "Permanent
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2 10-19% temporary herbaceous.

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8

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