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**The Use of Volunteer Geographic Information
for Producing and Maintaining
Authoritative Land Use and Land Cover Data**

Workshop organized by
EuroSDR and the LandSense Project

November 24th - 25th 2020 – Online Conference

Editors: Ana-Maria Olteanu-Raimond, Joep Crompvoets,
Inian Moorthy, Clément Mallet, Bénédicte Bucher

Workshop Report

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EuroSDR Secretariat

KU Leuven Public Governance Institute

Faculty of Social Sciences

Parkstraat 45 bus 3609

3000 Leuven

Belgium

Tel.: +32 16 37 98 10

Email: euroedr@kuleuven.be

Web: www.euroedr.net

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Editors:

Ana-Maria Olteanu-Raimond, Joep Crompvoets, Inian Moorthy, Clément Mallet, Bénédicte Bucher

“The Use of Volunteer Geographic Information for Producing and Maintaining Authoritative Land Use and Land Cover Data”

Workshop of EuroSDR and the LandSense Project, November 24th-25th 2020, Online Conference

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THE USE OF VOLUNTEER GEOGRAPHIC INFORMATION FOR PRODUCING AND MAINTAINING AUTHORITATIVE LAND USE AND LAND COVER DATA

Workshop of EuroSDR and the LandSense Project
November 24th-25th 2020 – Online Conference

With 20 figures

Editors:

Ana-Maria Olteanu-Raimond^a, Joep Crompvoets^b, Inian Moorthy^c,
Clément Mallet^a, Bénédicte Bucher^a

^a Univ. Gustave Eiffel, IGN-ENSG, LASTIG
F-94160 Saint-Mandé, France

^b KU Leuven
Leuven, Belgium

^c IIASA – International Institute for Applied Systems Analysis
Laxenburg, Austria

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INTRODUCTION

The report refers to the workshop that was organized on behalf of EuroSDR and the LandSense project¹ (24-25 November 2020). LandSense aims to build a citizen observatory for Land Use and Land Cover (LULC) monitoring by proposing innovative technologies for data collection, change detection, data quality assessment and offering tools and systems to empower different communities (e.g., private companies, Non Governmental Organisation, National Mapping Agencies, research, public authorities) to monitor and report on LULC. The workshop was co-organized by the LASTIG laboratory of the University Gustave Eiffel and IGN-ENSG, the French National Mapping agency (Ana-Maria Olteanu-Raimond, Clément Mallet, Bénédicte Bucher), the Katholieke Universiteit Leuven (Joep Crompvoets), the International Institute for Applied Systems Analysis (Inian Moorthy) and EuroSDR.

LULC data are necessary for different applications (e.g., urbanization growth, biodiversity conservation, climate change) in monitoring our environment at national, regional and local scales. Different European initiatives such as CORINE Land Cover, Copernicus, Urban Atlas allow the production of LULC data in vector format (i.e. feature-based LULC). The National Mapping Agencies (NMAs) also produce feature based LULC data at regional or national scales based on demand and available resources.

The feature-based LULC data are generally cyclically produced every 3 to 6 years, which is not always adequate. Moreover, producing LULC data is costly and a lack of in-situ information can generate incompleteness or inaccuracies. Recent research shows that LULC databases may take advantage of the use of Volunteer Geographic Information (VGI) to produce or improve update LULC data. For example, different approaches allowing to derive LULC data from OpenStreetMap are proposed. In this context the objective of the workshop was to bring together different actors (e.g., National mapping agencies, academic communities, private companies) having experiences in feature-based LULC data production or change detection in order to 1) dress an exhaustive list of the current practices and issues in mapping feature-based LULC data and 2) share innovative approaches allowing to produce, monitor and update LULC data.

The workshop was divided into four parts:

Part 1- **Introduction**, chaired by Bénédicte Bucher, including short descriptions to specificities and challenges related to Land Use and Land cover data (Clément Mallet, IGN France) and VGI and Citizen science for LULC monitoring (Inian Moorthy, IIASA; Ana-Maria Olteanu-Raimond, IGN France).

Part 2- **Use of VGI for LULC data production**. This session, chaired by Clément Mallet, gave a nice overview of the current VGI-use for LULC data production covering the following presentations: National Land Cover and Land Use Information System of Spain (Julián Delgado Hernández Julián, IGN Spain); A fusion data approach for integrating VGI to update and enrich authoritative LULC data (Lanfa Liu, Ana-Maria Olteanu-Raimond, Laurence Jolivet, Arnaud Le Bris, IGN France); OpenStreetMap for Earth Observation (OSM4EO) land use application and benchmark (Michael Schultz, University of Heidelberg); and Using OpenStreetMap as a data source for training classifiers to generate LULC maps (Cidália Fonte, Joaquim Patriarca, Ismael Jesusand Diogo Duarte, University of Coimbra).

Part 3- **Data collection and Validation**. This session, chaired by Ana-Maria Olteanu-Raimond, referred to data collection and validation aspects of VGI usage for LULC. This interesting session

¹ <https://landsense.eu/>

covered the following presentations: Global land cover monitoring, validation and participation: experiences from several case studies (Martin Herold, Nandika Tsendbazar, Arun Pratihast, Agnieska Tarko, Lilin Liu Laboratory of Geo-Information Science and Remote Sensing, Wageningen University & Research); a mobile application for collecting snow data in support to satellite remote sensing (Zacharie Barrou Dumont, CESBIO); and a mapping prototype for land use mapping by land users, Marcos Moreu, Muki Haklay, Claire Ellul and the Extreme Citizen Science (ExCiteS) team, University College London).

Part 4- **Sustainability**. This final session, chaired by Inian Moorthy, referred to the sustainability aspects of VGI usage for LULC. It included the following presentations: Crowdsourcing reference data collection for land cover and land use mapping: Findings from picture pile and Fotoquest (Go, Steffen Fritz, IIASA); Land Cover Monitoring System with Sentinel-Hub and eo-learn - Is it possible to build a fast and cost-effective LCMS? (Matej Aleksandrov, Matej Batič and Grega Milčinski, Sinergise); Regular monitoring of landscape changes with Copernicus data - The German land cover change detection service (Patrick Knöfel, BKG); and Authentication as a Service - A LandSense contribution to improve the FAIR principle in Citizen Science (Andreas Matheus, SecureDimension).

The presentations of the workshop covered a wide range of topics, such as: feature-based LULC data production, feature-based LULC update, LULC Change detection, LULC Monitoring services, Use of VGI to produce LULC data, VGI and authoritative LULC data integration, LULC data quality assessment, LULC data infrastructure, and LULC data policies.

The workshop is at the overlap between two domains, Volunteered Geography on the one hand and Land Use and Land Cover data production and maintenance on the other hand, which today present complementary challenges and opportunities. The large panel of the addressed topics allows highlighting the following conclusions:

1. About the use of deep learning approaches to classify time series of high resolution images in order to produce LC data. These promising results showed that progress still needs to be made in order to improve classification maps for some difficult classes (e.g. agricultural areas, herbaceous vegetation) and to comprehensively validate the obtained data.
2. The use of VGI to produce LULC data or to complement LULC authoritative data is a common practice nowadays. Issues regarding data quality, multi-sources data integration and licenses consistencies need more research work.
3. In terms of VGI data collection, it is evident that the main issue VGI initiatives faced are the motivation and participation of the contributors. Different strategies were noted such as organising thematic challenges, mapathons, given prizes to the “best contributors”, or proposing gamification tools have been noted. How to build a sustainable VGI initiative is still a major question. Giving a more prominent place to the local and regional public authorities in VGI data collection initiatives seems to be the way to go further.
4. A topic which is little addressed concerned the update. There are many LULC and validation data produced by innovative methods, the question is how these data will be updated and how the link between different time-series would be defined in order to facilitate the LULC monitoring over time. Interoperability between products is not always straightforward.
5. Finally, this workshop shows the very large panel of available LULC data at different spatial (e.g., from global to very local) and temporal resolutions. One issue which should be addressed is the usability: How can we help users to choose a LULC product? How can we help users to measure the uncertainty which is specific to each LULC product and use case depending on production and validation used methods?

1 Part 1 - Introduction

1.1 Land Use and Land Cover data: specificities and challenges

Clément Mallet

Univ. Gustave Eiffel, IGN-ENSG, LASTIG, F-94160 Saint-Mandé, France

Land-Cover maps target to describe the observed (bio-)physical cover of the Earth surface while Land-Use products are focusing on the human interaction counterpart. Therefore, Land-Use and Land-Cover (LULC) geodatabases document all types of objects and surfaces, whether they may not remain stable over time (state and trend). The multiple geodatabases produced over the last 30 years at various spatial and semantic scales have shown their high relevance for numerous applications, in particular for setting up and monitoring public policies. Accurate and up-to-date LULC maps, especially at large scales, are subsequently mandatory core information layers on which by-products are derived, decisions are taken, thematic researches are performed (ecology, economy, agriculture, urban planning, etc.).

Remote sensing has proved over the two last decades to be the only suitable solution for automatically generating LULC maps, in particular at global and continental scales. Multiple operational frameworks have been set up and routinely process the ever growing amount of satellite imagery available today. Nowadays, it is possible, over a given area of interest, to have access to several LULC maps providing complementary information at multiple scales. Such maps (either raster or vector format) often propose hierarchical nomenclatures, thematic by-products (e.g., the *Tree Canopy* and *Impervious surfaces* layers for the US NLCD, the *Urban Atlas* for the European CLC), and multiple versions (starting in the 1990's), permitting detecting changes over significant time spans. In order to ease the update, harmonization over scales or change detection processes and in order to permit a direct transition for LU to LC, mapping agencies often rely on an object-based or hardbone strategy: a permanent stable partition of the territory is first defined (SIOSE in Spain, a skeleton based on networks in France, the hardbone/softbone concepts for CLC+).

Currently, most LULC map generation strategies rely on the supervised classification of geospatial images. Recent years have witnessed a change of paradigm:

- With the plethora of images available today, we moved from a mono-sensor to a multi-sensor and multi-temporal solution. Additional spectral and temporal information allows to steadily improve the discrimination of various classes of interest: richer nomenclatures are conceivable (crop types, tree species) as maps with higher spatial resolutions (1km/100m → 5m).
- More complex classifiers and post-processing strategies are proposed, in particular in the deep learning era. This allows to foster information extraction from multi-modal geospatial imagery, this enables to efficiently learn class appearance from outdated LULC maps (the so called *reference data*) and subsequently this participates in proposing richer LULC maps and with superior accuracy.
- Citizen science has shown its relevance in multiple domains for which fully automatic state-of-the-art machine learning techniques cannot act or do not perform well: proposing reference data for poorly documented classes or areas, validating the automatic products or tailoring them to a given specification (e.g., Minimal Mapping Unit), detecting changes.

National Mapping Agencies are focusing on defining operational solutions, that are not fully addressed by the large body of literature on the field today: automatic solutions, that are scalable, qualified, with limited heuristics, delivering frequent and consistent maps, interoperable with other products and

versatile, i.e., that can suit multiple purposes (various end-users with mapping or statistical goals). Multiple methodological challenges stem from such requirements and pave the way for future research in the domain. Those for which VGI can significantly help are indicated below with (*):

- Data fusion: how to extract meaningful information from the large amount of multi-modal geospatial imagery?
- Semi-supervised learning (*): how to limit the volume of reference data fed into the classifiers and benefit from the vast amount of unlabelled pixels? How to learn from imbalanced and rare classes?
- Multi-task learning: how to simultaneously derive multiple outputs (change maps, bio-geophysical parameters, classes)?
- Map generation (*): how to move from per-pixel raster classification outputs to geodatabases? How to learn map specifications and acceptable accuracies?
- Map interoperability: how to generate consistent and comparable maps?
- Evaluation (*): how to perform an unbiased and comprehensive evaluation of the maps?

1.2 VGI and citizen science for LULC monitoring

Ana-Maria Olteanu-Raimond¹, Inian Moorthy²

¹ Univ. Gustave Eiffel, IGN-ENSG, LASTIG, F-94160 Saint-Mandé, France

² International Institute for Applied Systems Analysis (IIASA), Austria

The goal of this introductory presentation is to expose the attendees how Volunteered Geographic Information (VGI) and Citizen Science could be used to monitor LULC.

Firstly, the two concepts, VGI and Citizen Science, are introduced. Citizen Science can be defined such as the participatory and combined analysis to science. Thus, the citizens are contributing by collecting information to science. This practice is a long standing one, the concept being defined around the seventies and many initiatives were proposed since then . It is wide spread nowadays all over the world and historically it was used to monitor species by following rigid protocols (See et al., 2015). VGI is concept meaning volunteered geographic information (Goodchild,2007). It defines that the geographic information is voluntarily produced or shared by the crowd (or citizens) by using Web 2.0 technologies. Thus, the user became a data producer, a practice coined by Bruns (2008) as *producer*. VGI has evolved during the time. In this evolution we can notice, the importance gained by OpenStreetMap from his creation back in 2004 to the structuring of an international community with its own annual conference State of the Map from 2007 on. Let us underline also an increasing interest for VGI such as data quality (Haklay, 2010; Jokar Arsanjani, 2015; Barron et al., 2014; Touya et al., 2017, Ivanovic et al., 2019), research questions on the community, the motivation of the crowd, sustainability of the VGI initiatives (Nielsen et al., 2013; Schmidt et Klettner, 2013; Jolivet and Olteanu-Raimond, 2017; Gomez-Barron et. al, 2016) as well as new challenges regarding the use of VGI (Zielstra et Hochmair, 2011, Van Winden et al., 2016).

Concerning the use of VGI in the National Mapping Agency, recent research showed the interest of NMAs in using VGI or developing their own platform (Olteanu-Raimond et al., 2016, Olteanu-Raimond et al., 2017).Secondly, the use of VGI in monitoring LULC data is illustrated by different pilots proposed in the LandSense project. LandSense technologies² are deployed across various themes to illustrate the potential of citizen observatories to tackle environmental challenges. Different pilots collecting in-situ or on web data for monitoring urban dynamics (Viena, Toulouse, Amsterdam), agricultural land use (Vojvodina-Serbia) or forest and biodiversity threats (Indonesia, Spain) are described.

In the second part of the Introduction, different pilots developed in the LandSense H2020 project have been presented. The pilots consist in engaging with different communities in order to collect *in-situ* information in different environments (e.g. urban, agricultural, forest, etc.) and to monitor LULC data.

² <https://zenodo.org/communities/landsense>

2 Part 2 - Session 1: Use of VGI for LULC data production

2.1 National Land Cover and Land Use Information System of Spain (SIOSE)- Coordination, production, maintenance and VGI

Julián Delgado Hernández

Instituto Geográfico Nacional, Madrid., Spain

One of the objectives of the Instituto Geográfico Nacional (IGN Spain), in its role of National Reference Centre on Land Cover, Land Use and Spatial Planning from the EIONET Network of the European Environment Agency, is the production and coordination of information on land cover and land use in Spain. During decades, IGN Spain collaborates and produces CORINE Land Cover and participates in the verification of Copernicus Land Monitoring Services products.

However, due to the need for more detailed information at the national level, in 2005 it was launched the project “Sistema de Información sobre la Ocupación del Suelo en España” (SIOSE), the National Land Cover and Land Use Information System of Spain. SIOSE integrated the information available by the National and Regional administrations, generating a land cover and use database for the whole country. Versions of 2005, 2009, 2011 and 2014 have a reference scale of 1:25.000. However after several versions, and taking into account the new needs of the main regional, national and international users, specially the new 2nd generation of CORINE Land Cover products, that look for higher geometric, thematic and temporal detail, since 2016 a new production strategy has been developed more focused on the data integration, called High Resolution SIOSE (HR SIOSE). Its main objective is the integration, harmonization and homogenization of highly detailed official sources to continue being a benchmark product on land cover and land use in Spain. Such as cadastre (1:500-1:5.000), agricultural identification systems (1:5.000), forest maps (1:25.000) or LiDAR data (0.5p/m2).



Figure 1: Example of HR SIOSE data

In order to provide a complete description of land, the volunteer geographic information plays an interesting role as complement of official data sources. IGN Spain has performed different researches in last years focused in OpenStreetMap (OSM) assessment in the context of the 2nd generation of CORINE Land Cover products. Research done in connection with Eionet Action Group on Land monitoring in Europe (LC/LU expert group) and with EuroGeographics. Main obstacles detected in these researches for the OSM use in the LC/LU production were connected with the non-official and non-responsible information provided by OSM that can carry with imprecision, unreliability, heterogeneity and derived costs for the production. However the benefits for its use also arisen during the research and motivated the reutilization of OSM data as complement of official data available.

In case of HR SIOSE, OSM data helps in the detection of elements and thematic content not identified previously by official sources. An automatic OSM download for entire country has been done, and resulting data have been divided in HR SIOSE production units that corresponds with more than 8000 municipalities, covering 500.000 km2. In practical term, it was necessary to establish a thematic mapping between OSM types-subtypes and national classes, and proceed with an overlap analysis between OSM elements and elements from official data sources. As result, 37 454 HR SIOSE elements (0,04%) were generated taking as geometric reference OSM, and 85 558 HR SIOSE (0,09%) elements were thematically improved by the OSM.

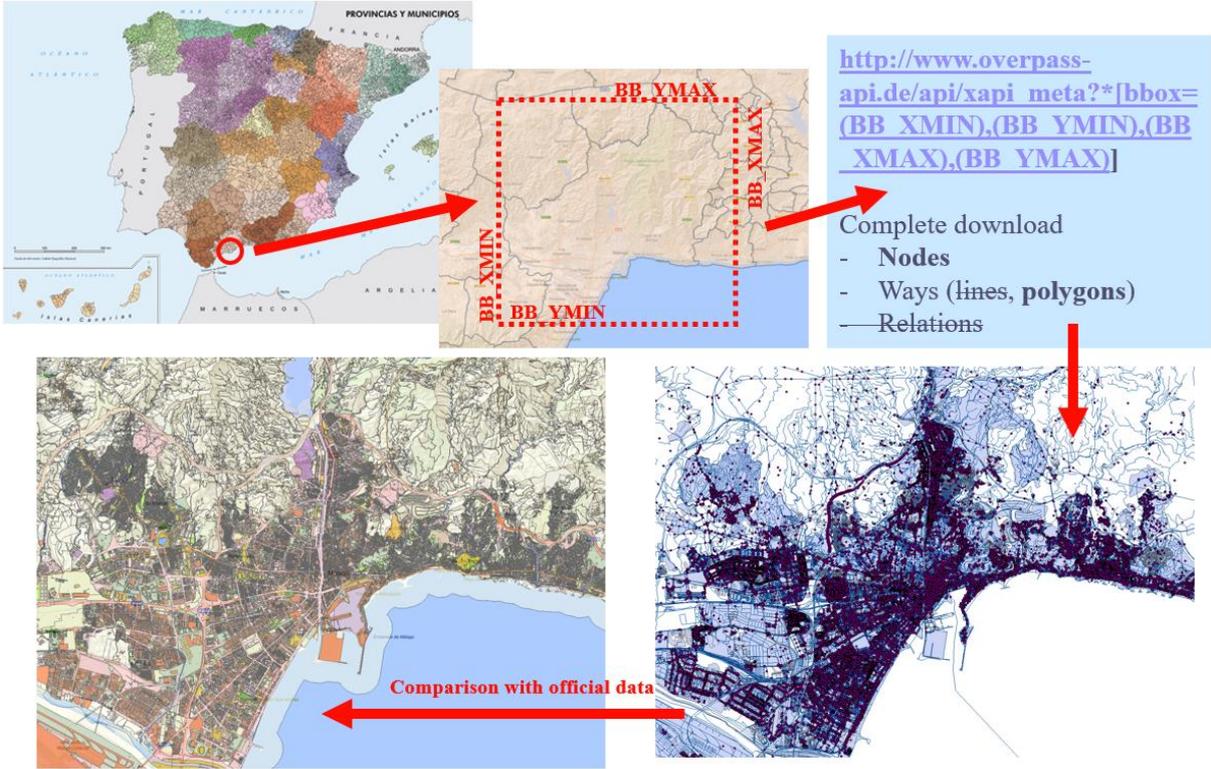


Figure 2: Example of OSM data extraction and its integration of HR SIOSE

2.2 A fusion data approach for integrating VGI to update and enrich authoritative LULC data

Lanfa Liu, Ana-Maria Olteanu-Raimond, Laurence Jolivet, Arnaud Le Bris

Univ. Gustave Eiffel, IGN-ENSG, LASTIG, F-94160 Saint-Mande, France

In this work, we present a workflow aiming to integrate authoritative LULC and VGI in order to update and enrich authoritative LULC data. The work is part of a pilot carried out by IGN France in the LandSense project and was published in Liu et al., (2020). The proposed approach was tested on citizen-observed data. The data were collected through different data collection campaigns organized from 2018 to 2020 by using the PAYSAGES tools (Olteanu-Raimond et al., 2017). These campaigns were run to obtain *in-situ* data or to collect visual interpretations of remotely-sensed images regarding the current LU for the study site. The data are available on the Zenodo platform (Olteanu-Raimond et al., 2019). Each type of VGI dataset is modelled such as a source of information (one data set for each type of data) and pieces of information are fused by using Dempster-Shafer Theory. The workflow is composed of four main steps: pre-processing, nomenclature mapping, data fusion and final decision. The input data are first analyzed and enriched during the pre-processing step (e.g. calculation of agreement between spatially close data including observations about the same feature, the characterization of spatial overlap, and data filtering). Secondly, the mapping between the nomenclature of VGI and authoritative LU data is defined. Then, the different inputs coming from the multi-source VGI data are fused under the framework of Dempster-Shafer Theory. The method is able to identify three types of decision: no-update, enrichment and change.

Figure 3 illustrates an example of where an initial LU polygon has the class LU6.3 (Not currently used). For this polygon, there are two types of VGI collected: change polygon manually edited by volunteers (purple area) and classified into LU5 (Residential use) and changes automatically detected and validated by volunteers (orange areas). It is about two change features indicating new residential buildings (LU5-Residential) and new infrastructure use (LU4.1-Transportation network). The solution proposed by the workflow is that the LU of the polygon should change and the new land use class should be LU5 (Residential). Thus, the LU for this polygon will then change from LU6.3 (Not currently used) to LU5 (Residential).



Figure 3: Example of multi-source VGI collected for LU polygons.
a (1) LU polygons and associated multi-source VGI; a(2) aerial imagery in 2016;
a(3) Pléiades imagery in 2019 ; from Liu et al., 2020

The results of the data fusion approach are manually validated for the 144 features having at least two contributions from two datasets. An overall accuracy of 85.6% is obtained. The validation step allows to identify different sources of errors such as the knowledge gap of the volunteers regarding the authoritative land use nomenclatures or the inaccurate geometries of the detected changes (see Figure 4). The LU polygon initially classified into LU6.3 (*Not currently used*) is characterised by change features (LU2-Industrial) representing industrial use within the LU polygon with LU . The

result of our approach is LU2 (*Industrial*). By comparing the imagery in 2016 and 2019, it can be seen that only part of the area has changed, and the majority part is still a tree-covered area. However, LU2 (*Industrial*) will be incorrectly assigned to this LU polygon according to the current framework.



Figure 4: Example of errors referring to a change that only covers part of the initial polygon; LU polygons and associated data (at the left); aerial imagery in 2016 (in the middle); Pléiades imagery in 2019 (at the right); issued from Liu et al., 2020

Despite the heterogeneity and limited amount of VGI used, the results are promising, with 99% of the LU polygons having volunteered observation are updated or enriched. These results show the potential of using multi-source VGI to update or enrich authoritative LU data and potentially LULC data more generally.

Despite the heterogeneity and the limited amount of the used citizen-observed data sets, the results are promising and show the interest in using citizen observed data to update or potentially enrich authoritative LULC data.

2.3 OpenStreetMap for Earth Observation (OSM4EO) land use application and benchmark

Michael Schultz¹, Ana-Maria Olteanu-Raimond², Gavin Long³, Giles Foody³, Alexander Zipf^d

¹ Heidelberg University, Heidelberg, Germany

² Univ. Gustave Eiffel, IGN-ENSG, LASTIG, F-94160 Saint-Mande, France

³ School of Geography, University of Nottingham, Nottingham, UK

By injecting known tags related to land use and land cover provided by OpenStreetMap (OSM) into a remote sensing feature space using deep learning, land use and land cover tags were predicted when absent. The contiguous map (www.osmlanduse.org) was produced for the member states of the EU. By design, our method can be applied when- and wherever OSM and Copernicus data is available. Our map was the first successful large area fusion of OSM and Copernicus at 10m spatial resolution or higher, where we acknowledged varying label noise and feature space quality, scales and effective use of artificial intelligence and computing. Our method solely relies on openly available data streams and does not depend on additional expert knowledge (Schultz et al. 2017). The outline of the method was shown in Figure 5.

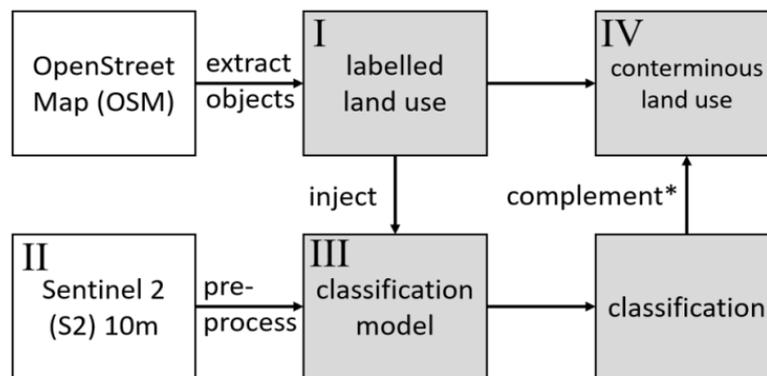


Figure 5: Research design for map production where roman letters I – IV show order and flow of events, grey boxes indicate data and models available within the paper’s repository;

*classification was used when labelled land use was absent; OSM data can be retrieved through OSM API, pre-processed S2 data through FAO’s sepal.io

We have compared this new data product OSM Landuse Landcover, with existing national products for France, Austria and Germany. Comparison benchmark results showed that residential and commercial/industrial usage was found to be particularly confused when comparing national products and the OSM based product. These differences could be attributed to the legend harmonization process due to differences in mixed classes. Both the Austrian and French national products allow a set of mixed classes regarding residential and commercial land use while the OSMLanduse map provides more rigorous class distinctions between residential and commercial/industrial. As a result, this created confusion particularly between urban and industrial classes. Thematic agreement of OSMLanduse and CLC was generally higher than with the converted national products. Like OSMLanduse, Corine Land Cover (CLC) avoids mixed classes. Second, the most common confusion was found between artificial vegetated green areas, agriculture and herbaceous surfaces. The level of spatial detail of the maps varied greatly. The German national product was only available in parts for Heidelberg. In contrast, the Austrian national product was available open data for the entire area of interest and in great spatial detail. Similarly, the French national product was available in great spatial detail. Legal issues for data usage and data availability varied by country, and therefore, affected the comparison. A detailed report was made available during LandSense (Long et al. 2020).

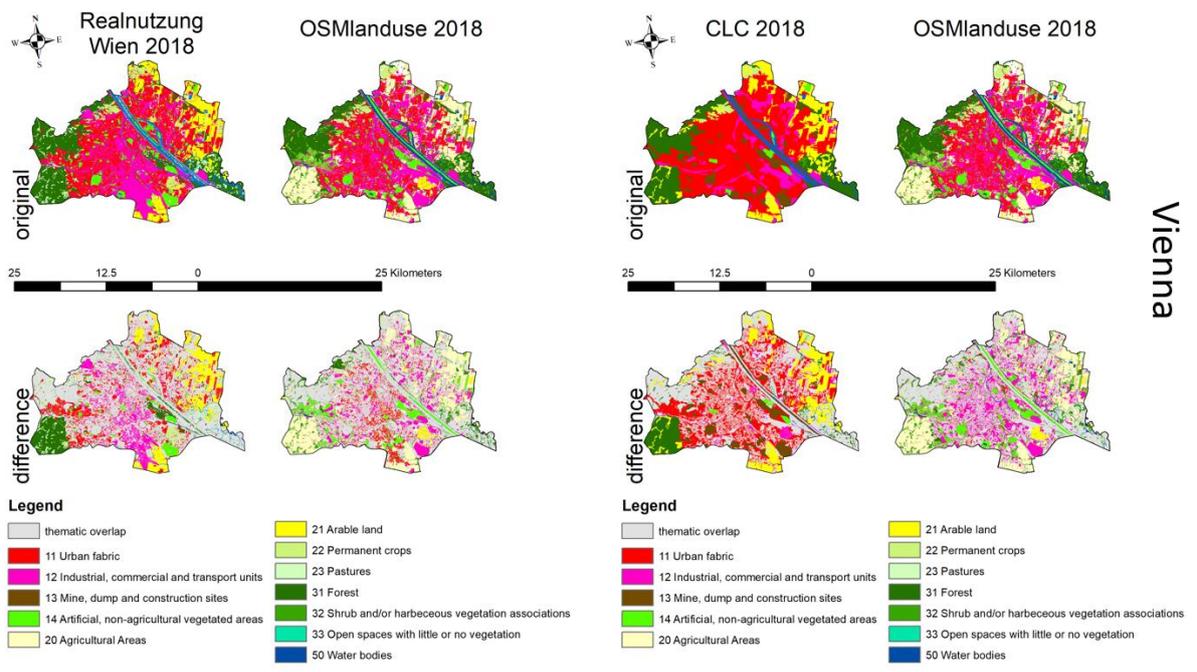


Figure 6: Example of benchmark comparison of OSMlanduse type products against local Realnutzung and CLC data for the city of Vienna

2.4 Using OpenStreetMap as a data source for training classifiers to generate LULC maps

Cidália Fonte¹, Joaquim Patriarca², Ismael Jesus², Diogo Duarte³

¹ University of Coimbra, INESC Coimbra, Department of Mathematics, Coimbra, Portugal

² University of Coimbra, INESC Coimbra, Dep. of Informatics Engineering, Coimbra, Portugal

³ INESC Coimbra, Coimbra, Portugal

The generation of Land Use/Land Cover (LULC) maps through the classification of satellite imagery using supervised classifiers requires training data. These data are usually obtained through the manual identification of regions that characterize each of the classes of interest. On the other hand, OpenStreetMap (OSM) is a collaborative project where volunteers contribute with vector data about many types of features of interest, such as buildings, amenities, road network, land use, water ways, among many others (https://wiki.openstreetmap.org/wiki/Map_features). OSM data can be downloaded in the vector format using an available Application Programming Interface (API). Then, it may be converted into LULC information (Patriarca et al., 2019; Fonte, Patriarca, et al., 2017; Arsanjani et al., 2013). Resulting LULC maps will likely have regions with no information where OSM has no available data (Fonte, Minghini, et al., 2017; Schultz et al., 2017). However, these data may also be used to train classifiers, or even for map validation (Fonte & Martinho, 2017; Schultz et al., 2017). Although, one of the main problems with the use of OSM extracted data both for training classifiers and for LULC map validation is its quality. Several factors may affect the quality of VGI, such as the subjectivity of the contributors, the heterogeneity of data completeness or positional quality over space (Basiri et al., 2019; Fonte, Antoniou, et al., 2017; Fonte et al., 2015). These will influence the quality of the LULC information generated using these training data.

Due to the above, the aim of the research work presented in the workshop was to, on one hand, enable the automation of the selection of training data using OSM data, and on the other hand, to use only high-quality data for training. This combination aims to enable the automatic generation of training data whenever new classifications need to be generated, which improves efficiency by increasing the speed of the process of creating new updated LULC maps whilst reducing costs.

The procedure illustrated in Figure 7 was followed to test several filtering methodologies.

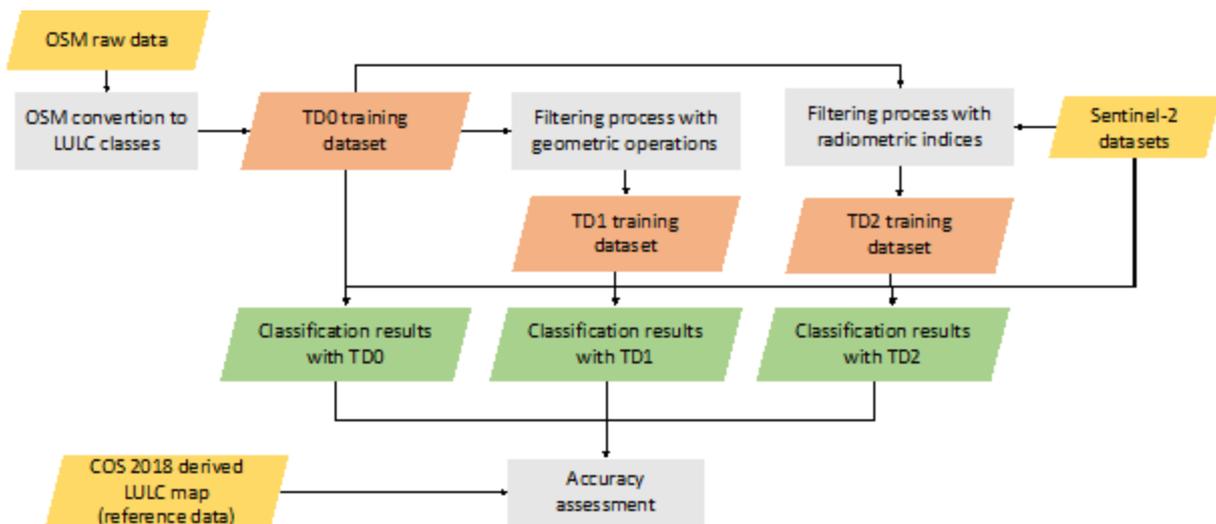


Figure 7: Workflow of the testing methodology used to filter OSM data to train classifiers to produce LULC maps.

The conversion of OSM data into LULC information was made using an automatic procedure developed using open source software (Patriarca et al., 2019; Fonte et al., 2020), which generated the training dataset TD0. Then, two filtering approaches were tested: 1) considering the uncertainty associated to the assignment of LULC classes to each pixel based on the overlapping of contradictory data and the presence of different classes within each pixel (generating the TD1 data set), 2) using radiometric indices extracted from the images to be classified (generating the TD2 data set). This methodology was applied to the classification of Sentinel-2 images for two study areas with different characteristics (one urban and the other rural). The separability of the classes was assessed for the three training datasets used for each study area and the classification results were compared. The accuracy of the results was assessed comparing the obtained maps with an authoritative LULC map of the same year, with a Minimum Mapping Unit (MMU) of 1 ha. Figure 8 shows the classification results for both study areas obtained with the training data extracted from TD2 and the reference maps used to assess the accuracy of the results.

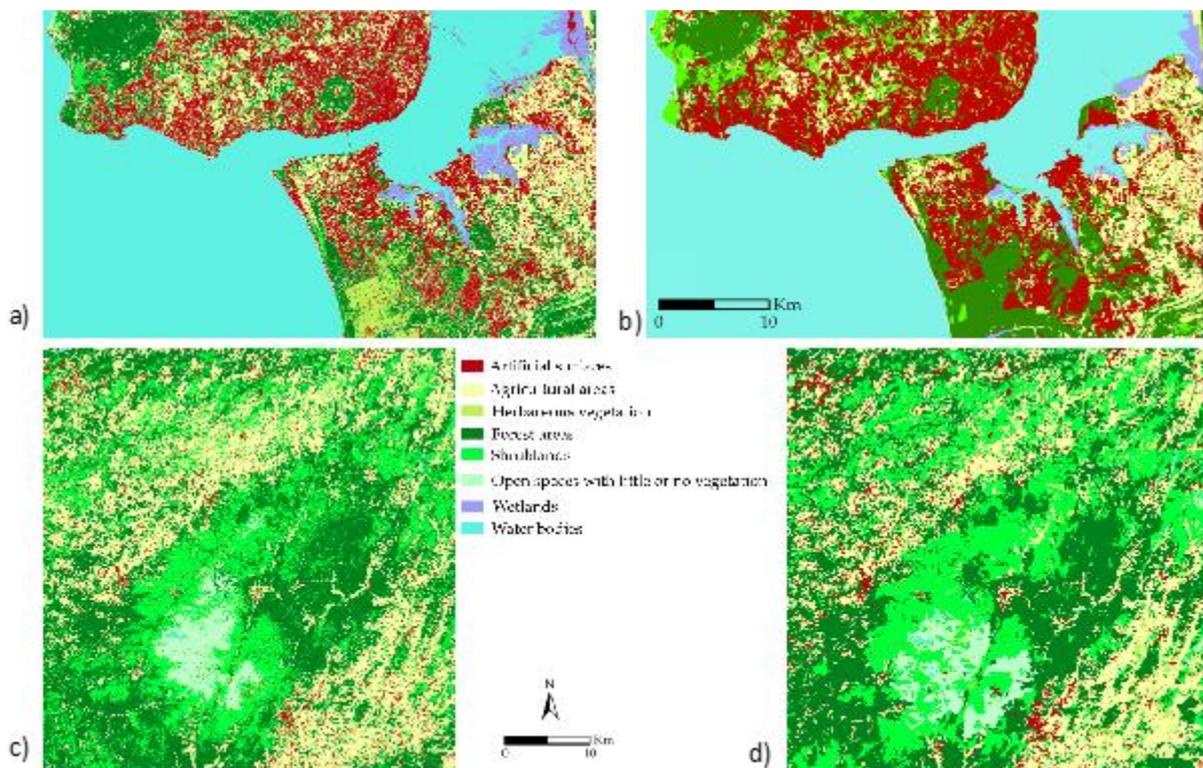


Figure 8: a) and b) show, respectively, the classification results obtained with the training data extracted from TD2 and the reference data for study area A (an urban area), while c) and d) show, respectively, the classification results obtained with the training data extracted from TD2 and the reference data for study area B (a rural area)

The results showed that, in general, the filtering processes improved the class separability, as problematic regions were removed from the training data. The accuracy of the classification results increased with the filtering procedures for the urban area but remained unchanged for the rural area. The nomenclature used in the case studies included land use and land cover classes, and therefore some classes were difficult to differentiate, in particular the classes with vegetation (agricultural areas, herbaceous vegetation, shrublands and open spaces with little or no vegetation). On the other hand, this analysis used a pixel-oriented classification and the reference map used to assess the accuracy of the results has a MMU of 1 ha, which does not enable the representation of small regions. Even though, an overall accuracy of 78% was achieved for the urban area with the training data TD2 (Fonte et al., 2020), with a procedure that is completely automated.

3 Part 3 - Session 2: Data collection and validation

This session contained three presentations: two of them focused on tools for data collection and one of them was focused on different experiences made for global land cover monitoring and validation.

3.1 *A mapping prototype for land use mapping by land users*

Marcos Moreu, Muki Haklay, Claire Ellul

ExCiteS group, Geography Dept., University College London

The Earth's surface is mainly mapped by professional surveyors, cartographers and geographers, algorithm developers and active volunteers or contributors of open collaborative mapping projects who are increasingly contributing to mapping processes (Wolf, 2002; Gorelick et al., 2017; Anderson et al., 2019). Often, land is not mapped by those who use³ it, but maps are non-neutral artefacts (Chambers, 2006). In the Digital Earth era, land cover and land use maps generated through the application of semi-automatic satellite or aerial image classification methods will likely continue their rapid growth (Brovelli et al., 2020). Nevertheless, automated methods for capturing land use information remotely have their limitations – pixel values alone do not capture local knowledge such as the location of sacred sites, migration corridors, farming techniques or the fuzzy boundaries of a hunting area. Though understanding how humans use land requires integrating the knowledge that land users hold into the mapping process, the democratisation of geographic data use and production which make this possible is not yet a reality (Haklay, 2013), especially in rural areas with limited or no internet penetration (ITU, 2020). There is currently a lack of collective knowledge and open data and information availability about human-land interactions (or people-to-land relationships), and this poses an obstacle to ensuring sustainable development for all by tackling the two interconnected problems of climate change and rural poverty associated with insecure land rights (Fritz et al., 2019; McLaren, 2011; Zevenbergen et al., 2015). In this context, Geospatial and Information and Communication Technologies (geo-ICTs) bring new opportunities, as well as risks.

Technology alone will not solve the problem of inequality in participation in geographic data production and use. Interdisciplinary multi-stakeholder collaboration and socio-technical approaches that consider how technology is used in situ are needed to minimise the risks and address the challenges. On this basis, we are co-developing a satellite imagery-based mapping prototype that aims fulfill the following requirements: *i*) useful to address local issues and global challenges; *ii*) usable, i.e., easy to use by anyone without or minimal training; *iii*) easy to deploy and share to address the scalability problem and stimulate collaboration; *iv*) easy to customize where needed; *v*) cross-platform to enable on-site and off-site mapping in (shared) mobile devices and public screens; *vi*) non-network dependent to allow offline mapping and transmission of geographic data over 2G networks *vii*) with 'universal applicability' that allows the creation of semantic information without restrictions. This lack of restrictions is done to not limit or condition the local knowledge that can be potentially captured, i.e., avoids a predefined or agreed classification criteria for attributing geographic information,

³ Land use is understood here in its broadest sense and a discipline-oriented definition is therefore not adopted. Consequently, 'land user' is understood here as the citizen – regardless of their formal citizenship status – that uses the land. We have adopted this term because is widely used across disciplines, which we would like to approach to appropriately identify potential improvements, applications and risks of the tool and concept proposed here – this research does not focuses on investigating how land user-generated land use maps can play a role in land-related disciplines such as Land Management and Land Administration (de Vries et al., 2020; Lemmen et al., 2015), Digital Earth (Guo et al., 2020) or Land Systems Science, among other.

assuming that land use data will not be completely self-organised and might require manual, semi, or automatic post-processing and standardisation especially if combined with authoritative spatial datasets – Precision for whom? (McCall, 2011). The prototype is being designed following the hypothesis that mapping apps are more likely to become popular if they ‘go’ where lay people are and be designed to align with what lay people are familiar with, i.e., popular messaging apps, as well as offering the flexibility to map exactly what lay people are interested in mapping.

In this research, which is at an early stage, we argue that co-creating mapping tools and methods that allow anyone, regardless of level of literacy (be it for reading and writing, digital technology, or map utilisation) to create and interact with digital land use maps will contribute to: reducing inequality in participation; enhance open data-driven, artificial intelligence-assisted collaboration between citizens with similar and different backgrounds, realities and land related geographic knowledge (Lewis, 2007); and ultimately, to better understand how humans use land for reducing inequalities and ensuring sustainable development for all.

The figure below situates this research, which lies at the intersection of Science, Geographical Information (GI) and Citizen, and highlights the inclusive approach that we follow here. The technological element (geo-ICT and Human-Computer Interaction in particular) is not represented, but it is at the core of this research.

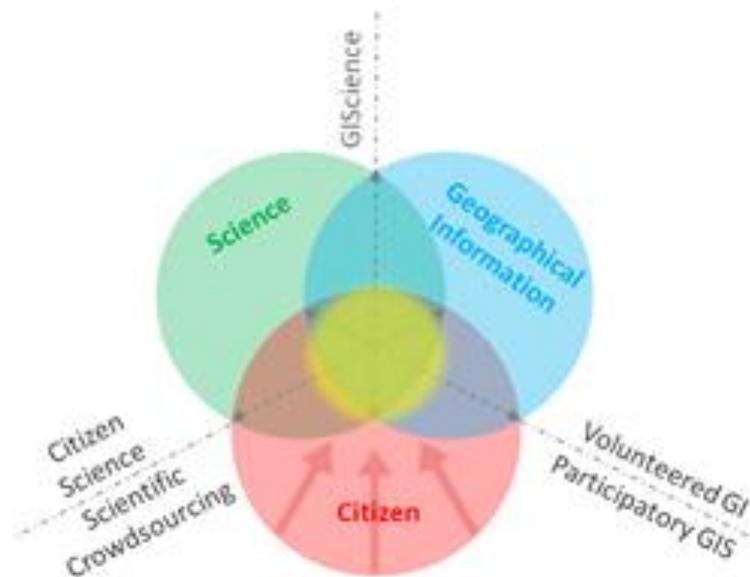


Figure 9: Representation of the relevant (sub) disciplines, the area of study (in yellow), and the inclusive approach (red arrows) of this research (Adapted from Kim, 2014).

Figure 10 is a workflow diagram that aims to represent the citizens’ role and some of the technologies and options for mapping, storing, sharing, visualising and analysing land use data. The flow starts with the mobile data collection, visualisation and analysis (left to right), then the data can be shared privately using messaging apps or as open data (center) for ‘others’ to comment, process, analyse etc. (right to left). The concept here goes beyond the role of crowdsourcing in artificial intelligence, i.e., citizens can not only create the maps but should participate in their interpretation and also benefit from the resulting shared understanding of their environment that is achieved through their use and wider dissemination.

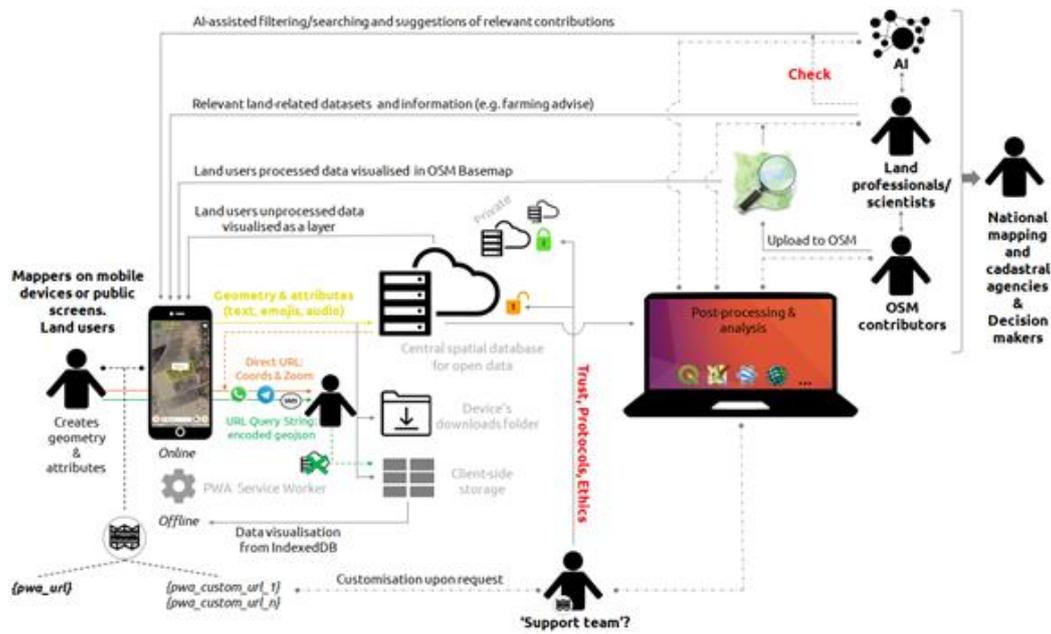


Figure 10: Open, multi-stakeholder, land use data-driven collaboration and knowledge exchange

The technological, social, institutional, legal and security challenges have not been discussed in this report. However, we need to highlight here that, due to the fact that mapping (by) the unmapped and open land use data can have negative consequences to local people (Abbot et al., 1998), the Progressive Web App mapping prototype is temporarily password protected during the testing period with rural and urban communities in Sub-Saharan Africa and Europe.

3.2 *A mobile application for collecting snow data in support to satellite remote sensing*

Zacharie Barrou Dumont,

Center for the Study of the Biosphere from Space (CESBIO), Toulouse, France

The Copernicus Snow & Ice Monitoring Service project aims to provide operational snow cover maps at Pan European scale from Sentinel-2 data. A main challenge of this project is the calculation, for a Sentinel-2 pixel with 20 meters resolution, of the fraction of the corresponding land surface covered by snow while considering the snow hidden under the trees. To evaluate the results of such calculation, a large amount of ground data in open and forest areas is necessary. However, ground observations of the fractional snow cover are scarce, especially under forest canopy. This difficulty has led us to ask the general public for help.

A first experiment was conducted using the Open Data Kit (ODK) Collect application. A specific form was set up to allow the user to enter the fractional snow cover around his/her position. From this experiment we obtained 337 measurements from 21 contributors that were successfully used to evaluate On Ground fractional snow cover maps from Sentinel-2 retrievals mainly in French mountain ranges. Despite the uncertainties from the data collection method, the results gave us a correlation of 67%.

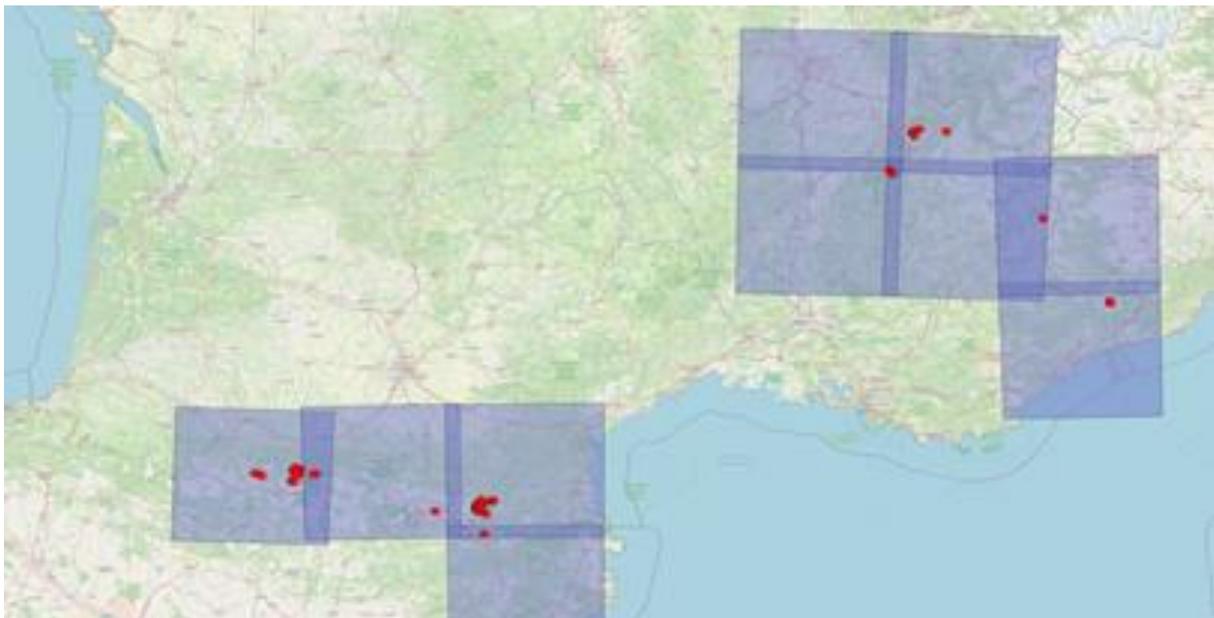


Figure 11: Overlapping of ODK data with Sentinel 2 tiles over the Alps and Pyrenees

However, the default ODK application was a bit complex to configure and this may have discouraged some users. Given that the first experiment was promising, the CESBIO created an easy-to-use open-source smartphone application named SDK that lets users collect and send snow data with their phone. The goal is to ask European hikers to fill a form with their coordinates and the perceived fraction of land surrounding them in a 10 meters radius covered by snow.



Figure 12: Utilization of SDK to fill and send one form

The collected VGI data will be made available to the public via the CESBIO website. To foster users interest their contribution will be displayed with other possible metrics and we are considering offering prizes to the best contributors.

SDK was made with the idea to involve the general public with land cover research in mind and has the potential to become a ground-truth data source. The fact that its coding is simple and easily editable makes it a potential template for other thematics such as hydrology or geology.

3.3 *Global land cover monitoring, validation and participation: experiences from several case studies*

Martin Herold, Nandika Tsendbazar, Arun Pratihast, Agnieska Tarko, Lilin Liu

Laboratory of Geo-Information Science and Remote Sensing, Wageningen University & Research, Droevendaalsesteeg 3, 6708 PB Wageningen, the Netherlands

While large-area/global land cover and forest monitoring systems rely on the analysis of remote sensing data, numerous case studies have also demonstrated that communities and local experts can play a pivotal role in the monitoring of forests. Thanks to their proximity and familiarity with the environment under concern, they have the capacity to identify changes at an early stage, including small-scale disturbances and progressive forest degradation that remain for a large part undetected by remote sensing observations. The integration of participatory data streams has therefore the potential to enhance data exchange and increase transparency and stakeholder engagement for sustainable and climate-smart land use practices. This integration presents however socio-cultural and technical challenges that need to be addressed to provide mutual benefits and ensure the sustainability of the scheme.

As part of the Copernicus Global Land Operations (CGLOPS) land cover service development, a system for the independent validation of global land cover and change datasets at 100m resolution has been designed. The reference data interpretation included the interaction and training of several regional and local experts to provide quality land cover interpretations for a statistically robust validation framework analysis. We will present the experiences of working with those experts and the effects of training and interactions on the quality of the land cover data provided.

Since 2014, Wageningen University and Research (WUR) has been working successively in Ethiopia, Peru and Indonesia to study the potential of interactive Near-Real Time (NRT) forest monitoring systems that combine remote sensing deforestation alerts with community-based monitoring (CBM) data collected using mobile phones. Following a first research project on CBM in Vietnam (Pratihast et al., 2012), an interactive web-based NRT forest monitoring system was implemented and evaluated in the UNESCO Kafa Biosphere Reserve in Ethiopia. Trained local experts could provide up-to-date and accurate information on forest change through mobile phones, that had the potential to be integrated into a national Monitoring, Reporting and Verification (MRV) system (Pratihast et al., 2014, Pratihast et al., 2016). Data collected by local forest experts over a 3-year period and dense-satellite time series spectral-temporal metrics were also used to train random forest models and predict deforestation, degradation and stable forests (DeVries et al., 2016).

In Peru, the Ministry of Environment (MINAM) has recently developed an online forest monitoring system providing deforestation alerts through the analysis of optical medium- and high-resolution imagery⁴. In addition, MINAM implemented Direct Conditional Transfers (TDC), a benefits scheme aimed at native communities for the conservation of forests. WUR supported MINAM by experimenting in 2016 the use of mobile devices for forest change data collection by 3 communities. In addition, 1,720 field observations collected manually by 43 communities from 2015 to 2017 were analysed to better understand challenges of the existing participatory monitoring system (incl. responding to satellite-based alerts) and evaluate how new technologies such as mobile phones or drones could empower the communities and contribute to a more efficient forest conservation scheme.

In Indonesia, WUR has been exploring since mid-2018 the development of an augmented interactive monitoring system relying on a NRT forest cover loss alerting approach based on Sentinel-1 radar data (Reiche et al., 2018). Radar-based forest cover loss alerts have the potential to overcome challenges met by optical-based systems, such as permanent cloud cover. Implemented in Google Earth Engine, a

⁴ <http://geobosques.minam.gob.pe>

first prototype of alerting system has already been experimented on Flores Island (Archipelagos of the Azores) in the scope of the LandSense project⁵. Further work will be conducted in 2019 to integrate participatory monitoring data streams and apply a large-area interactive monitoring system for sustainable supply chain management in the oil palm industry.

Our ultimate objective is to implement a scalable participatory forest monitoring system based on open-source technology that increases spatial and temporal accuracy of forest change detection, as well as the confidence in the changes detected.

⁵ <https://landsense.eu/>

4 Part 4 - Session 3: Sustainability

4.1 Crowdsourcing reference data collection for land cover and land use mapping: Findings from Picture Pile and FotoquestGo

Juan Carlos Laso Bayas, Linda See, Tobias Sturn, Mathias Karner, Dilek Fraisl, Inian Moorthy, Anto Subash, Ivelina, Georgieva, Gerid Hager, Myroslava Lesiv, Hadi Hadi, Olha Danylo, Santosh Karanam, Martina Dürauer, Domian Dahlia, Dmitry Shchepashchenko, Ian McCallum, Inian Moorthy and Steffen Fritz

International Institute for Applied Systems Analysis (IIASA), Austria

This presentation focused on findings for collecting crowdsourced reference data by using two innovative applications: Picture Pile and FotoQuestGO which are part of the Geo-wiki platform.

FotoQuestGO is a mobile application for citizens to report land use and land cover at specific locations. The application asked and guided the user to take pictures in the four cardinal directions and to answer different questions. Figure 13 illustrates the screens allowing selecting the appropriate land cover at the target point at different levels. Different campaigns were carried out in Austria (2015) and different EU countries (2018) where users were asked to visit the selected locations which match LUCAS points.

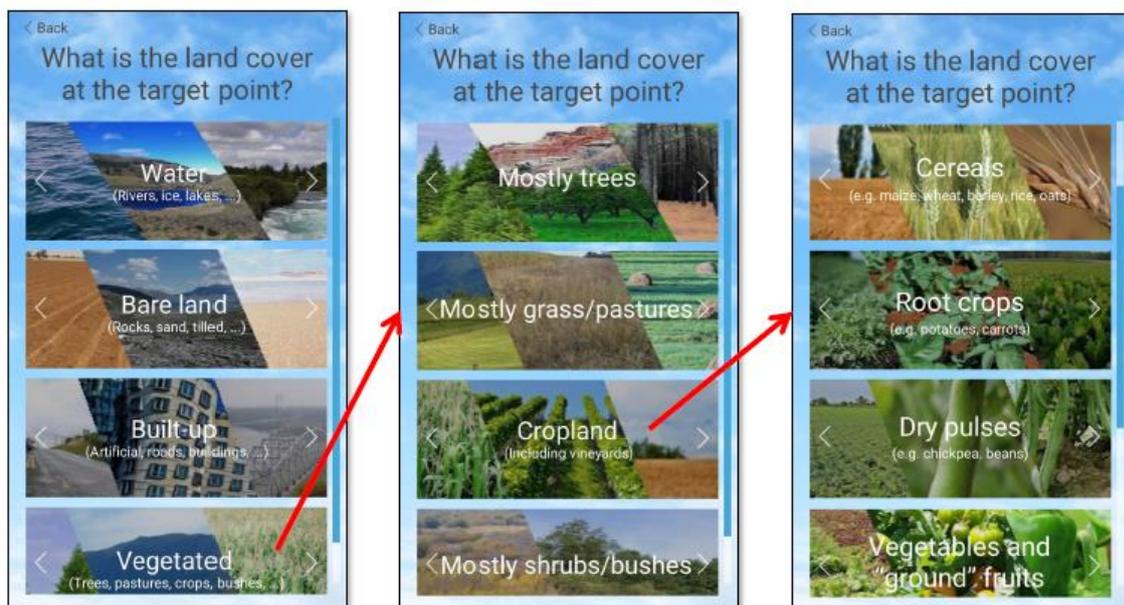


Figure 13: Screens for the FotoQuest Go application allowing land cover selection at level 1, corresponding level 2, and 3 sequentially

Picture Pile is a mobile and web application designed for rapid image assessment and change detection. Designed to be generic and flexible tool customizable to different domains that requires Earth Observation data as an input resource (e.g. cropland, deforestation, damages) as illustrated in Figure 14.



Figure 14: Screens capture from Picture pile illustrating questions addressed to users

The 2018 campaign has been specified to address limits fund during the 2015 campaign. It is Europe-wide, and quest can be visited only once. There are training videos provided online. Rewards are immediate instead of at the end of the campaign. A user friendly land cover decision tree interface is provided to guide user choice, with several auxiliary map layers. There is a near real-time feedback and quality control. As a result, the number of users has doubled (from 76 to 140) and the ratio of contributions that can be used for analysis (from 300 out of 1699 to 700 out of 1612).

4.2 Land Cover Monitoring System with Sentinel-Hub and Python Machine Learning Library eo-learn. Is it possible to build a fast and cost-effective LCMS?

Matej Aleksandrov, Matej Batič and Grega Milčinski

Sinergise Ltd, Ljubljana, Slovenia

With the plethora of both open-source as well as commercial satellite data available, creation of Land Use /Land Cover maps is moving from the niche solutions, where data was almost hand processed, towards the services run real-time updates based on recurring satellite observations and Machine Learning pipelines.

With in-house Sentinel-Hub services, geo-spatial and Earth observation expertise, we at Sinergise are at a perfect position to provide such solutions. Sentinel Hub is a satellite imagery processing service, capable of on-the-fly gridding, re-projection, mosaicking, compositing and other actions required for efficient fetching of data for end-users, either for integration in web-applications, where pictures are mostly served, or in machine learning and other analysis/interpretation processes, where pixel values and statistics are essential.

It has been operating in production for many years, processing hundreds of millions of requests for satellite data every day.

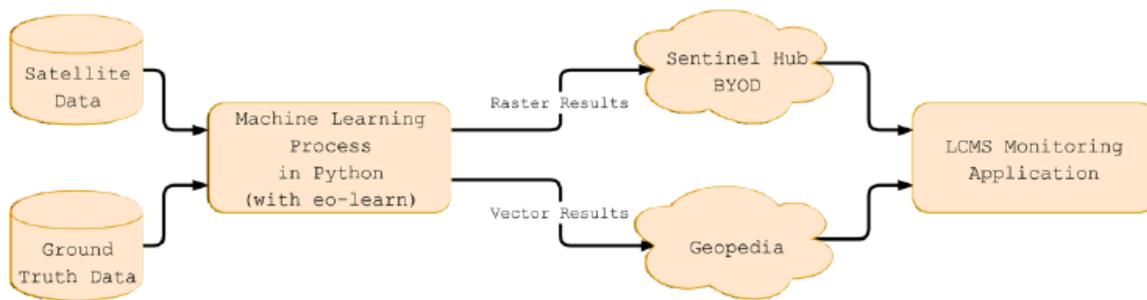


Figure 15: basic data-flow of the system

We have built a LandCover Monitoring System (LCMS) on top of our Sentinel Hub services. It allows us to process huge amounts of data for a large geographical area, extract relevant information and provide them in a format that is easy to understand and take action on. The system couples Sentinel Hub services, our Python ML framework eo-learn and our spatial data infrastructure Geopedia to implement an end-to-end solution for LCMS.

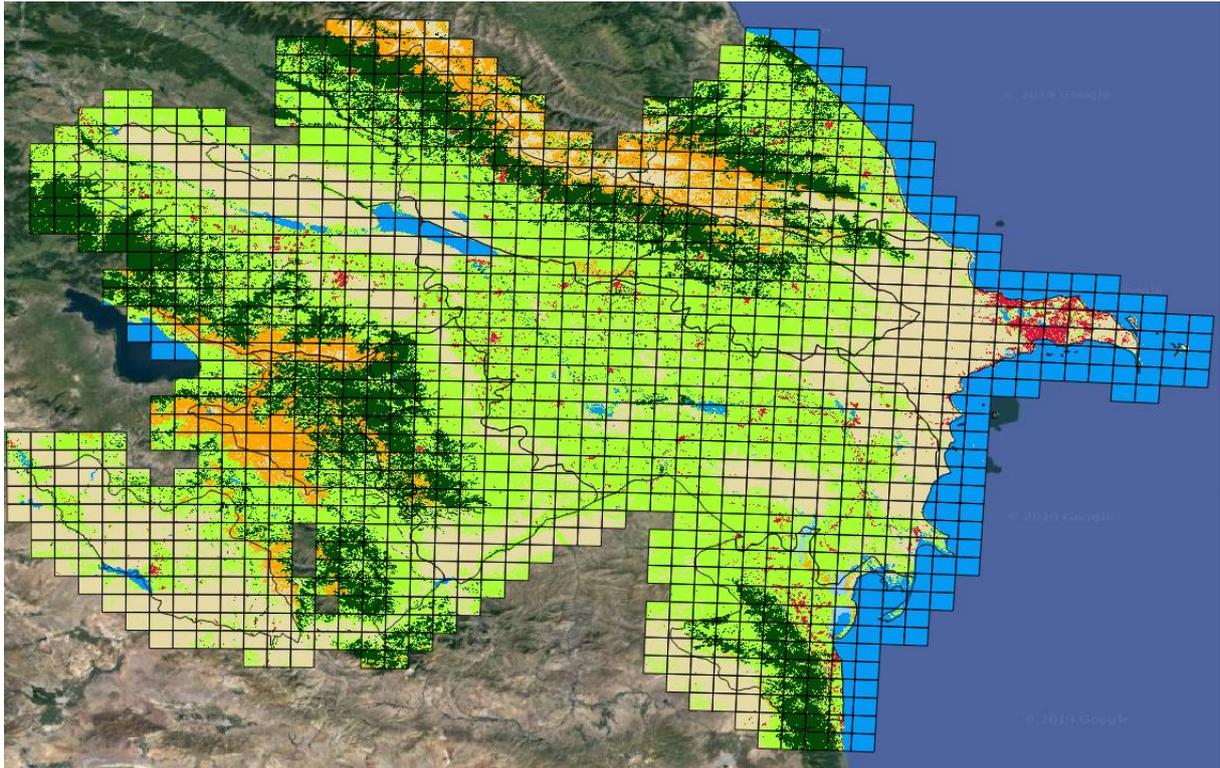


Figure 16: Land cover prediction map for Azerbaijan, divided into 1224 EOPatches over Google Satellite imagery, ©2019 Google

We have implemented a production-ready version of LCMS for the Republic of Azerbaijan. It is being used by governmental officials to automatically detect and track how the land is changing through time. We have also utilized LCMS for numerous experiments in Slovenia and recently we have developed it for Turkey as well.

We will present the challenges we have faced when building the necessary infrastructure, data pipelines, and models, and show the results of the work in Azerbaijan. We will open up discussion on how Open Street Map or similar volunteer geographic information (VGI) could be used in our system to provide most up-to-date results. On top of workflows to produce LU/LC maps we will show how we have implemented a pipeline for building detection from commercial satellite imagery. The LCMS system, coupled with Geopedia and a simple web application is used to validate the detected buildings, improving the models when fed back to the training data. We believe that such system, when employed with feedback loop (e.g. through VGI), provides the most agile approach to land monitoring.

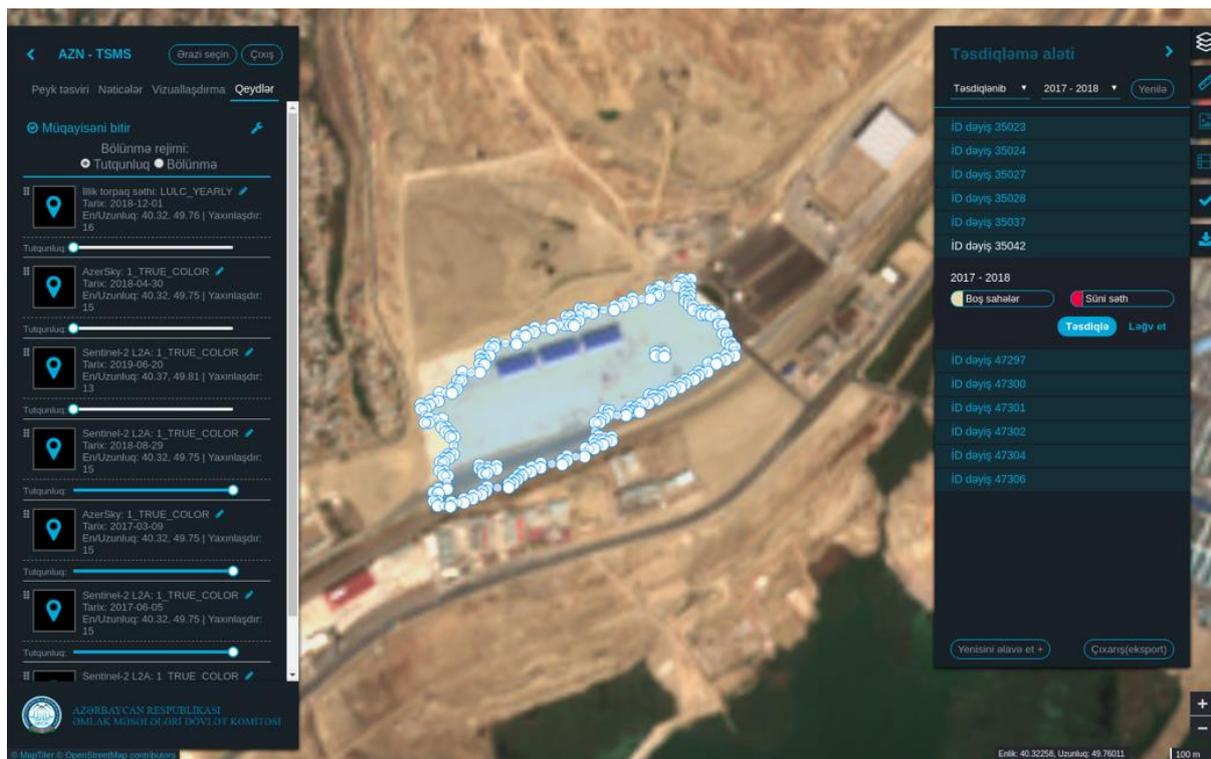


Figure 17: A web application allows straight-forward validation of detected land cover change, and provides valuable feedback to the system.

4.3 Regular monitoring of landscape changes with Copernicus data- The German land cover change detection service

Patrick Knoefe

Federal Agency for Cartography and Geodesy, Frankfurt., Germany

The research and development project called Landscape Change Detection Service (LaVerDi) was initiated by the Federal Agency for Cartography and Geodesy (BKG) in spring 2017. The project developed a landscape change monitoring service that uses free Copernicus satellite data to automatically derive land cover change indications. These indications are used to update or continue in-house products, such as the Digital Land Cover Model (LBM-DE), in a comprehensive and consistent quality. The results can be further used for numerous applications or as change information for administration and planning as well as for the production of spatial statistics. It meets the users' need for a national service for open land cover change data and thus represents the first automatic national satellite product for land cover change in Germany. A screenshot of the service website is illustrated in Figure 18.



Figure 18: Website screenshot of the LaVerDi web application

As input data, the service utilises pre-processed Sentinel-2 data from the European Copernicus satellite programme as well as image segmentation approaches for the extraction of change objects. Using an improved cloud mask algorithm, tiles with a maximum cloud coverage of 60% can be used for the analysis. The service (data processing, change detection, viewing) runs on the German "Copernicus Data and Utilization Platform" (CODE-DE) and the launch of the operational, INSPIRE-compliant LaVerDi web service was in December 2020. The thematic accuracy of the generated change layers is above the specified requirements (at least 80%) in the test areas, taking into account the 95% confidence interval for all relevant land cover classes. Figure 18 gives an example of detected tree losses (in red). Under normal conditions, the methodology is able to detect both long-term and seasonal changes reliably.

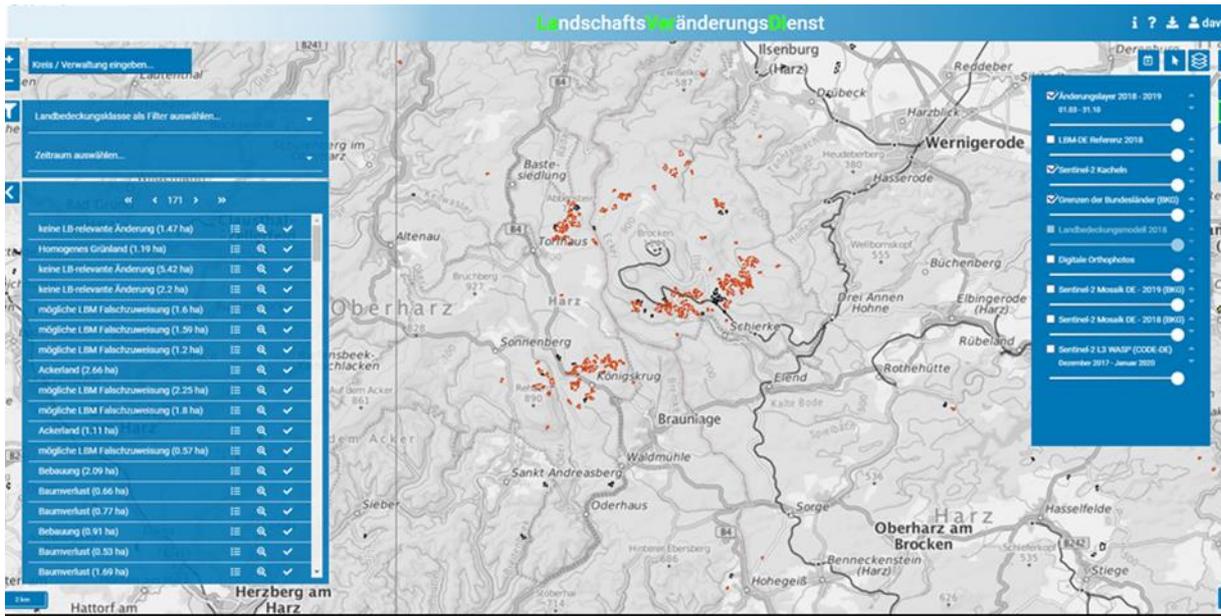


Figure 19: An example of the change class “tree loss” in red color

4.4 Authentication as a Service - A LandSense contribution to improve the FAIR principle in Citizen Science

Andreas Matheus

Secure Dimensions GmbH, Munich, Germany

The situation nowadays (i.e. Authoritative and Citizen Science data is often stored in insolation - in data-silos): Very many different operators provide APIs to access the data that they storing. In order to create value by combining data from several operators, it is important to ensure seamless access not only for open data. The FAIR (Findable, Accessible, Interoperable and Reusable) principle and the outlined action plan "Turning FAIR into Reality" published by the European Commission Expert Group on FAIR data⁶, is an important consideration when building data infrastructures such as the European Open Science Cloud (EOSC). For implementing the "A"-principle⁷ states that for data to be accessible, "the protocol allows for an authentication and authorization procedure, where necessary." and for implementing the "R"-principle, states that "(Meta)data are released with a clear and accessible data usage license".

Looking at Citizen Science and the H2020 project LandSense, we implemented the LandSense Engagement Platform that - from an architectural perspective - is very similar to the EOSC: A federation of applications and services (available from different operators) is accessible to citizen scientists and academia. To ensure seamless access, one of the core services is the Authentication as a Service (AaaS) that supports user logins from social media operators as well as from the worldwide federations of universities and research institutions connected to eduGain⁸.

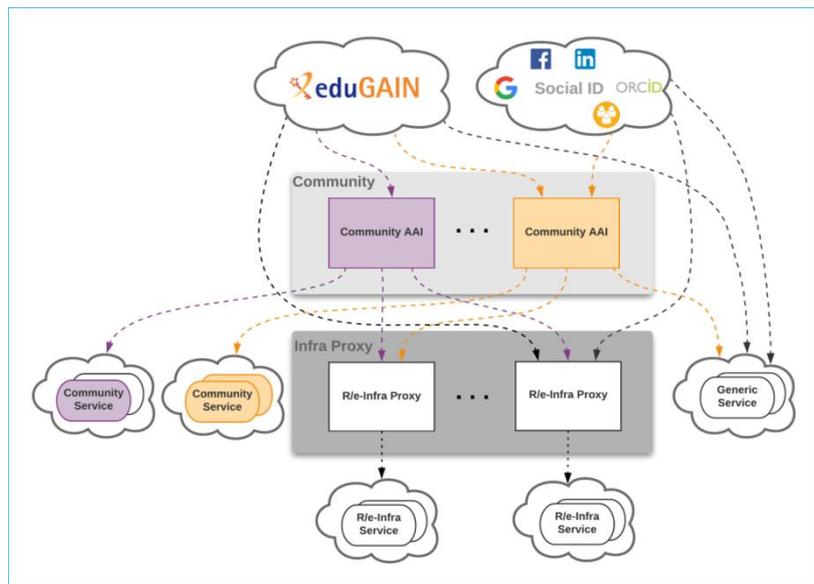


Figure 20: Architecture of AaaS implementing the Community AAI Interface

Providing direct support to the FAIR principles A1.2 and R1.1, the AaaS can be understood as a broker of personal data to applications and services with respect to GDPR. Ensuring swift

⁶ https://ec.europa.eu/info/sites/info/files/turning_fair_into_reality_0.pdf;

⁷ <https://www.go-fair.org/fair-principles/>

⁸ <https://edugain.org>

development of Web- Mobile- or Server-Applications by leverage the AaaS, the API is based on well known international open standards like OAuth2⁹ and OpenID Connect.

To ensure the GDPR minimisation aspect (an application may only use as little personal data as necessary), the AaaS provides different brokering policies: (i) Authenticate Policy can be used when an application just needs to know the user is logged in but does not require any personal information about the user; (ii) Cryptoname Policy can be used to request a unique - non-tradable, non-resolvable - user identifier; (iii) GDPR Policy can be used to receive personal information after the user's consent.

In our contribution, we introduced the concept of the AaaS, discussed the lessons learned and showed uptake opportunities to ensure seamless access to open and protected authoritative data.

⁹ <https://tools.ietf.org/html/rfc6749>

5 Conclusion

The workshop shows the very large panel of available LULC data at different spatial and temporal resolution and the interest that different communities have on LULC data.

The chairs are grateful to EuroSDR, LandSense H2020, and IGN France for their support in organising this workshop as well as to all speakers and participants.

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