Land Cover Semantic Annotation Derived from High Resolution SAR Images

Corneliu Octavian Dumitru, Gottfried Schwarz, and Mihai Datcu

***Abstract*— Users of remote sensing images analyzing land cover characteristics are very much interested in classification schemes that define a consistent set of target categories. Up to now, a number of established classification schemes are mainly being used by interpreters of medium resolution optical satellite images focusing on large scale land cover. In contrast, we concentrate in this publication on the definition of a new classification scheme for high resolution synthetic aperture radar (SAR) images that are mostly taken over built-up areas. Here we can see many small details of buildings, industrial facilities, and infrastructure that have to be classified. However, the appearance of details in high resolution SAR images is often difficult to understand for human observers and therefore calls for an automated semantic annotation of the target objects that has to follow a number of specific scientific guidelines. We demonstrate that a selection of representative SAR images with subsequent feature extraction and relevance feedback classification during the generation of a classification scheme leads to a reliable definition of a new high resolution multi-level SAR image classification scheme that can be applied globally for semantic annotation in an automated chain.**

***Index Terms*—Annotation; land cover; semantics; SAR**

I. Introduction

A comprehensive in-depth content-oriented analysis of images needs detailed information about their semantics (i.e., the meaning of the local and global image content taken from a thesaurus of semantic labels). When we look at satellite images as we know them from a variety of Earth observation missions, we are able to extract much more knowledge from our image archives once we can query, for instance, the temporal evolution of *airport runways within a given country*, or the

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percentage of a city area occupied by parking lots. To this end, we have to annotate visible objects with local content descriptors following a common scheme (e.g., *public park*, *skyscraper*, *power plant*). Then these annotations can be used for further investigations. However, the image annotation has to be scientifically valid, shall be consistent over large collections of image data, and, in order to be comprehensive, should cover complete images rather than a few isolated regions of interest, and should be done with the help of automated tools.

We managed to set up a rule set of scientific guidelines and - based on these guidelines - created an initial framework of manual and partly automated steps to perform the required semantic annotation together with the definition of a robust multi-level classification/annotation scheme tailored to X-band high resolution SAR images. The focus of this paper will be on the description of the scientific guidelines and the generation of our semi-automated classification/annotation scheme where image patches are classified into categories and annotated. This scheme is embedded within a hierarchical multi-level approach allowing us to integrate elementary annotations within higher level annotations. The multi-level approach seems to be a mandatory step for the annotation of high resolution images where local pixel-based information is not sufficient for context recognition.

At a first glance, our three-level scheme with a total number of 150 categories is rather similar to already existing schemes. However, we offer increased discrimination power for individual objects in urban areas. To our knowledge, this is a new capability that is not yet offered by other existing classification systems. As a proof of concept, we applied statistical analyses to the annotation results of images taken over different continents and countries. It turns out that we can clearly see typical regional characteristics. Future work will aim at the integration of our annotation scheme within ontology concepts and geographical information systems.

In the following, we will concentrate on land cover information derived from radar images taken by satellites [42], i.e., space-borne SAR images notably of the TerraSAR-X mission [52]. Images of this civil SAR mission are comparable to other high resolution SAR data being available as standard products where an image (or a time series of images) typically comprises several thousand rows and columns with a resolution of up to 1 m, and signal-to-noise ratios that permit automated image classification. For more detailed product descriptions, see, for instance, [52]. In our case, we mainly look at the high resolution characteristics of urban scenes, of infrastructure, and of vegetation and we could apply classification to single images as well as to time series of images and obtained useful results. Thus, this publication aims at advanced Earth observation, the digital modelling of human activities on our planet, and new database applications.

The paper is organized as follows: Section 2 explains the scientific background of our approach, followed by Section 3 containing a survey of already existing land cover description approaches, in particular with regard to urban characteristics and multi-level description schemes. Section 4 summarizes past and current related work already being done within the community,

while Section 5 outlines the specific characteristics of our selected high resolution SAR images. Section 6 details our approach and explains our targeted data sets and the required processing chain. Validation results are presented in Section 7, followed by an outlook in Section 8 and a conclusion in Section 9. Finally, the Appendix compares further details of several existing classification schemes.

II. Scientific Background

Automated land cover classification derived from satellite images is an important research topic that has to be adapted continuously to the evolving imaging characteristics of new sensors and their image products. In order to obtain reliable user-oriented classification results, one needs annotation schemes that fully exploit the data content of advanced imagers and their data processing chains. The conceptions of these annotation schemes are of profound interest to the scientific community, as they tell us what level of information extraction can be attained routinely from the available images.

In our case, we concentrate on an annotation scheme for X-band SAR images with meter scale resolution. Typical instruments delivering such images are TerraSAR-X, COSMO-SkyMed, or airborne SAR images with many similar characteristics [50]; however, we are not aware of a common annotation scheme for these data that fully exploits the imaging potential of high resolution SAR images notably over urban and industrial areas. Thus, we were prompted to conceive and validate a new multi-instrument approach for high resolution SAR images with the aim of providing compatible annotation results.

Our concept had to be based on a number of requirements and constraints:

- Our overall goal was to annotate full scenes with all local target characteristics. Due to the high local variability of urban and industrial sites, we had to foresee spatially detailed annotation based on small image patches with individual annotation. Thus, for classification and annotation, we cut all images into a series of patches with a typical size of 200 × 200 pixels for images with a resolution of 1 m (cf. Section 6.3.2).
- Another goal was to provide reliable annotation despite the presence of typical SAR imaging effects such as the wide dynamic signal range, the large diversity of targets, speckle noise, multiple reflections, radar shadows, and overlays. As a consequence, we had to minimize misclassifications by including a category of *unclassified* for unidentifiable local targets. This additional category prevents the spoiling of classification results by outliers. In addition, we can use data of different quality levels (e.g., signal-to-noise ratio) by considering their respective metadata annotations.
- In order to get robust patch annotation despite a big quantity of image data, we had to resort to (semi-)supervised classification and a top-down multi-level image annotation approach explaining the spatial semantic context of a patch (e.g., *Settlements* / *Inhabited built-up areas* / *High density residential areas*). A three-level structure turned out to be our preferred solution. From a technical standpoint, this multi-level annotation can be supported by a visual display of the full

image that contains all contextual information needed by an operator for visual annotation support. The operator support will be minimized by limiting it to an initial training phase and auto-annotation during further operations. This technique is described in [5].

- Reliable classification and annotation calls for realistic sample data to be used during an initial training phase. When it comes to the classification of vegetation and built-up areas, we have to take into account regional vegetation zones, seasonal effects, and local architecture. On the other hand, we can use image metadata to determine dates, locations and various other recording parameters. The consequence for our annotation scheme is to re-use the same annotation labels but to re-train and to store them separately when necessary.
- Finally, a number of technical requirements to be met were easy scalability to incorporate new classes (see the examples being contained in [47], efficient operations, traceability of classification results, provision of internal analysis tools, removal of outdated information, and the capability of re-processing).

III. Land Cover Description Approaches

Our land cover description scheme shall exploit the full information content of image data. Thus, during a first classification step, we had to consider the spatial and temporal neighborhood relationships of our data prior to any semantic annotation. In addition, our stringent discrimination requirements necessitated specific classification approaches. Typical examples are contained in [40] and [53]. Based on our experience with high resolution SAR images, we know that pixel-based classification approaches do not provide good results. As a consequence, we had to resort to sliding windows, medium sized patches, irregularly shaped regions, full images, image stacks, and sequences of images. Then, the semantic information extraction will rely on pixel windows, extracted features, detected clusters, and derived categories. Internally, this can result in a variety of database structures and can culminate in fuzzy approaches. Additional support may be gained from already existing semantic catalogues and interfaces with geographic databases [45] and [23].

As will be described in Section 6, we took all these requirements into account and developed a new land cover description scheme specifically tailored for high resolution SAR images. This scheme is based on the decomposition of images into medium-sized regular patches and exploits the multi-level interrelationships of features and clusters.

IV. Related Work

In this section, we outline some well-known taxonometric classification/nomenclature schemes that are currently being available. Our description is structured into four parts: the first part contains an overview of classification schemes mainly addressing global land cover and vegetation, the second part is related to Europe or specific European countries (e.g., the UK and Germany) and is based on additional in-situ measurements, the third part contains open-source community services, and the last

part gives an example of commercially available products. As a conclusion, Table I contains a summary of key figures presented in this section. Ongoing standardization and embedding approaches (e.g., ISO and INSPIRE) for land cover description will be dealt with in Section 8. Please note that the existing classification schemes are mostly vegetation-oriented and have not been developed for high resolution SAR images. Therefore, our SAR image classification/annotation system will be described in Section 6.

TABLE I.

EXISTING CLASSIFICATION SCHEMES AND THEIR NUMBER OF LEVELS AND CATEGORIES.

Classification scheme	**Levels**	**Categories**
Anderson	2	46
LCCS	4	>250
GTOS	not specified	3 main
CLC	3	65
Urban Atlas	4	27
LUCAS	3	84
LCM	2	23
ATKIS	3	212
OpenStreetMap	1	not specified
GeoNames	1	not applicable
Global Land Cover 30	1	10
ArcGIS	not specified	proprietary

4.1. Global vegetation oriented schemes

The following schemes have been developed for the analysis of global land cover and land use based on medium resolution optical satellite images. Thus, these schemes cannot be used for a detailed analysis of urban scenes.

4.1.1. Anderson classification scheme

Anderson proposed one of the first land cover/land use classification schemes in 1976 [1]. The Anderson scheme has been defined because different types of satellite images had become available. Its levels 1 and 2 are generally for US users who desire data on a nationwide, interstate, or state-wide basis, while levels 3 and 4 are usually for users who need local information at the intrastate, regional, county, or municipal level. This classical classification system was mainly applied to medium resolution Landsat and Skylab data. For further details, see Appendix Table A.I.

4.1.2. Land Cover Classification System

The Land Cover Classification System (LCCS) of the Food and Agriculture Organization (FAO) has been designed to fulfil specific crop yield requirements with respect to crop types, fruits, etc. and to generate maps at various scales. This classification concept has the goal to identify changes that affect the global Earth system, or occur in isolated places [12]. Table A.I in the Appendix contains the LCCS land cover classification scheme [49], [12]. Recently, this classification system was expanded into a land cover meta-language (LCML) that allows flexible parameterizations. The LCCS approach has been applied successfully to a number of projects.

Global Land Cover 2000 is a global and regional land cover map project managed by the European Commission's Joint Research Centre (JRC). A short description is given in [35]. For further details, see [36].

The ESA-GlobCover project delivered global land cover maps covering the entire Earth [6]. The GlobCover project [21] contributed to land use, ecosystems, and climate change.

The U.S. Geological Survey (USGS), the JRC, and the University of Nebraska-Lincoln have generated the GLCC (Global Land Cover Characterization) 1 km resolution global land cover data set to be used for different applications [60].

From the USGS National Map Urban Area Imagery collection, 100 images that cover various urban areas were selected and grouped in the UC Merced Land Use Dataset [54].

4.1.3. Global Terrestrial Observing System

The Global Terrestrial Observation System (GTOS) of the United Nations describes land dynamics [27]. It provides coarse resolution land cover data on a five-year cycle and periodic monitoring of forest areas at fine resolution. GTOS provides information about the land cover distribution of vegetation and the related land use. Currently, the produced global land cover maps are at a resolution between 250 m to 1 km.

4.2. European in-situ supported schemes

The next five schemes have been compiled with support from field experts who collected in-situ ground truth measurements. Therefore, the defined categories are more detailed in the sense of human-made infrastructure than the previous ones (see Section 4.1).

4.2.1. CORINE Land Cover

CORINE Land Cover (CLC) is a continuous activity of the European Environment Agency (EEA) and provides information on land cover with a mapping unit of 25 hectares and a mapping scale of 1:100,000. Currently, CLC covers 38 European

countries. A detailed list of categories is contained in Appendix Table A.II. Since end of 2014, a new version of CLC, namely CLC2012 with a mapping unit of 5 hectares has been available to the users [8], [57]. CLC is characterized by the introduction of categories describing artificial surfaces and water bodies.

4.2.2. Urban Atlas

The Urban Atlas of EEA offers a high resolution land use map of 228 urban areas (i.e., cities) in Europe [39]. The cities are mapped at a geometric resolution of approximately 1:10,000 having a minimum mapping unit of 0.25 hectares. The Urban Atlas (UA) [19] uses an extension of the CLC nomenclature with respect to artificial surfaces. Its full list of categories is shown in Appendix Table A.II.

4.2.3. LUCAS

The LUCAS survey is a recurring activity of Eurostat [22]. It is an in-situ land cover/land use survey. Its data is mainly gathered by surveyors on ground. In the LUCAS 2009 survey 235,000 points were visited by 500 field surveyors on the spot. Those spots were selected from a standard 2 km grid with in total around 1 million points covering 23 European Union countries. A survey point corresponds to a circle with a 1.5 m radius so the point represents an area of about 7 square meters. The land cover and the visible land use around each survey point were classified according to the harmonized LUCAS land cover and land use nomenclatures [22]. A list of the LUCAS level 1 and 2 categories is presented in Appendix Table A.II. The advantages of LUCAS are a detailed description of crop types and woodland.

4.2.4. Land Cover Map

The British Land Cover Map (LCM) represents a repeated thematic classification of the United Kingdom recorded by satellite images and by external data sets used to refine the classification [24]. They were classified using a hierarchical nomenclature corresponding to the Joint Nature Conservation Committee (JNCC) [34]. The minimum mappable area is 0.5 hectares [38].

4.2.5. ATKIS

ATKIS is an official German topographic/cartographic information system and aims at the semantic and geometric integration of geo-scientific data sets. ATKIS uses geological and soil science maps with scales of 1:5,000, 1:25,000, 1:50,000, and 1:100,000 [44]. Depending on the map scale, different categories are defined. This classification scheme [33], [3] is very specific and it is very difficult to convert remote sensing image data into the detailed ATKIS categories.

4.3. Open source community schemes

During the last years, a number of crowd source services became available that support the analysis of satellite images with highly detailed geographical information.

4.3.1. OpenStreetMap

OpenStreetMap (OSM) [28] maintains an open source public domain global editable map based on information provided by users. OSM is built by a community of users that contribute and maintain the data [43]. OSM has millions of entries covering all continents. First results of time-evolving linked geospatial data are described in [4].

4.3.2. GeoNames

GeoNames [25] is a public domain collection of 10 million geographical names and consists of over 8 million unique features whereof 2.8 million populated places and 5.5 million alternate names. GeoNames is integrating geographical data such as names of places in several languages, elevations, population, etc. from various sources. GeoNames allows the user to combine its data with remote sensing data. In our case, GeoNames can be used for the semantic annotation of our target areas. First results of our in-house applications are described in [4].

4.3.3. Global Land Cover 30

We expect that future publications will also rely on the recently published Global Land 30 dataset [56] that provides a near-global high resolution land cover annotation of our planet.

4.4. Commercial schemes

A number of commercial vendors offer annotation packages that support the classification of remote sensing images.

4.4.1. Example: ArcGIS

ArcGIS(TM) is an example of a commercial product that supports the generation of maps, data management, the analysis of geographic data, data editing, geomatic processing, and the handling of metadata. For semantic annotation, ArcGIS uses ArcCatalog, an annotation tool that administrates GIS data, raster images, etc. Further details are contained in [7].

V. Our Selected High Resolution SAR Images

In our case, we concentrated on TerraSAR-X, an X-band instrument with various operating modes, selectable polarization, and

a number of product generation options [52]. A typical TerraSAR-X image taken in High Resolution Spotlight mode can be acquired with an incidence angle between 20° and 50°. When recorded with a range bandwidth of 300 MHz, it has an along-flight scene size of about 5 km and an across-flight scene size between 5 km and 10 km. Its pixel spacing lies between 0.5 m and 1.5 m with a resolution between 1.1 m and 3.4 m. The radiometric resolution will range from 1.4 dB to 3.1 dB. The product size may be up to 800 MB.

VI. Our Approach

6.1. Rationale

High resolution SAR images contain a lot of information about target characteristics. A detailed inspection of TerraSAR-X images revealed that human settlements can be classified into inhabited and un-inhabited built-up areas with a large number of sub-categories. The same holds for industrial production areas, for military facilities, and for transport. For instance, a more detailed analysis of airport images resulted in 11 clearly identifiable sub-categories ranging from control towers and hangars to test stands and individual airplanes. Hence, we defined a classification scheme based on reliably discernible categories that can be retrieved from available high resolution SAR images (see Section 6.2.1 and Appendix Table A.I).

Currently, this proposed semantic annotation scheme will become a general semantic catalogue for various kinds of Earth observation images [20].

6.2. Data set

6.2.1. Target area selection

We generated a test and validation data set that mainly covers urban and industrial areas together with their infrastructure from all over the world, selected from the TerraSAR-X archive [52]. The data set contains 288 full scenes of urban and non-urban target areas (41 scenes from Africa, 6 from Antarctica, 59 from Asia, 80 from Europe, 40 from the Middle East, 54 from North and South America, and 8 from ocean surfaces). These scenes were selected based on their availability, their content, the typical diversity of country-specific land cover, and the recording parameters of each scene. The locations of the scenes are marked with red colored diamonds in Fig. 1. If a country comprises too many scenes, only one red diamond is shown for this country.

6.2.2. Product type selection

We selected high resolution Spotlight mode images because they provide a lot of details in urban areas. We took horizontally polarized (HH) images as this option is most frequently recorded over land and we used images taken from ascending and descending pass directions.

As for the product generation options, we selected multi-look ground range detected data as they are not affected by geometrical interpolation effects over mountainous terrain and thus are most suited for feature extraction. This was also the reason for choosing radiometrically enhanced products that are optimized with respect to radiometry (i.e., reduced speckle) [52]. As a result of the product mode and product parameter selection, our images have a pixel spacing of 1.25 m and a resolution of about 2.9 m. The average size of each full scene is 4,200 × 6,400 pixels (rows × columns).

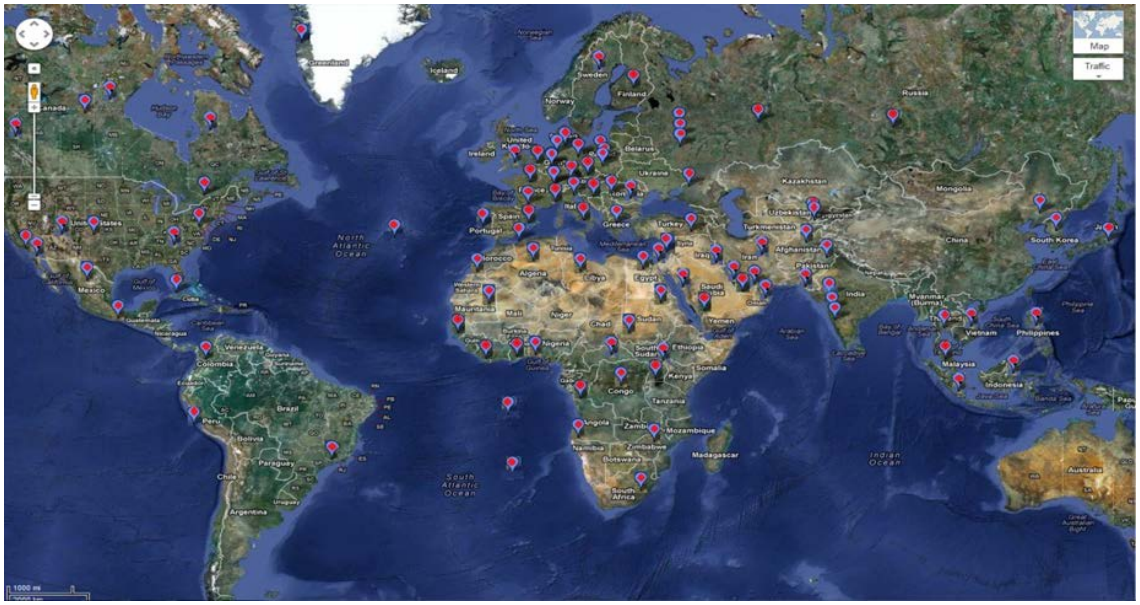


Fig. 1. Locations of our target areas on a Google map [26] marked with red diamonds.

6.3. Classification/annotation chain

6.3.1. Processing chain

For all our TerraSAR-X images we need classification and semantic annotation. As we have high resolution images, pixel-based methods do not capture the contextual information, and global features describing the overall properties of images are not accurate enough for local features. Therefore, our general approach during the annotation scheme development was to tile each TerraSAR-X image into a number of non-overlapping patches, and to perform feature extraction, classification and annotation for each individual patch. The corresponding processing chain is shown in Fig. 2.

The main steps of the processing chain are:

- Tile the selected images into patches of 160 × 160 pixels. This patch size has been selected based on the findings of [15] as it yielded the best precision/recall results (for more details, see also Section 6.3.2).
- Generate a quick-look image of each tiled patch for the operator making the classification.
- Extract a feature vector from each patch using Gabor filtering and compute the mean and standard deviations of the Gabor coefficients. We inter-compared a number of promising alternatives and options [15]. It turned out that a combination of

patches consisting of 160 × 160 pixels with 4 scales and 6 orientations yielded the best precision/recall results – even for a high number of different categories when trained interactively by active machine learning and combined with an appropriate classifier (see below).

- Classify the feature vectors of each patch and group the feature vectors into categories using a Support Vector Machine (SVM) with relevance feedback [11]. Each patch is assigned to a single category based on the dominant content of the patch (including the category *Unclassified*).

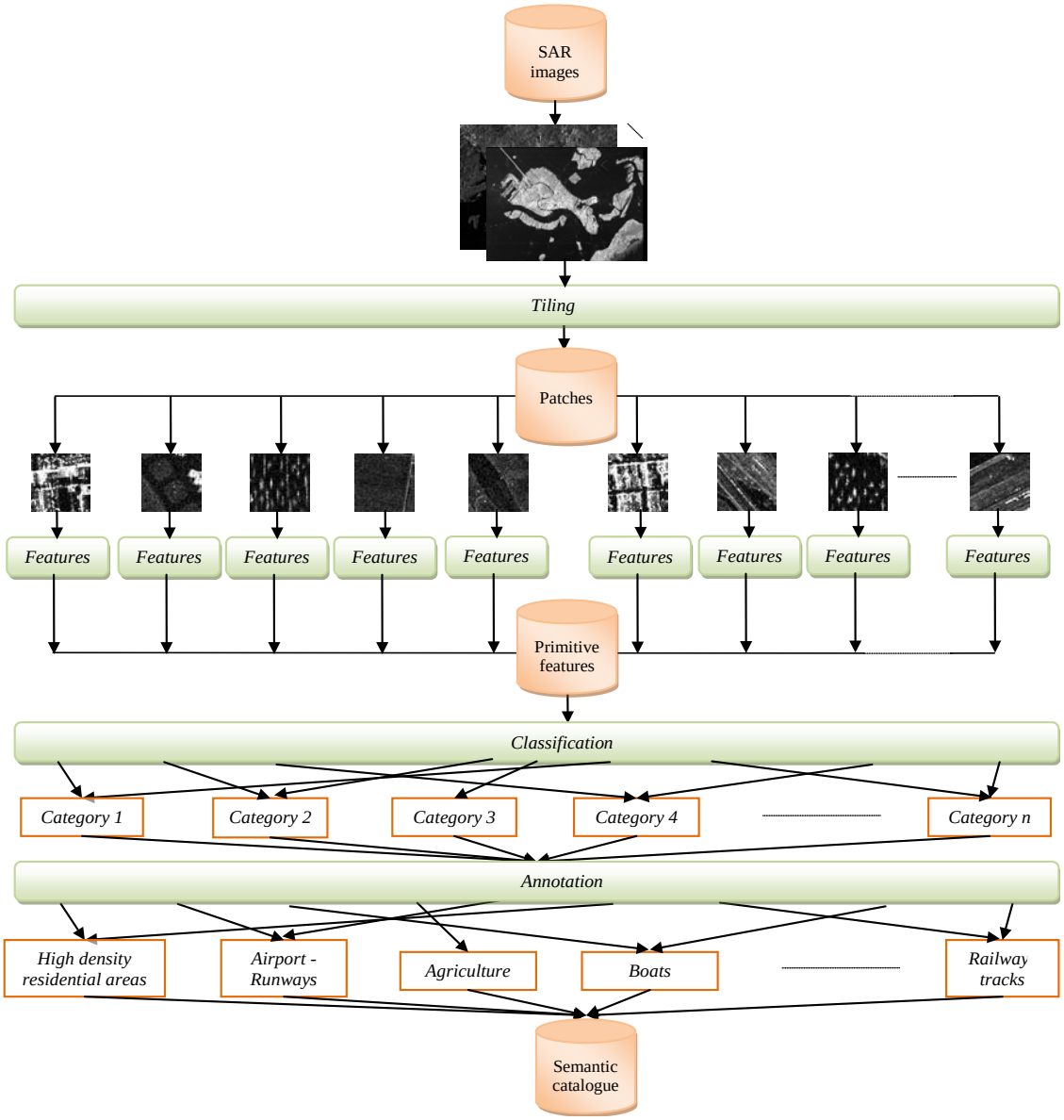


Fig. 2. Classification/annotation processing chain: Download and store the selected image data, tile each image into patches and generate quick-looks, extract a feature vector from each patch, classify the feature vectors into categories using an interactive learning algorithm based on SVM, and manually select a semantic annotation for each category (based on our annotation scheme).

- Annotate each category by giving an appropriate semantic meaning to each category [14]. For this we use reference data (e.g., Google Earth) for visual support. The annotations may be region-specific and are stored in a corresponding semantic catalogue.

This full chain is semi-automated, i.e., the first three functions of the chain are automated, while the last two functions require manual operator interaction. The latter functions are: (a) Classification including an operator to rank the patches via Human-Machine Interaction. The operator has to give positive and negative examples which are grouped into categories of relevance (i.e., active learning with at least one positive and several negative examples typically resulting in 15 to 20 image patches being used for training). By experience, we need about 5 to 7 interactive iteration clicks to obtain satisfactory classification accuracy for each category. (b) Annotation, i.e., the (time consuming and manual) selection of the proper semantic labels for each category.

After the generation of our annotation scheme, we use the derived feature sets and the set of semantic categories for a fully automated semantic annotation of newly arriving images.

6.3.2. Selection of tiling, feature extraction, and classification parameters

The processing chain defined above needs some additional parameters. Our selection of the patch size was made so that a patch covers a typical object on ground. In common remote sensing scenes as described by [48], this value lies around 200 × 200 m, and given our pixel spacing of 1.25 m, results in a patch size of 160 × 160 pixels.

We also had to choose a feature extraction algorithm. After detailed comparisons between gray level co-occurrence matrix techniques, bag-of-words techniques, non-linear short time Fourier transforms, filter banks, and Gabor filters, we selected a Gabor filter set with 4 scales and 6 orientations [37] and [15].

For classification, we chose a Support Vector Machine (SVM) with Relevance Feedback (RF). We selected a χ^2 kernel for this learning machine that makes highly accurate classifications with a small number of examples for each category [10]. Our SVM was embedded into an environment that supports users with a RF software tool being linked to our image database and a precision/recall tool [16].

6.4. Our proposed classification/nomenclature scheme

Currently, there are only a few publications dealing with the definition of semantic categories for high resolution SAR images (e.g., [41], [46], and [51]), while the situation is less critical for optical images where we already have, for instance, a number of higher level object-based categories such as delineations of central business districts [58]. In our case, we were able to define a nomenclature adapted to our TerraSAR-X images and we propose a hierarchical semantic annotation scheme with 3 levels and

with a total of 150 categories of which 9 categories belong to level 1, 73 categories belong to level 2, and 68 categories belong to level 3 (cf. Appendix Table A.I). Interestingly, the level 3 categories describe details of man-made infrastructure, while the categories describing natural environments do not have level 3 refinements.

Table II shows, as an outline, a selected number of semantic categories extracted from the full hierarchical annotation scheme. The semantic annotation of each category is depicted on the left, while the right side contains a quick-look example of each semantic annotation. For graphical illustrations and a deeper understanding of typical feature vectors and cluster centers for each category, the reader is referred to [59].

In the following, we show two examples using fully detailed data: In the first example, we semantically annotate different cities of the world and demonstrate that the regional characteristics have a profound impact on the obtained categories. In the second example, we annotate a time series of a disaster area images of Sendai, Japan. Here, one can clearly see that a flooding caused by a tsunami changed many of the previously retrieved surface cover categories.

For the first example, we chose four cities from different continents: Bangkok in Asia (Fig. 3), Beirut in the Middle East (Fig. 4), Venice in Europe (Fig. 5a), and San Francisco in North America (Fig. 5b). Fig. 6 summarizes the annotation results for the city of Venice, Italy.

For the second example, we chose a pre- and a post-disaster image from a time series of images that illustrate the effects of the March 2011 tsunami in Japan. Fig. 7 shows three categories that were identified as damages caused by the tsunami. We can use our classification/nomenclature scheme for change detection by comparing the pre- and post-event classification results of geographically overlapping image pairs. This semantic annotation can be used for qualitative analysis in rapid mapping scenarios. For further details, see [13].

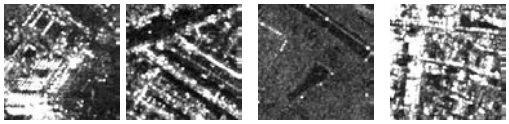


Fig. 3. Four examples of categories that can be retrieved from a Bangkok, Thailand image. From left to right: Skyscrapers, roads, ploughed agricultural land, and medium density residential areas.

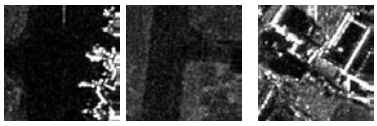
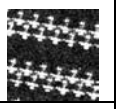
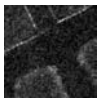
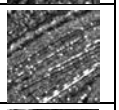
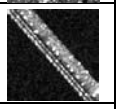
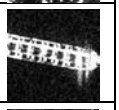
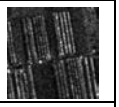
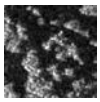
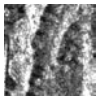
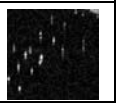


Fig. 4. Three examples of categories that can be retrieved from a Beirut, Lebanon image. From left to right: Airport taxiways, airport runways, and industrial buildings.

TABLE II.

OUR PROPOSED THREE LEVEL SCHEME: LEVEL 1 (BOLD FACE CATEGORY NAMES) GIVES GENERAL INFORMATION ABOUT THE CATEGORIES, LEVEL 2 (BULLETS) GIVES MORE DETAILS FOR THE CATEGORIES DEFINED IN LEVEL 1, AND LEVEL 3 (CIRCLES) IS THE MOST DETAILED LEVEL OF THE PROPOSED SCHEME.

Settlements • Inhabited built-up areas o High density residential areas ……..	
• Uninhabited built-up areas o Skyscrapers ……..	
Industrial production areas • Industrial facilities o Industrial buildings ……..	
• Industrial storage areas o Depots and dumps ……..	
Military facilities • Air force facilities ……..	
Transport • Airports o Runways ……..	
• Roads o Streets and roads ……..	
• Railways o Railway tracks ……..	
• Bridges and tunnels o Bridges and fly-overs ……..	
• Ports and shipbuilding facilities o Harbor infrastructure ……..	
• Water vessels o Small vessels (boats) ……..	
Agriculture • Greenhouses ……..	
Natural vegetation • Mixed forest ……..	
Bare ground • Mountains ……..	
Water bodies • Buoys ……..	

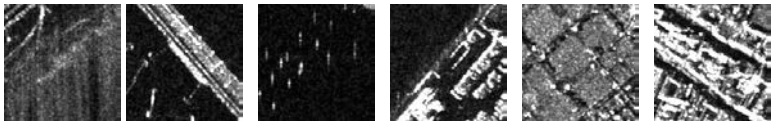


Fig. 5a). Six examples of categories that can be retrieved from a Venice, Italy image. From left to right: Breaking waves, bridges, buoys, docks and shipyards, cemeteries, and high density residential areas.

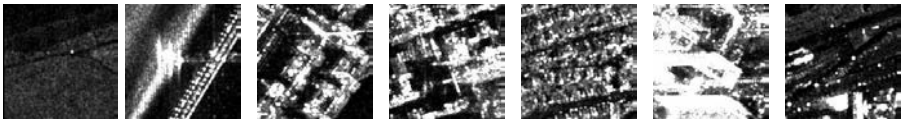


Fig. 5b). Seven examples of categories that can be retrieved from a San Francisco, USA image. From left to right: Beach, bridges, docks and shipyards, high density residential areas, medium density residential areas, skyscrapers, and streets.

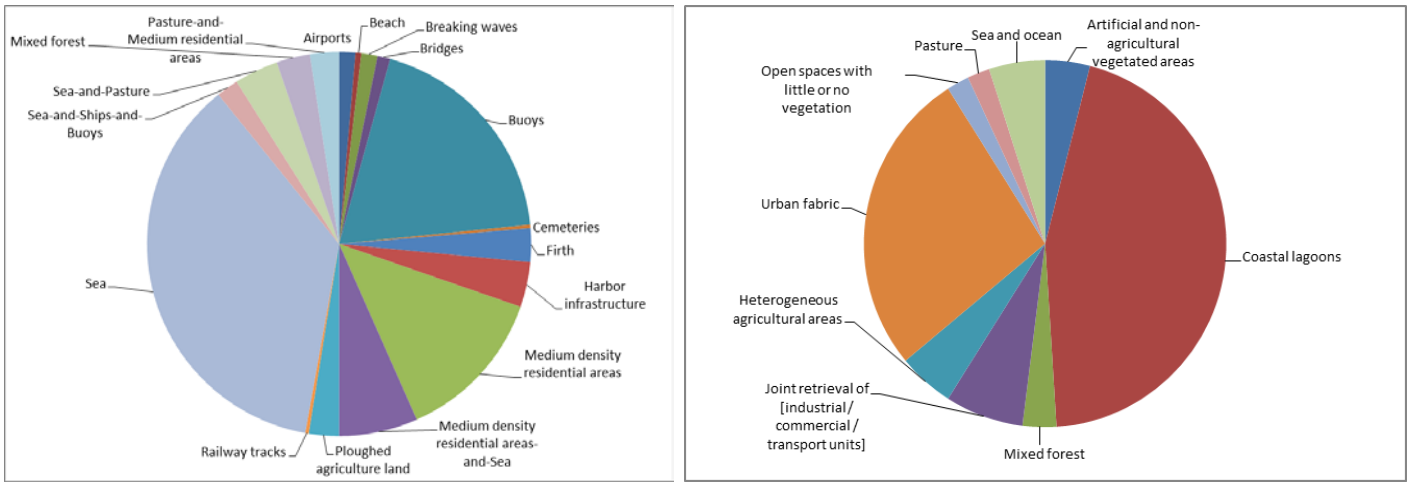


Fig. 6. Left: Diversity of categories identified from an image of Venice, Italy. The classification quality is given in Table III. Right: Diversity of categories defined by the CLC nomenclature.

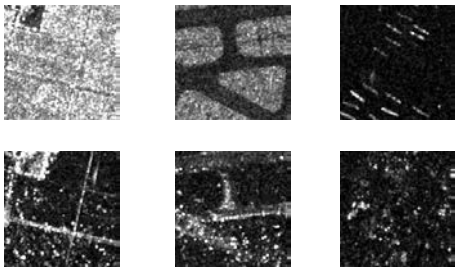


Fig. 7. Three examples of categories identified in a pre-disaster image (top row) and a post-disaster image (bottom row): Ploughed agricultural land, runways (of an airport), and aquaculture versus flooded areas, flooded areas, and debris.

VII. Performance Testing and Validation

For performance testing (after testing and verifying the basic software components), we compared running the complete

processing chain from ingestion to annotation on two computer systems, namely a desktop PC with software coded in different languages, and a high performance server.

Initial tests of our software have been performed on a standard PC with a processor clock rate of 2.40 GHz, and a RAM capacity of 8 GB. The software for the PC has been coded in MATLAB R2015a and Java 8. Typically, we obtain a CPU usage of less than 25% as we store all image files on a disk and have to wait for the completion of data transfers to and from the local PC disk. The actual memory consumption of our PC configuration is less than 50 MByte per image.

The practical run time results are: (1) data ingestion and patch tiling take together 1.7 ms per patch of 256x256 pixels; (2) feature extraction (e.g., Gabor filtering) requires 2.4 ms per patch; (3) classification and display of a new set of retrieved patches needs about 4 to 6 ms when we have a collection volume of 2 GByte of image data.

In contrast, our operational system [20] consists of powerful server machines equipped with large RAM capacity (32 GByte). In this configuration, all operations can be done in the RAM and no intermediate disk storage is required. The run times on the server [20] are at least one order of magnitude shorter as we converted all MATLAB code into Java and used optimized Java compilation parameters.

For the validation of our proposed semantic annotation scheme, we mainly performed two tasks for selected target areas: The first one was to visually compare our annotation results with the existing CLC 2006 categories [18] even if the comparison is based on different spatial resolutions. The second task was to compute the precision/recall metric [29] for each category.

These two tasks will be demonstrated in the following example of Venice, Italy:

- The existing CLC 2006 categories of Venice are (in alphabetical order): *Artificial and non-agricultural vegetated areas, coastal lagoons, heterogeneous agricultural areas, joint retrieval of [industrial / commercial / transport units], mixed forest, open spaces with little or no vegetation, pasture, sea and ocean,* and *urban fabric* (see Fig. 6 right). In contrast, our retrieved and annotated categories are: *Agricultural land, airport, beach area, breaking waves, bridge, buoys, cemetery, firth, harbor infrastructure, medium density residential urban area, mixed forest, pasture, railway tracks, sea,* and *ships* (see Fig. 8a). Please note that these categories are more detailed than the CLC categories as shown in Fig. 8c. For instance, CLC does not discriminate between *bridges, buoys,* and *sea water*. In order to show the resulting maps, we present (as a typical example) the results for a SAR image of Venice. Fig. 8b (left) gives an impression the original full SAR image, while Fig. 8b (right) depicts the retrieved and annotated semantic categories for each color-coded image patch.
- An Urban Atlas classification of Venice as produced by the European Environmental Agency (EEA) [61] is shown in Fig. 8d. This screenshot demonstrates that the Urban Atlas generates a detailed labeling of the inner city area with a high number of categories; however, these categories are rather general when compared with our classification scheme.

- The corresponding precision/recall results of our 17 Venice categories are shown below (see Table III). Here, we compare reference data (i.e., manually annotated image patches) with retrieval results of our processing chain. It turns out that other satellite SAR images result in very similar annotation quality levels. In contrast to multimedia images, many remote sensing images yield low recall values. This is due to the fact that remote sensing images are more diverse and contain multiple categories/classes within an image patch.

Another example is shown in Fig. 9 depicting the city of Ottawa, where a comparable annotation quality level is reached.

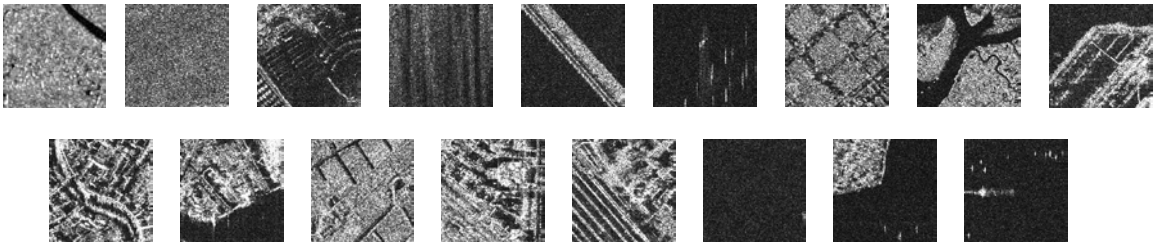


Fig. 8a). Our categories retrieved from an image of Venice, Italy (from left to right and top to bottom): Agriculture land, airports, beach, breaking waves, bridges, buoys, cemeteries, firth, harbor infrastructure, medium density residential areas, medium density residential areas / sea, mixed forest, pasture / medium density residential areas, railway tracks, sea, sea / pasture, and sea / ships / buoys.

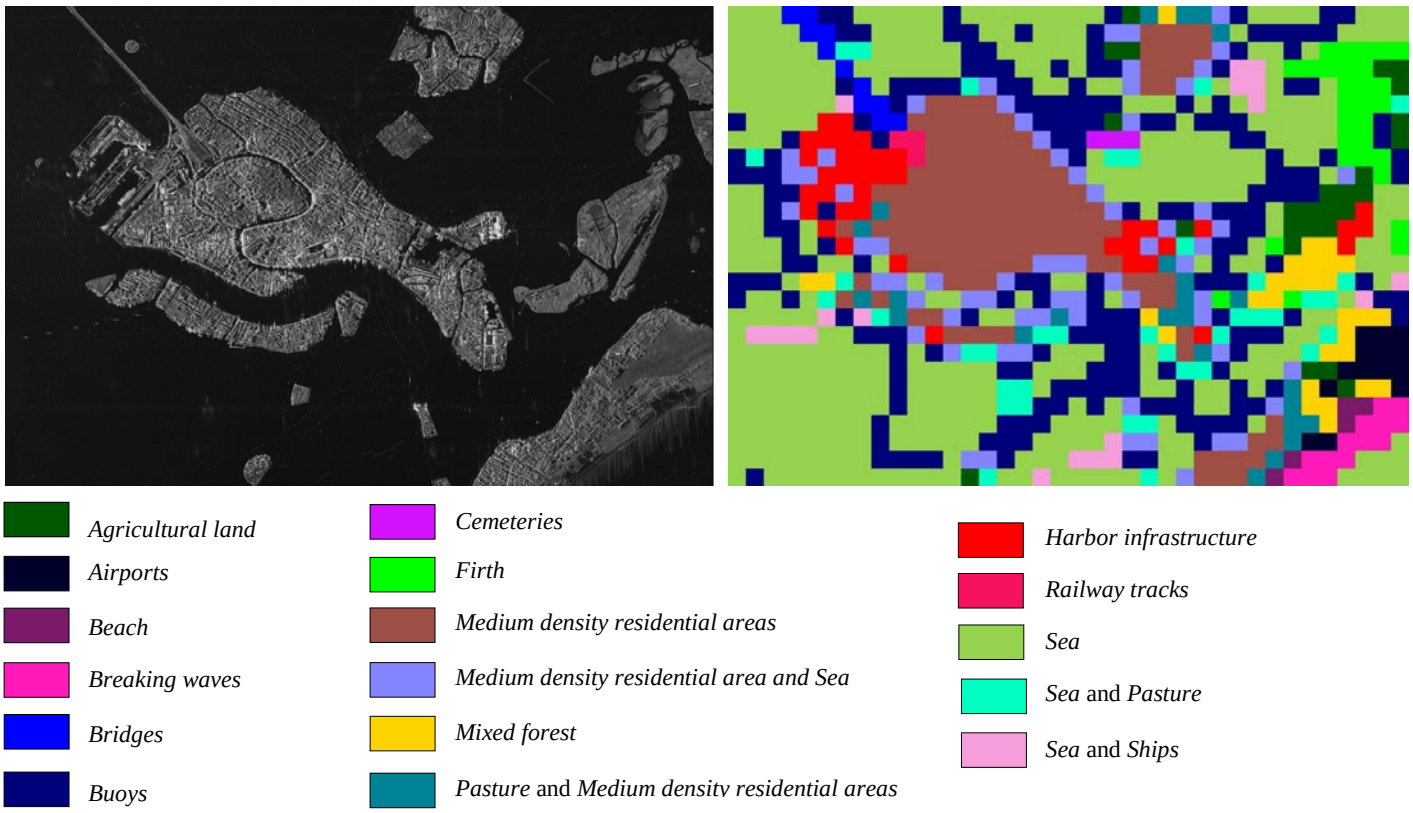


Fig. 8b). Left: Quick-look representation of the SAR image of Venice. Right: Retrieved and annotated semantic categories for all image patches. The annotation accuracy is detailed in Table III.

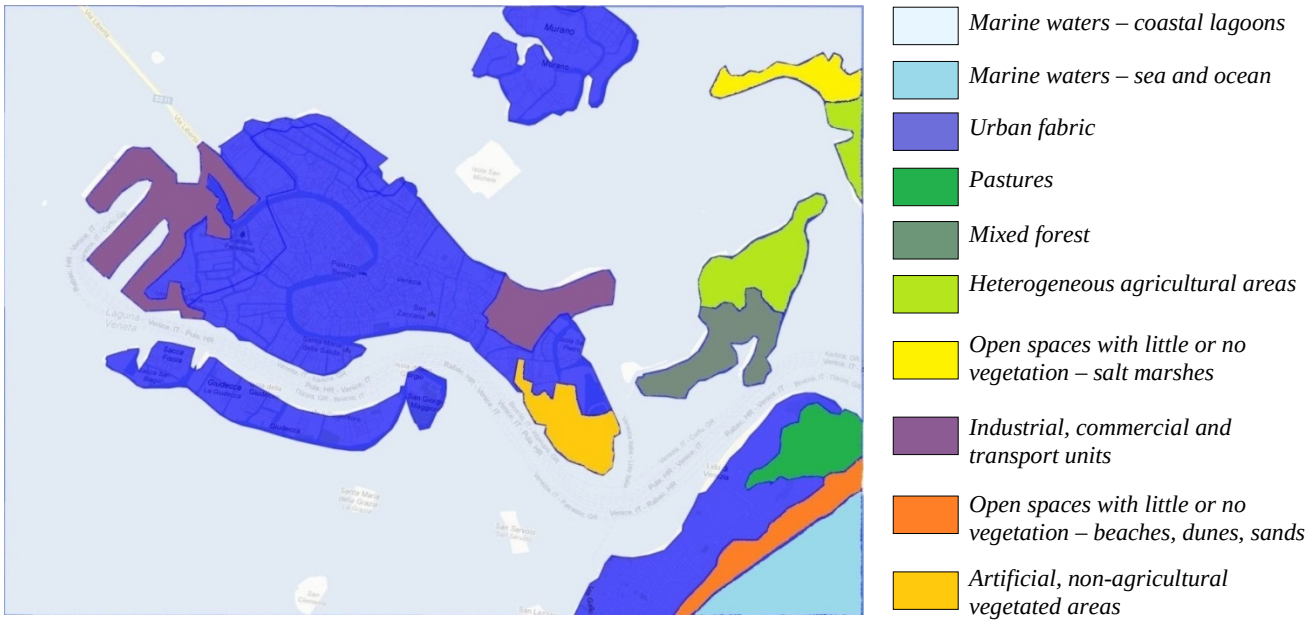


Fig. 8c). CLC Land Cover map of Venice (background by [26] and annotation by [51]).

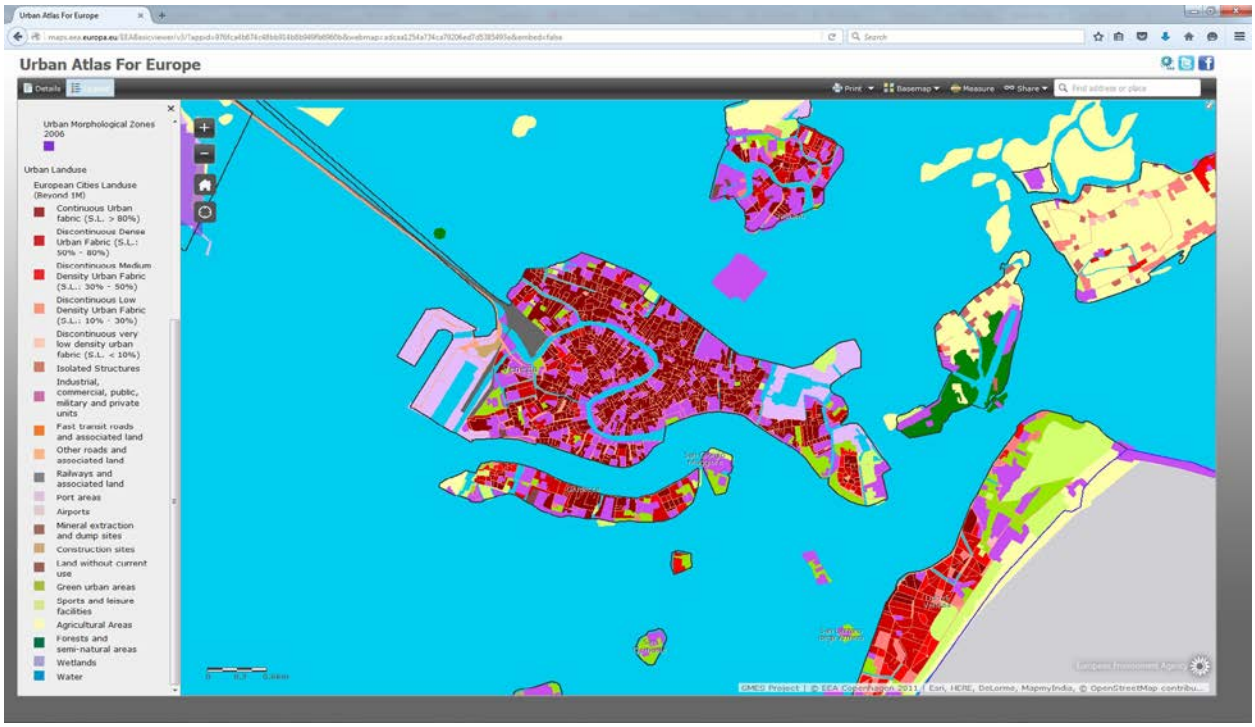


Fig. 8d). Urban Atlas map of Venice produced by EEA [61].

TABLE III.

PRECISION/RECALL PERCENTAGE RESULTS FOR VENICE.

Semantic annotation	Precision (%)	Recall (%)
Agriculture land	93.33	53.85

Airports	100.00	78.57
Beach	100.00	100.00
Breaking waves	100.00	92.86
Bridges	100.00	100.00
Buoys	87.63	86.73
Cemeteries	66.67	66.67
Firth	88.46	79.31
Harbor infrastructure	62.07	46.15
Medium density residential areas	90.91	97.02
Medium density residential areas and *Sea*	85.71	52.94
Mixed forest	72.41	72.41
Pasture and *Medium density residential areas*	64.29	36.00
Railway tracks	100.00	100.00
Sea	98.89	55.76
Sea and *Pasture*	100.00	55.27
Sea and *Ships* and *Buoys*	100.00	73.68

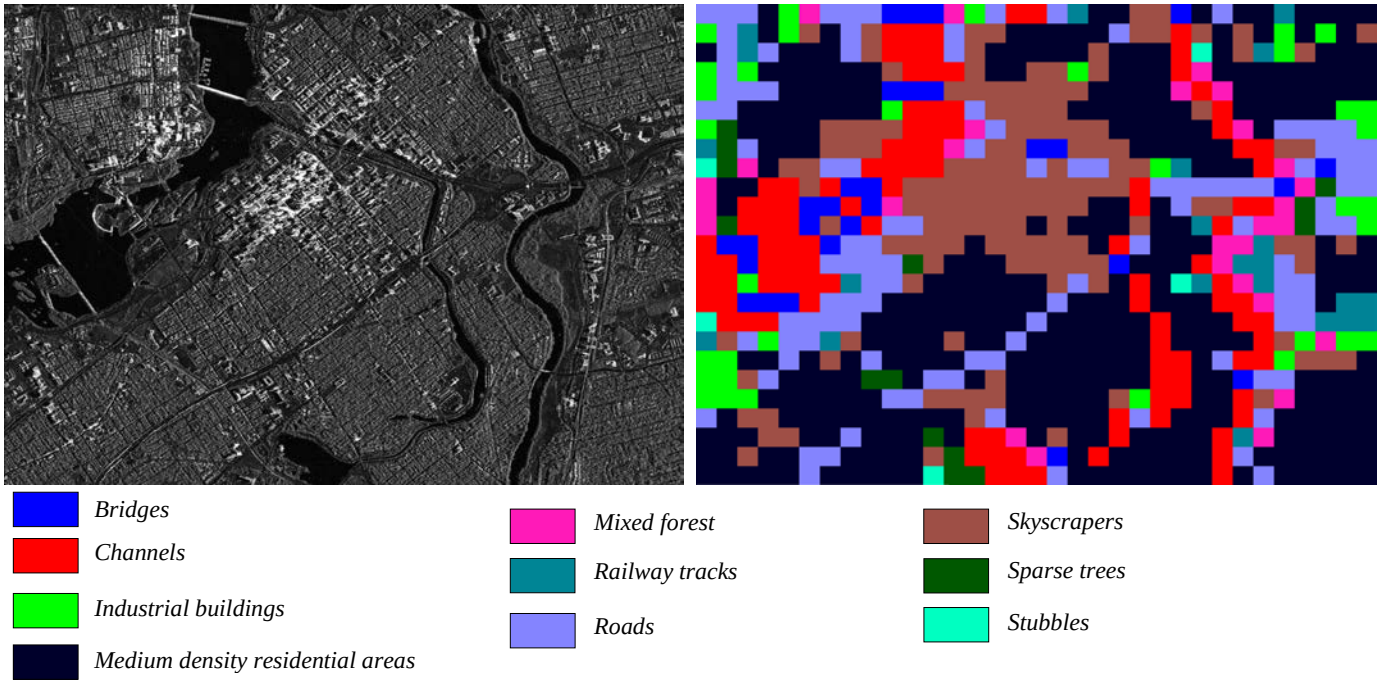


Fig 9. Left: Quick-look representation of a SAR image of Ottawa. Right: Retrieved and annotated semantic categories for all image patches. The annotation accuracy is detailed in Table IV.

TABLE IV.

PRECISION/RECALL PERCENTAGE RESULTS FOR OTTAWA.

Semantic annotation	Precision (%)	Recall (%)
Bridges	100.00%	95.00%
Channels	100.00%	54.38%
Industrial buildings	100.00%	54.48%
Medium density residential areas	100.00%	67.66%
Mixed forest	100.00%	81.25%
Railways tracks	84.62%	75.29%
Roads	96.00%	47.59%
Skyscrapers	91.84%	69.82%
Sparse trees	100.00%	49.13%
Stubble	90.63%	40.99%

Similar precision/recall values are obtained for other target areas. This shows that our annotation scheme seems to be consolidated.

In addition, we analyzed whether images of similar target areas can be grouped into specific collections to be annotated jointly. To this end, we determined the number of existing categories by separate annotation of individual images in order to get an idea about the semantic categories that can be retrieved globally. Then we studied pairs of urban images from different geographical regions in order to learn whether the same urban categories appear in both regions. Finally, we studied larger sets of urban images and investigated the resulting categories. It turns out that images of architecturally similar cities can be annotated jointly. The same seems to hold for related vegetation zones. On the other hand, existing categories have to be re-trained in other geographical areas if necessary. This may result in considerable effort. We learned that the transferability of image information does require a lot of care as different architectural styles of each country result in country-specific categories and internal tables.

The pie charts of Figs. 6, 10, 11, and 12 show the different categories that can be identified for each inner city even if the actual extent and the environment of each city differ.

As a first example, we show a pie chart of the nine semantic categories that can be retrieved from an image of Oslo, Norway (Fig. 10). The second example (Fig. 11) illustrates the retrieval of categories from two images (Belgrade, Serbia and Skopje, FYROM). One can see that the retrieved categories differ considerably as the two cities (i.e., Belgrade and Skopje) have a quite different architecture. A third example (Fig. 12) depicts the results of a joint retrieval of categories from a group of five architecturally similar North American cities.

The next two illustrations present typical examples where a joint annotation can be made for architecturally similar urban areas (Fig. 13) or cannot be made for dissimilar urban areas (Fig. 14).

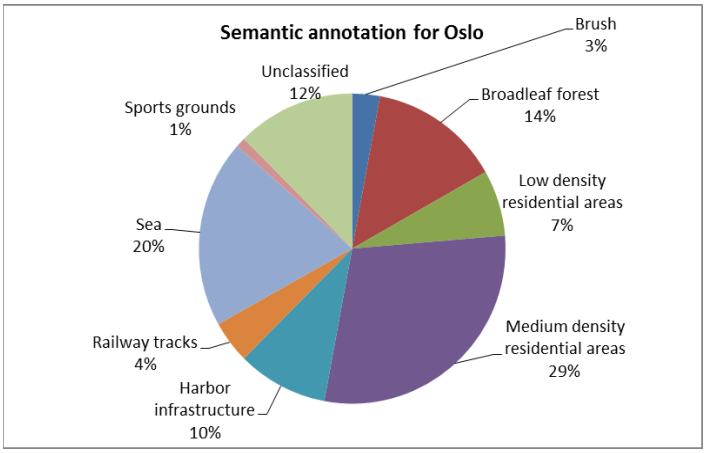


Fig. 10. Percentage of semantic categories for Oslo, Norway.

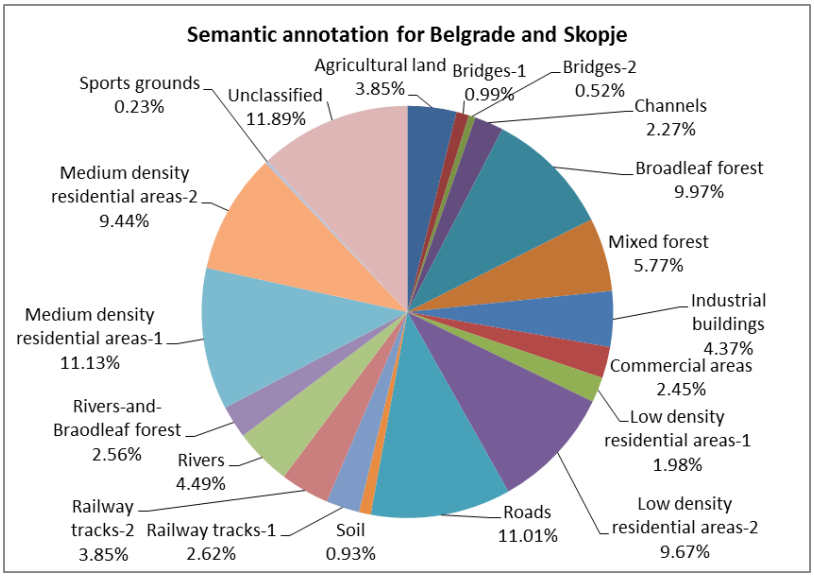


Fig. 11. Percentage of semantic categories for Belgrade, Serbia and Skopje, FYROM.

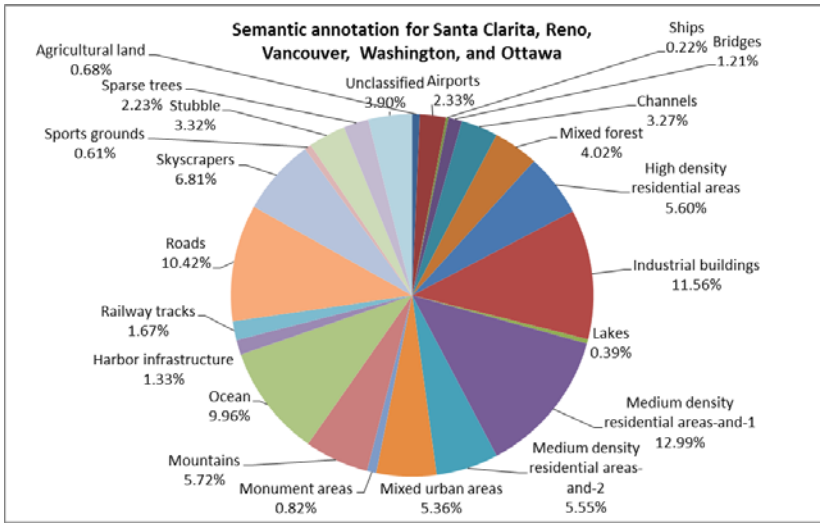


Fig. 12. Percentage of semantic categories for five North American cities, namely Santa Clarita, Reno, Vancouver, Washington, and Ottawa.

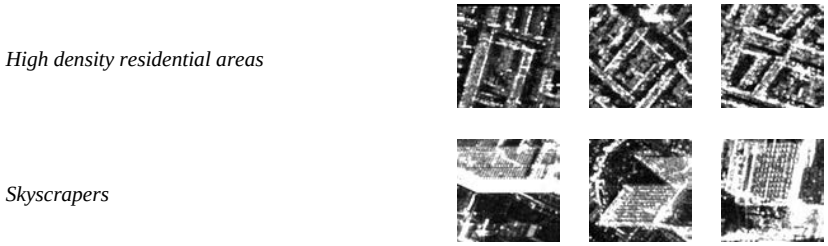


Fig. 13. Architecturally similar urban areas. Top row: Munich, Germany / Kiel, Germany, and Basel, Switzerland. Bottom row: Tokyo, Japan / Dubai, UAE, and Los Angeles, USA.

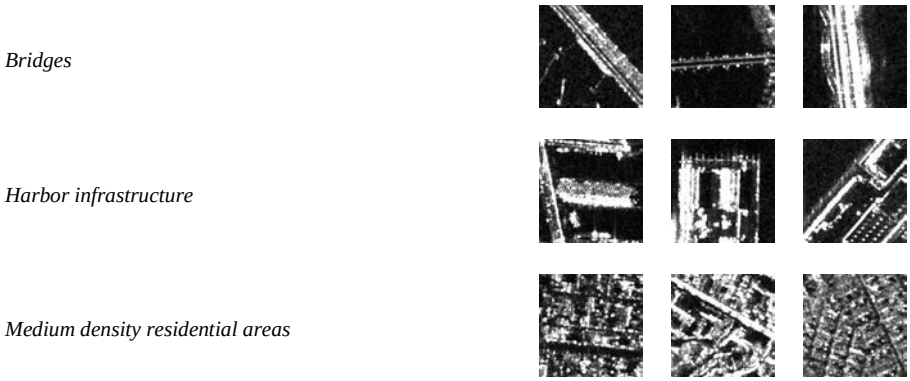


Fig. 14. Architecturally dissimilar urban areas. Left column: Venice, Italy. Middle column: Toulouse, France. Right column: Pyongyang, North Korea.

VIII. Outlook

When we try to find out more about future land cover applications based on satellite images (mainly from a European perspective), we have to take into account applications envisaged by the Copernicus Land Monitoring Services initiative [9], the data processing environments compiled by the EAGLE group [17], the challenges of Big Data, and the use of linked open data.

Future applications (e.g., [30]) will call for embedded solutions that include more aspects than a simple list of semantic annotation terms:

- Some users want to identify and classify complex and highly structured objects in satellite images. For these applications one has to find and apply complex feature extraction or deep learning techniques together with the application of rule sets (i.e., ontologies that contain formalized rules about the components of complex structured objects and their spatial arrangement). The extraction of complex features from satellite images is described by [55], while the current state of remote sensing ontologies is summarized by [2].
- Another aspect is the use of existing international standards and the formalization of annotation schemes for a standardized description of land cover semantics. On the one hand, international bodies such as ISO or OGC set standards for digital geographic information in their ISO 19100 series [32]. On the other hand, institutions such as the European

Union embed these ISO standards in much larger directives that prescribe how to represent and access geographical information in European networks (e.g., [31]) that support web-based services.

During the next years, we expect a growing number of publications covering these aspects.

IX. Conclusion

We demonstrated how the availability of a new SAR sensor generation with increased target discrimination capabilities will impact the data interpretation steps that are based on existing tools and embedding systems (including annotation schemes). It will be interesting to observe how the next 10 years of imaging sensors with all the capabilities and constraints set up by new data distribution concepts will influence the current schemes.

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APPENDIX

TABLE A.I.

COMPARISON BETWEEN OUR CLASSIFICATION SCHEME AND THE GLOBAL LAND COVER AND VEGETATION CLASSIFICATION SCHEMES [1], [12].

Our scheme	Anderson	LCCS
1 Settlements 11 Inhabited built-up areas 111 Very low density residential areas (e.g., individual farm houses) 112 Low density residential areas 113 Medium density residential areas 114 High density residential areas 115 Mixed urban areas 116 Urban houses in residential areas 117 High buildings 118 Informal settlements/refugee camps 12 Uninhabited built-up areas 121 Churches 122 Commercial areas 123 Sports grounds 124 Administrative compounds 125 Skyscrapers 126 Educational buildings and campuses 127 Monument areas 128 Assembly halls 129 Fountains 130 Cemeteries 131 Parking areas 132 Open squares (e.g., market places) 14 Leisure time facilities 141 Amusement parks 142 Castles 143 Hotel resorts 144 Tents 145 Public parks 15 Towers (e.g., TV or radio towers, chimneys, beacons, light houses) 16 Green spaces **2 Industrial production areas** 21 Industrial facilities 211 Industrial buildings 212 Chemical plants 213 Sewage treatment 214 Storage tanks 215 Solar parks 216 Wind parks and farms 217 Off-shore platforms 22 Industrial storage areas 221 Stockpiles 222 Depots and dumps 23 Mining facilities and quarries 24 Truck line-up **3 Military facilities** 31 Barracks 32 Command posts 33 Bunkers 34 Depots and vehicles 35 Camouflaged targets 36 Fences 37 Probing grounds, test and shooting ranges 38 Naval facilities 39 Airplane carriers 40 Airforce facilities 41 Launch pads 42 Antenna fields	**1 Urban or built-up land** 11 Residential 12 Commercial and services 13 Industrial 14 Transportation, Communications, and utilities 15 Industrial and commercial complexes 16 Mixed urban or built-up land 17 Other urban or built-up land	**1 Heavily Developed or disturbed Land**
4 Transport 41 Airports 411 Airport buildings 412 Control towers 413 Passenger terminals		

414 Cargo areas 415 Hangars 416 Runways 417 Taxiways 418 Aprons 419 Open terrain 420 Test stands 421 Airplanes 43 Roads 431 Streets and roads 432 Highways 433 Feeders 434 Roundabouts 435 Gasoline and maintenance stations 44 Railways 441 Railway tracks 442 Elevated tracks 443 Shunting areas 444 Depots 445 Station buildings 446 Control centers 45 Bridges and tunnels 451 Bridges and fly-overs 452 Tunnel portals 46 Ports and shipbuilding facilities 461 Quays 462 Harbor infrastructure 463 Warehouses and depots 464 Docks and shipyards 465 Cranes 466 Container stacks 467 Pontoons 47 Water vessels 471 Small vessels (boats) 472 Big vessels (ships) 48 Power grid 481 Power plants 482 Transformer stations 483 High voltage lines 484 Power line corridors		
5 Agriculture 51 Cropland 52 Stubble/bare/ploughed agricultural land 53 Rice paddies 54 Pasture 55 Plantations and vegetables 56 Greenhouses 57 Vineyards	**2 Agricultural land** 21 Cropland and pasture 22 Orchards, groves, vineyards, nurseries, and ornamental horticultural areas 23 Confined feeding operations 24 Other agricultural land	**2 Cultivated Land**
6 Natural vegetation 61 Coniferous forest 62 Broadleaf/deciduous forest 63 Mixed forest 64 Rain forest 65 Sparse trees 66 Thrown trees 67 Clear cuts 68 Regrowth 69 Prairies and grassland 70 Tundra 71 Taiga 72 Burn scars	**3 Rangeland** 31 Herbaceous rangeland 32 Shrub and brush rangeland 33 Mixed rangeland **4 Forest land** 41 Deciduous forest land 42 Evergreen forest land 43 Mixed forest land **6 Wetland** 61 Forested wetland 62 Non-forested wetland **8 Tundra** 81 Shrub and brush tundra 82 Herbaceous tundra 83 Bare ground tundra 84 Wet tundra 85 Mixed tundra	**3 Herbaceous Cover and Shrubland** 31 Herbaceous Cover 311 Managed Herbaceous Cover 312 Unmanaged Herbaceous Cover 3121 Unmanaged Upland Herbaceous Cover 3122 Tidal Marshes 3123 Non-tidal Marshes and Bogs 3124 Other Unmanaged Herbaceous Cover 32 Shrubland 321 Managed Shrubland 322 Young Pine Shrubland 323 Unmanaged Evergreen Shrubland 3231 Pocosin and Bog Evergreen Shrubland 3232 Unmanaged Upland Evergreen Shrublands 324 Unmanaged Deciduous Shrubland 3241 Unmanaged Deciduous Lowland Shrubland and Pocosin 3242 Unmanaged Deciduous Upland Shrublands 325 Other Shrubland **4 Forest Land** 41 Broadleaf Deciduous Forest Land 411 Oak-Hickory and Oak-Chestnut Forests 412 Mixed Mesophytic Upland Hardwoods 4121 Maple-Beech-Birch 4122 Yellow Poplar-Eastern Hemlock

		413 Bottomland and Wet Hardwood 414 Hardwood Swamps 415 Other Deciduous Broadleaf Forest Land 42 Needleleaf Coniferous Forest Land 421 White Pine Forests 422 Hemlock Forests 423 Spruce-Fir Forests 424 Longleaf Pine Forests 425 Loblolly-Slash- Pine Forests 426 Other Yellow Pine Forests 427 Pond Pine Forests 428 Atlantic White Cedar Forests 429 Other Needleleaf Coniferous Forest Land 43 Non-deciduous Broadleaf 431 Maritime Non-deciduous Broadleaf Forests 432 Bay Forests 433 Artificial Broadleaf Evergreen Plantings 434 Other Non-deciduous Broadleaf 44 Mixed Deciduous-Coniferous Forest Land 441 Oak-Pine 442 Oak-Gum-Cypress 45 Orchards and Tree Farms 46 Other Forest Land
7 Bare ground 71 Grassland 72 Brush/rangeland 73 Barren, rock, soil or sand 74 Desert 75 Cliffs 76 Hills 77 Mountains 78 Mountain shadows 79 Ice on ground 80 Derelict land	**7 Barren land** 71 Dry salt flats 72 Beaches 73 Sandy areas other than beaches 74 Bare exposed rock 75 Strip mines quarries, and gravel pits 76 Transitional areas 77 Mixed barren land	**6 Bare Land** 61 Beaches, Bare Coastal Land, and Upland Sand Areas 62 Riverbanks and Bars 62 Exposed Rock 64 Other Bare Land
8 Water bodies 81 Rivers 82 Lakes 83 Channels/canals 84 Sea 84 Ocean 85 Delta 86 Beach 87 Tidal flats 88 Firth 89 Breaking waves 90 Breakwater 91 Ice on water 92 Flooded areas 93 Reservoirs 94 Debris (Flotsam) 95 Buoys	**5 Water** 51 Streams and canals 52 Lakes 53 Reservoirs 54 Bays and estuaries **9 Perennial snow and ice** 91 Perennial snowfields 92 Glaciers	**5 Water Bodies** 51 Coastal/Marine Water Bodies 52 Inland Water Bodies 53 Linear Drainage 54 Other Water Bodies
9 Unclassified		**7 Other Unclassified Land Cover**

TABLE A.II.

COMPARISON BETWEEN THREE CLASSIFICATION SCHEMES RELATED TO EUROPE [18], [39], AND [22]. THE ORDER OF THESE CATEGORIES IN THIS TABLE FOLLOWS THE ORDER OF THE CATEGORIES SHOWN IN TABLE A.I.

CORINE Land Cover	Urban Atlas	LUCAS
1 **Artificial surfaces** 11 Urban fabric 111 Continuous urban fabric 112 Discontinuous urban fabric 12 Industrial, commercial, and transport units 121 Industrial or commercial units 122 Road and rail networks and associated land 123 Port areas 124 Airports 13 Mine, dump, and construction sites 131 Mineral extraction sites 132 Dump sites 133 Construction sites 14 Artificial, non-agricultural vegetated areas 141 Green urban areas 142 Sport and leisure facilities	**1 Artificial surfaces** 11 Urban fabric 111 Continuous urban fabric 112 Discontinuous urban fabric 1121 Discontinuous dense urban fabric 1122 Discontinuous medium density urban fabric 1123 Discontinuous low density urban fabric 1124 Discontinuous very low density urban fabric 113 Isolated structures 12 Industrial, commercial, public, military, private, and transport units 121 Industrial, commercial, public, military, and private units 122 Road and rail network and associated land 1221 Fast transit roads and associated land 1222 Other roads and associated land 1223 Railways and associated land 123 Port areas 124 Airports 13 Mine, dump, and construction sites 131 Mineral extraction and dump sites 132 Construction sites 133 Land without current use 14 Artificial non-agricultural vegetated areas 141 Green urban areas 142 Sports and leisure facilities	**1 Artificial land** 11 Built-up areas 111 Buildings with one to three floors 112 Buildings with more than three floors 113 Greenhouses 12 Artificial non-built up areas 121 Non built-up area features 122 Non built-up linear features
2 Agricultural areas 21 Arable land 211 Non-irrigated arable land 212 Permanently irrigated land 213 Rice fields 22 Permanent Crops 221 Vineyards 222 Fruit trees and berry plantations 223 Olive groves 23 Pastures 231 Pastures 24 Heterogeneous agricultural areas 241 Annual crops associated with permanent crops 242 Complex cultivation patterns 243 Land principally occupied by agriculture, with significant areas of natural vegetation 244 Agro-forestry areas	**2 Agricultural areas, semi-natural areas and wetlands**	**2 Cropland** 21 Cereals 211 Common wheat 212 Durum wheat 213 Barley 214 Rye 215 Oats 216 Maize 217 Rice 218 Triticale 219 ... 22 Root crops 221 Potatoes 222 Sugar beet 223 Other root crops 23 Non-permanent industrial crops 231 Rape and turnip rape 232 Soya 233 ... 24 Dry pulses, vegetables, and flowers 241 Dry pulses 242 Tomatoes 243 ... 25 Fodder crops 251 Clovers 252 ... 26 Permanent crops: fruit trees 261 Apple fruit 262 ... 27 Other permanent crops 271 Olive groves 272 ...
3 Forest and semi natural areas 31 Forests 311 Broad-leaved forest 312 Coniferous forest 313 Mixed forest 32 Scrub and /or herbaceous vegetation associations 321 Natural grasslands 322 Moors and heathland	**3 Forests (Natural and plantations)**	**3 Woodland** 31 Broadleaved woodland 32 Coniferous woodland 321 Spruce dominated coniferous woodland 322 ... 33 Mixed woodland 331 Spruce dominated mixed woodland 332 ...

323 Sclerophyllous vegetation 324 Transitional woodland-shrub 33 Open spaces with little or no vegetation 331 Beaches, dunes, sands 332 Bare rocks 333 Sparsely vegetated areas 334 Burnt areas 335 Glaciers and perpetual snow		**4 Shrubland** 41 Shrubland with sparse tree cover 42 Shrubland without tree cover **5 Grassland** 51 Grassland with sparse tree/shrub cover 52 Grassland without tree/shrub cover 53 Spontaneously re-vegetated surfaces
4 Wetlands 41 Inland wetlands 411 Inland marshes 412 Peat bogs 42 Maritime wetlands 421 Salt marshes 422 Salinas 423 Intertidal flats		**8 Wetland** 81 Inland wetlands 811 Inland marshes 812 Peatbogs 82 Costal wetlands 821 Salt marshes 822 ...
		6 Bare land and lichens/moss 61 Rocks and stones 62 Sand 63 Lichens and moss 64 Other bare soil
5 Water bodies 51 Inland waters 511 Water courses 512 Water bodies 52 Marine waters 521 Coastal lagoons 522 Estuaries 523 Sea and ocean	**4 Water**	**7 Water** 71 Inland water bodies 72 Inland running water 73 Coastal water bodies 74 Glaciers, permanent snow