# A UNIFIED FRAMEWORK FOR LAND-COVER DATABASE UPDATE AND ENRICHMENT USING SATELLITE IMAGERY

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## ABSTRACT

2D land-cover databases (LC-DB) have been established at various levels (global, national or regional scales), various spatial samplings and for various themes of interest (forest, agriculture, urban areas, etc.). However, they exhibit many flaws (limited geometric accuracy, low coverage) and require to be updated with automatic algorithms. Very High Resolution satellite imagery offers a suitable solution for setting up such on-purpose algorithms, and a large body of literature has tackled this topic. This paper proposes a framework that is able to deal with both LC-DB update of any kind and their enrichment in case of incomplete DB. The supervised classification-based solution integrates an efficient learning strategy that allows to capture the heterogeneity of the appearances of the various themes of interest. The proposed framework is favorably compared with two state-of-the-art methods, on a reconstructed dataset, composed of sub-metric satellite image patches.

***Index Terms*—** Remote sensing, change detection, land cover, satellite imagery.

## 1. INTRODUCTION

Land-cover databases (LC-DB) are inevitable inputs for better resource management decisions, more effective use of natural resources and improved environmental management. Thereby, many administrative entities have produced their own LC-DB, resulting in various levels of description (global, national or regional), with various spatial samplings and for various themes (forest, agriculture, urban areas, etc.). Nevertheless, these LC-DB are carried out by merging several existing 2D databases, introducing many flaws (limited geometric accuracy, low coverage). Moreover, users of such LC-DB require data as recent as possible. Consequently, LC-DB have (1) to be completed and corrected of geometric flaws and (2) to be updated (*e.g.* of a yearly basis). Due to the amount of data and their significant spatial extent automatic algorithms need to be developed.

The aim of this paper is to demonstrate that both LC-DB updating and completing issues are related, and, therefore that a unified framework can be proposed for solving both issues. A regular coverage of large areas can be obtained using Very High Resolution (VHR, inferior to 1 m) satellite sensors, such as Pléiades, GeoEye-1 or Worldview-2. These data allow to compute a large number of attributes [1], allowing to discriminate many land-cover types. In order to capture the high heterogeneity of acquired landscapes, supervised classification method are widely adopted to complete DB using remote sensing data (*e.g.*, k-nearest neighbours, Support Vector Machine (SVM) or Random Forests (RF) ) [2, 23]. Change detection has also been extensively investigated in the remote sensing domain. An overview and discussion of change detection methods are provided in [3]. For instance, changes can be directly detected between image pairs [4, 5, 6], or based on time-series analysis, benefiting from a larger amount of available information [7, 8, 9, 10]. For LC-DB producers, change detection between such DB and a more recent image is also mandatory and mainly focus on very specific objects/themes [11, 12, 13]. In particular, when dealing with VHR images, one can note that, in addition to basic radiometric information, most of existing methods require 3D features, computed from multi-view images, in order to more efficiently discriminate objects such as roads and buildings [13, 14, 15]. However, such data is not always available and cannot be used over large extents. Consequently, the efficiency of proposed methods heavily rely on the performance of the training step for the supervised classification task [16]. A major assumption is that the existing LC-DB can be used for that purpose: for instance, objects of the DB (polygons) can be matched with image saliencies in order to detect stable regions and select good training pixels [17]. Images can also be segmented according to DB outlines in order to perform an object-based classification, eventually compared to the initial DB [18]. These methods are efficient in retrieving relevant training sets, but require an end-user to find the suitable level of segmentation, which is not known beforehand. An interesting solution has been proposed in [19], which gather several specific methods in a global semi-automatic workflow for change detection between an up-to-date image and a LC-DB. Even if it remains tailored for well-known objects (roads, buildings, etc.), the idea of retrieving the most suitable features and training set for each theme of interest should be conserved.

In this paper, since no assumption is taken on the initial DB and on the satellite image, we propose a generic framework, able to deal with any kind of LC-DB for updating and enrichment, using a single image. We assume that the radiometric content of the image is sufficient for discriminating the various themes of interest. The method is based on a classical hierarchical inspection of the initial DB: a per-object learning pixel selection, and a two-level classification fusion (at theme and DB levels, respectively). Then, two different conclusions are drawn depending on whether updating or enrichment has to be performed. The framework is first detailed in Section 2. Then, experimental results are shown on Section 3. Finally, conclusion are provided on Section 4.

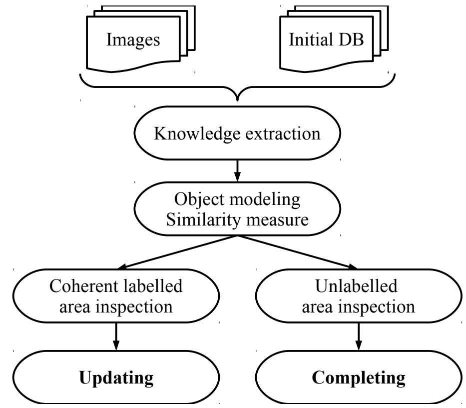



**Fig. 1**. Illustration of the theoretical framework.

## 2. METHODOLOGY

Two different issues are exposed in this paper: the update and the completion of 2D land-cover databases. In both cases, two kinds of information can be derived from (1) the satellite image, and (2) the initial database (Fig. 1). First, the projection of the DB objects onto the satellite image allows to extract knowledge from the image, and to define similarity measures between pixels. Secondly, the initial DB provides an *a priori* knowledge on the semantic relation between objects (they can be grouped by *theme*). Finally, those image-knowledge and DB-knowledge can jointly be used to solve our two issues by focusing either on the previously labelled areas (consistency), either on the previously unlabelled areas (completion).
Since two slightly distinct objectives are targeted, an object-based analysis is not necessary and a pixel-based reasoning is preferred. Therefore, the 2D vector LC-DB is rasterized, which resolution is compatible with the VHR image and the DB geometrical accuracy. 0.5 m resolution is chosen and each pixel is assigned to a single label: a *theme* label if it intersects the DB, *background* otherwise. In this section we first detail our unified workflow for LC-DB completion and change detection. Then, the specificities of the two different applications are detailed.

### 2.1. The unified workflow

The hierarchical structure of geographical DB allows to focus our analysis at three inspection levels: (1) the object level (2D polygons), (2) the theme level and (3) the DB level, which is the basis of our hierarchical method. The first inspection level is the finest one: the objects are separately analysed to learn their specific appearances, knowing that an object may have several appearance. Learning is composed of two steps. First, two subsets of pixels (*inside* / *outside*) that best discriminate the object from the rest of the image excluding the theme of interest are retrieved. The subset selection is based on the maximization of the recall rate of the object pixels in a binary classification (*inside*/*outside*). Secondly, all the pixels of the image are classified with respect to these two classes: it allows to obtain, for each object of the DB, an object-level confidence map $\mathcal{P}_O$, that describes the probability of a pixel to belong to the theme of the current object. The second inspection level permits to take into account the several appearances of the objects of a given theme. At this step, object-level confidence maps $\mathcal{P}_O$ (result of the latter step for objects $O$ of the theme $T$) are merged into a single confidence map, as the mean of all contributions (Eq. 1). This value is considered as the probability of each pixel to belong to the current theme.

$$\mathcal{P}^T = \mathit{Mean}(\{\mathcal{P}_O, \quad O \in T\}). \tag{1}$$

Eventually, the final labelling decision is taken at the DB level by integrating the probability maps of each theme. Each pixel is assigned to the class of the DB with the highest confidence measure derived from the previous step, using the function L:

$$L(p) = \underset{T \in \{\mathrm{DB}\}}{\arg\max} \ \mathcal{P}^T(p). \tag{2}$$

We can notice that all pixels are labelled by a theme of the initial DB (*i.e.*, there is no label: "*unlabelled*"). During the process, a confidence map is generated, as the maximum membership value to one theme:

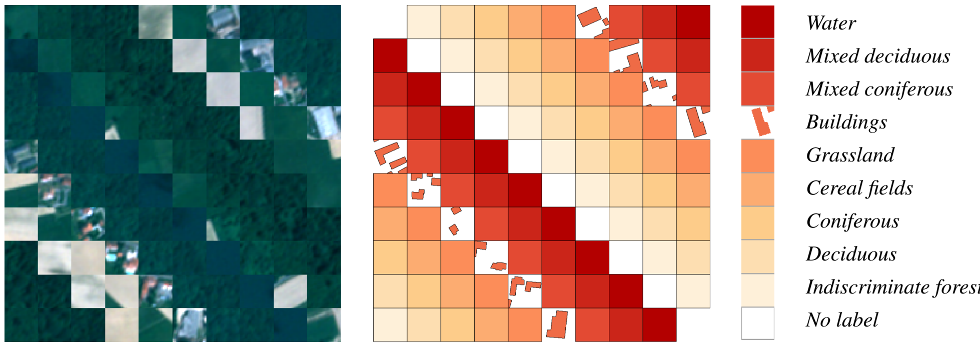
$$C_{max}(p) = \mathcal{P}^{T_{L(p)}}(p). \tag{3}$$

### 2.2. For updating and completing

The labels and the confidence measure are used in two different ways, depending on whether we have to update or to complete the initial DB. In order to update the label of a pixel, the new class (Equation 2) is compared with the initial one so as to first obtain a binary *change* / *no change* map. In addition, this binary map is weighted by the confidence measure in order to derive a probability of change map $\Pi$:

$$\Pi(p) = \Delta(p) * C_{max}(p), \tag{4}$$

where $\Delta$ is the binary *change* / *no change* labelling function that return $-1$ in case of change, and $+1$ otherwise.




(a) (b) (c)

**Fig. 2**. (a) The *simulated data*, textural synthesis from an actual satellite image (used to update the DB), (b) the ground truth and (c) the legend of the themes covered by the DB. Each object is $100 \times 100$ pixels.

For pixels without initial label (*background*), the classes and the confidence measure previously obtained are directly used to complete the DB without additional processing. Subsequent refinement steps are possible so as to improve the accuracy, smoothing the results and introducing high-level reasoning. For instance, hierarchical ontology and object-based methods would be perfect to handle geographic LC-DBs [20]. They will be the subject of future research.

## 3. EXPERIMENTS ON RECONSTRUCTED DATA

### 3.1. Dataset

Since obtaining high quality ground truth data is rather challenging and remains a main issue in the remote sensing domain, a reconstructed dataset has been generated from real VHR satellite images (namely Pléiades images at a resolution of 0.5 m). Several patches of previously known labels have been extracted in order to build a $1000 \times 1000$ pixels images. Each patch is a square of $100 \times 100$ pixels, and is labelled with a single theme, expect for themes with objects smaller than this level of analysis (*e.g.*, buildings): in such a case, surrounding pixels are unlabelled. The nomenclature is composed of 9 themes extracted from a standard national LC-DB (namely the French one): *water, mixed deciduous forest, mixed coniferous forest, buildings, grassland, cereal fields, coniferous forest, deciduous forest and indiscriminate forest.* The resulting image is shown on Fig. 2a, the corresponding labels and the legend on Fig. 2b&c. Objects of a same theme are distributed on a diagonal in order to mix them (therefore, one object of one theme has neighbouring objects of various themes). The associated labels constitute the ground truth for our two experiments on DB completing and updating.

### 3.2. Features and Classification

Several features are derived from the 5 channels (red, green, blue, near infrared and panchromatic) of the input Pléiades image. Those features can be classified into three classes: spectral, textural, and morphological. The features used in the experiments of this paper are distributed as follows: 13 spectral features are computed (standard remote sensing indices, *e.g.*, NDVI, SAVI, ...), 10 textural features (Haralick coefficients and gradient entropy, describing the complexity of the image in a neighborhood of each pixel), and approximately 150 morphological ones (Morphological Attributes Profiles computed at various scales [21]).
Moreover, as expected in Section 2, the classification method has to provide a confidence map. For instance, SVM allow to compute estimate probability [22], and the margin function from RF classifiers [23] give a robust confidence measure. In this paper, the second one has been used.

### 3.3. Completing task

The first series of experiments focuses on DB completion. In order to study the influence of the coverage of the initial DB, several DB are derived from the ground truth by randomly selecting objects, covering more or less the area of the image. Thus, 90 distinct DB are generated: the first ten ones having a single object of each theme, and the last ten ones being composed of nine objects of each theme. Then, our method is applied on each DB, and the resulting overall accuracies are averaged by percentage of coverage. Finally, in order to compare our methods with two state-of-the-art classification methods, same protocol is applied using a RF and a multi-classes SVM (with a linear kernel). Results are shown on Figure 3 (left). In these experiments, our method outperforms both RF and SVM in term of overall accuracy. First, when the coverage of the initial DB is low ($< 30\%$), the three methods have almost similar performance. However, the difference increases with the coverage, and, our method, thanks to the multiplication of classifications, enables more robust results.

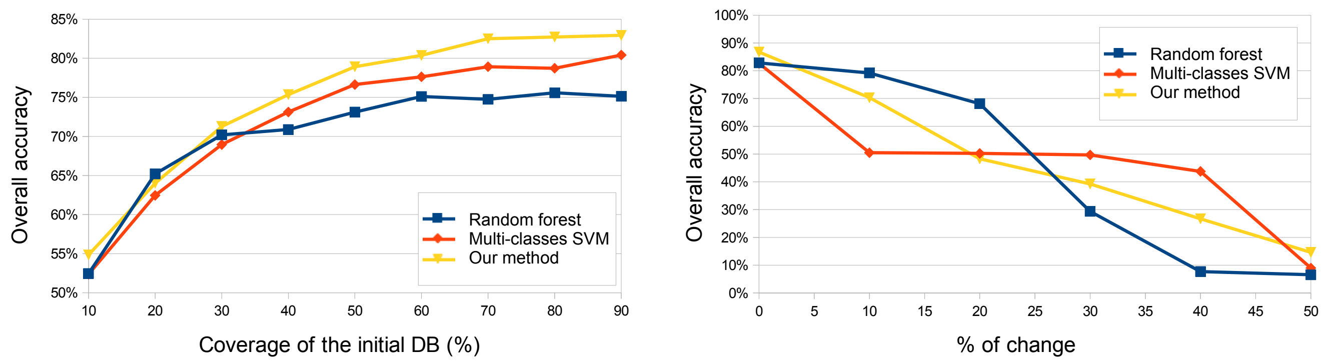



**Fig. 3**. Evolution of the classification Overall Accuracy with respect to (**left**) the number of objects in the simulated DB, and (**right**) the percentage of change introduced in the DB, for RF ■, multi-classes SVM ♦ and our method ▼.

### 3.4. Updating task

Secondly, the impact of the percentage of change in the initial DB is studied. For that purpose, 6 DB are generated by translating each object on the right, by an increasing number of pixels (from 0 to 50 pixels, corresponding to 0% to 50% of change). As in the previous experiments, our method is compared with RF and SVM. Results are shown on Figure 3 (right). Here, the RF method gives better results when few changes exist (less than 25%). But, in case of a higher ratio of change, the SVM becomes a better solution. Our method is always between the two curves, indicating the stability of our method. Furthermore, one can notice that the overall accuracy steadily decreases with high change values (less than 0.5 of average accuracy for 30% of changes), which shows that improvements are conceivable. However, such high change values (distributed over all the themes of the DB) are not so realistic.

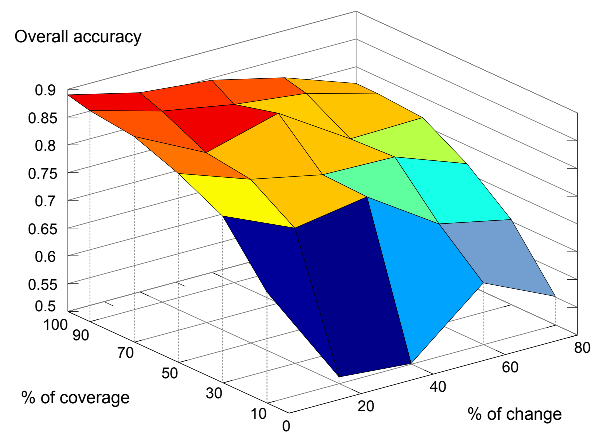



**Fig. 4**. Evolution of the overall accuracy of our method in respect with the number of objects in the simulated DB and the % of change introduced in the simulated DB.

### 3.5. Both completing and updating

Finally, our method has been assessed in terms of DB completing and updating at the same time. For this purpose, several DB are generated by ranging two parameters: the percentage of coverage (from 10 to 100%) and the percentage of change (from 0 to 80%). Results are shown on Figure 4. The resulting 3D surface aims to confirm the stability of our method both in term of coverage and of change. Indeed, for low change values ($< 40\%$) the coverage of the initial database (until $30\%$) has a low influence on the overall accuracy (still superior to 0.7). This area corresponds approximately to what may exist in real LC-DB.

## 4. CONCLUSION AND PERSPECTIVE

A unified framework for both 2D land-cover database updating and completing has been presented in this paper. The proposed method aimed to retrieve the most relevant information from a newly acquired satellite image using an imperfect knowledge of the area of interest in order to improve an existing database. A hierarchical inspection of the database was designed so as to efficiently capture the various appearances of the objects and the themes and to deal with potential changes in the learning data. In particular, the stability and the robustness are strengthened by computing and merging several classifications. Our method was assessed in reconstructed data, derived from real satellite Pléiades images, and favorably compared with two state-of-the-art methods. Future work will focus on two mandatory improvements when dealing with national land-cover databases: (1) scalability, tackled through the inspection method and (2) versatility by increasing the number of features and by introducing theme-by-theme feature selection.

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