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To cite this article: C O Dumitru *et al* 2020 *IOP Conf. Ser.: Earth Environ. Sci.* **509** 012014

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Knowledge extraction from Copernicus satellite data

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Abstract. We describe two alternative approaches of how to extract knowledge from high- and medium-resolution Synthetic Aperture Radar (SAR) images of the European Sentinel-1 satellites. To this end, we selected two basic types of images, namely images depicting arctic shipping routes with icebergs, and - in contrast - coastal areas with various types of land use and human-made facilities. In both cases, the extracted knowledge is delivered as (semantic) categories (*i.e.*, local content labels) of adjacent image patches from big SAR images. Then, machine learning strategies helped us design and validate two automated knowledge extraction systems that can be extended for the understanding of multispectral satellite images.

1. Introduction

In this paper, we describe the pros and cons of two alternative knowledge extraction approaches for space-borne SAR imagers [1]. The first approach tries to detect icebergs along shipping routes, while the second one tries to categorize different types of coastal areas and landscapes. The reason for this selection was to find and compare knowledge extraction algorithms for iceberg images that are mostly containing only dark water and bright ice, and images of coastal areas that are characterized by more continuous brightness histograms and regularly shaped targets such as agricultural fields or buildings.

When we compare the image classification results for both cases we can demonstrate whether rather distinct image types also call for separate parameterizations during semantic content classification. This extends SAR image classification beyond traditional SAR image description techniques merely based on their frequency band, signal polarization, incidence angle, pixel size, and signal-to-noise ratio, thus paving the way for integrating image patch labelling with higher-level artificial intelligence applications.

On the other hand, we preserve a traditional classification and machine learning framework comprising data pre-processing, patch cutting, feature extraction, and semantic labelling based on automated learning. The differences between our two classification approaches are mainly the applied filtering algorithms for feature extraction.

For discriminating ice from ocean water, we can apply a compact and fast discriminator based on Weber's law [2], and a more complicated Gabor filter bank [3] for extended land areas allowing more categories with different orientations being discriminated. The first discriminator needs larger image patches (256×256 pixels), while the second one allows the use of smaller patches (128×128 pixels).

2. Data set

For the purpose of our analysis, we chose and downloaded various freely available Copernicus Sentinel-1 data sets provided by this C-band SAR instrument. Our areas of interests cover Belgica Bank in Greenland as a polar case for the first application, and the protected areas of the Danube Delta



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in Romania as well as the Wadden Sea in the Netherlands for the second application aimed at their ecosystem conditions.

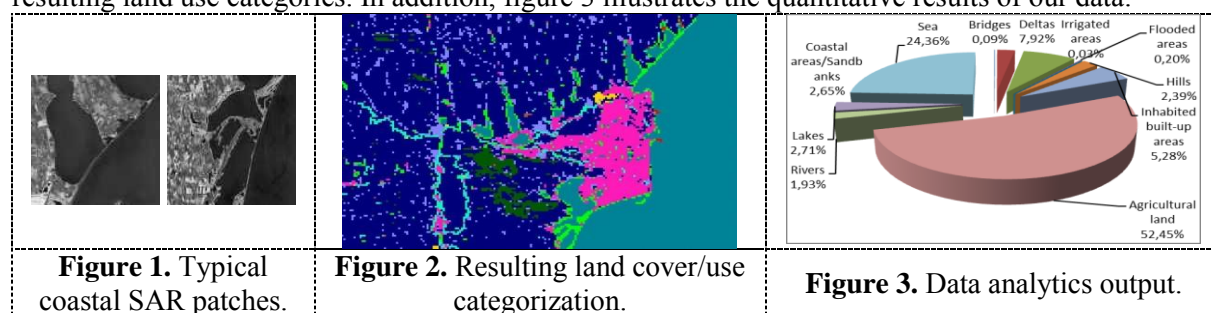
Thus, we obtain data for validation, the generation of a training data set, the development and testing of machine learning algorithms, and the demonstration of the results. Then we can develop data analytics techniques and technologies that combine Copernicus satellite data with information and knowledge extraction, and exploiting them on exploitation platforms.

3. Procedure

After designing and implementing our automated knowledge extraction software [4], we used typical remote sensing images for testing and performance verification. The quality verification needed a carefully selected data set with known content that covered all seasons and characteristic events. If sufficient reliable ground truth data are available, they should be used for quantitative estimates of the obtained classification accuracy.

4. Results

The following figures demonstrate the power of automated knowledge extraction from SAR image data. Figure 1 depicts a collection of SAR image patches (Danube Delta), while figure 2 shows the resulting land use categories. In addition, figure 3 illustrates the quantitative results of our data.



5. Discussions

The usefulness of our approaches becomes fully visible when we combine the selection of the filtering technique with an optimal patch size. This can be extended to an automated combination system that relieves the user from this task.

In future, we plan to study the applicability of our concept to multispectral satellite images such as the European Sentinel-2 images. If this leads to reliable results, one can think of combining overlapping SAR and multispectral images for joint content classification.

However, when we envisage joint image classification, we must be aware of how to select and/or generate appropriate test images. We plan to extend the approach already described in [4].

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Acknowledgments

This work was supported by the European Union's H2020 ExtremeEarth project (under grant agreement No. 825258) and by the H2020 ECOPOTENTIAL project (under grant agreement No. 641762). We acknowledge the support provided by all our international project partners.