LEONSEGS

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NEW SPACE ECOSYSTEM
GROUND SEGMENT

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EXECUTIVE SUMMARY

Collection of scientific and technical abstracts published or presented by the consortium related to the LEONSEGS project developments.

It will be periodically updated throughout the project's duration. Subsequent versions will be released as Deliverable 5.9 (Version 2) and Deliverable 5.10 (Version 3).

TABLE OF CONTENTS

ABBREVIATIONS

BiDS	Big Data from Space
EARSeL	European Association of Remote Sensing Laboratories
EO	Earth Observation
ESA	European Space Agency

1. OVERVIEW SCIENTIFIC AND TECHNICAL ABSTRACTS

Scientific abstracts from the project's first period were published and presented at the ESA BIG Data from Space (BiDS) conference in Vienna (November 6-9, 2023) and at the EARSeL symposium in Manchester UK (June 17-20, 2024).

The following scientific abstracts have been published:

No	Title	Authors	Conference/Paper
I	An Advanced Framework for Semantic Querying of The Dynamic World Dataset	Martin Sudmanns, Lisah Ligono, Hannah Augustin, Lucas van der Meer, Dirk Tiede	Proceedings of the 2023 conference on Big Data from Space, Soille, P., Lumnitz, S. and Albani, S. editor(s), Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/46796, JRC135493, pp 357-360
II	Semantic World – A Novel Benchmark Dataset for Semi-Supervised Semantic Segmentation	Felix Kröber, Dirk Tiede, Andrea Baraldi, Sébastien Lefèvre.	43rd EARSeL Symposium, Manchester, UK, June 17th to 20th, 2024; conference proceedings (book of abstracts)
III	An Approach for the Semantic Enrichment of Sentinel-1 Imagery Suitable for Large-scale Analysis	Luke McQuade, Martin Sudmanns, Dirk Tiede	43rd EARSeL Symposium, Manchester, UK, June 17th to 20th, 2024; conference proceedings (book of abstracts)

IV	One-layer RGB representation of big EO data analyses for supporting the visual communication of multi-temporal change detection	Dirk Tiede, Hannah Augustin, Thomas Strasser, Steffen Reichel, Markus Kerschbaumer, Kristýna Měchurová, Martin Sudmanns	43rd EARSeL Symposium, Manchester, UK, June 17th to 20th, 2024; conference proceedings (book of abstracts)

TABLE 1: OVERVIEW SCIENTIFIC ABSTRACTS PUBLISHED IN THE FIRST PROJECT PERIOD

The presentations and scientific abstracts presented at the 43rd EARSeL symposium were part of a scientific workshop organisation related to LEONSEGS research activities from PLUS. The prestigious conference, focused on Earth Observation (EO) research, attracted around 200 researchers, students, and professionals from Earth and environmental sciences who work with remotely sensed data.

PLUS organized a dedicated workshop on "Semantic & Explainable Analysis of Big Data," directly related to research conducted within LEONSEGS. The workshop was planned by Martin Sudmanns, Dirk Tiede, and Hannah Augustin from PLUS, and included external expert Gregory Giuliani from the University of Geneva.

At the event, organized by the European Association of Remote Sensing Laboratories (EARSeL), PLUS contributed with three presentations, highlighting the project's commitment to advancing Earth observation analysis through innovative research and collaboration.

Workshop:

https://manchester2024.earsel.org/?page_id=184

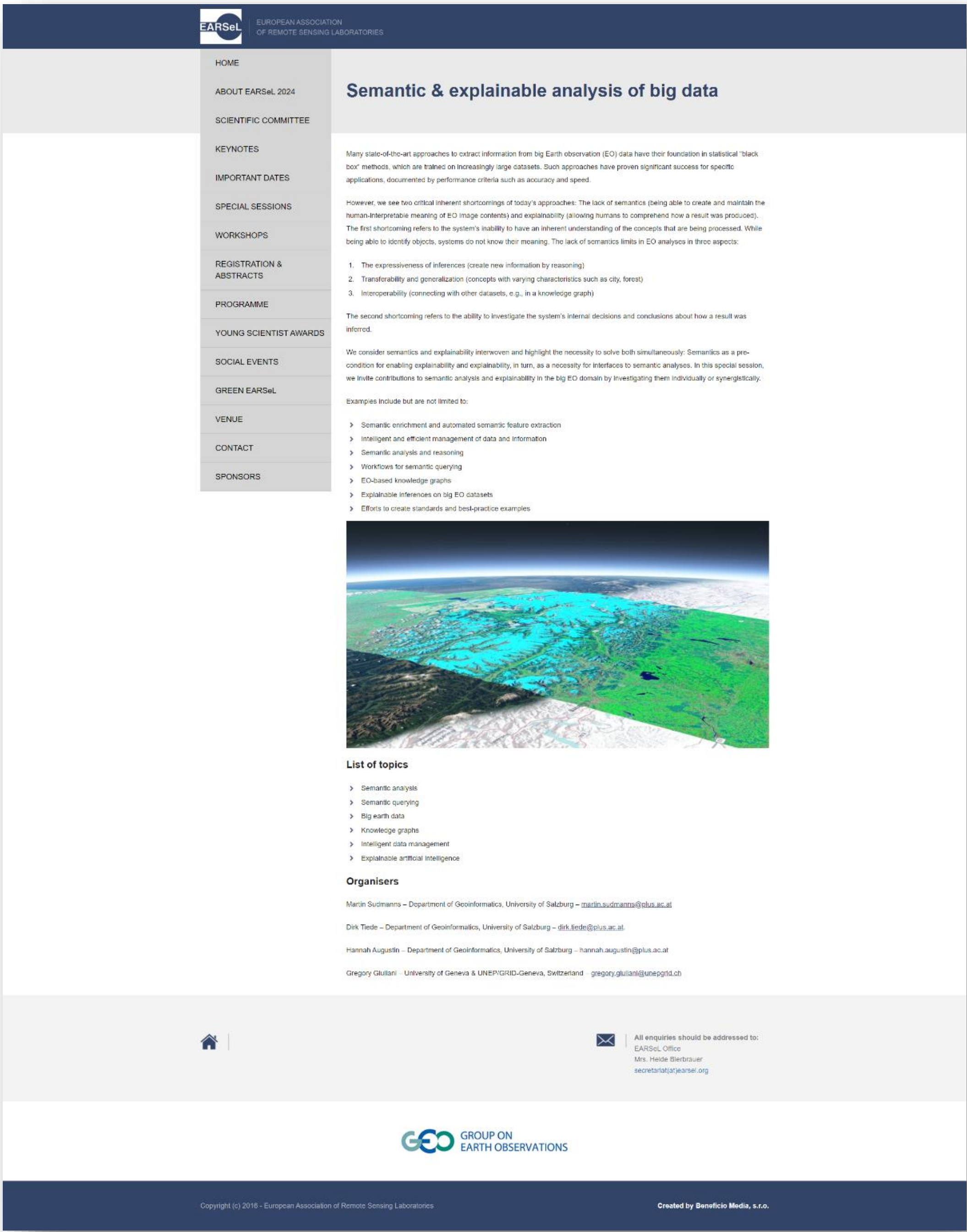

FIGURE 1-1: SCIENTIFIC WORKSHOP ORGANISATION RELATED TO LEONSEGS RESEARCH ACTIVITIES FROM PLUS AT THE EARSEL CONFERENCE 2024

The scientific abstract, published in the conference proceedings of the ESA Big Data from Space conference in Vienna, included a poster presentation that was awarded with the best poster award:

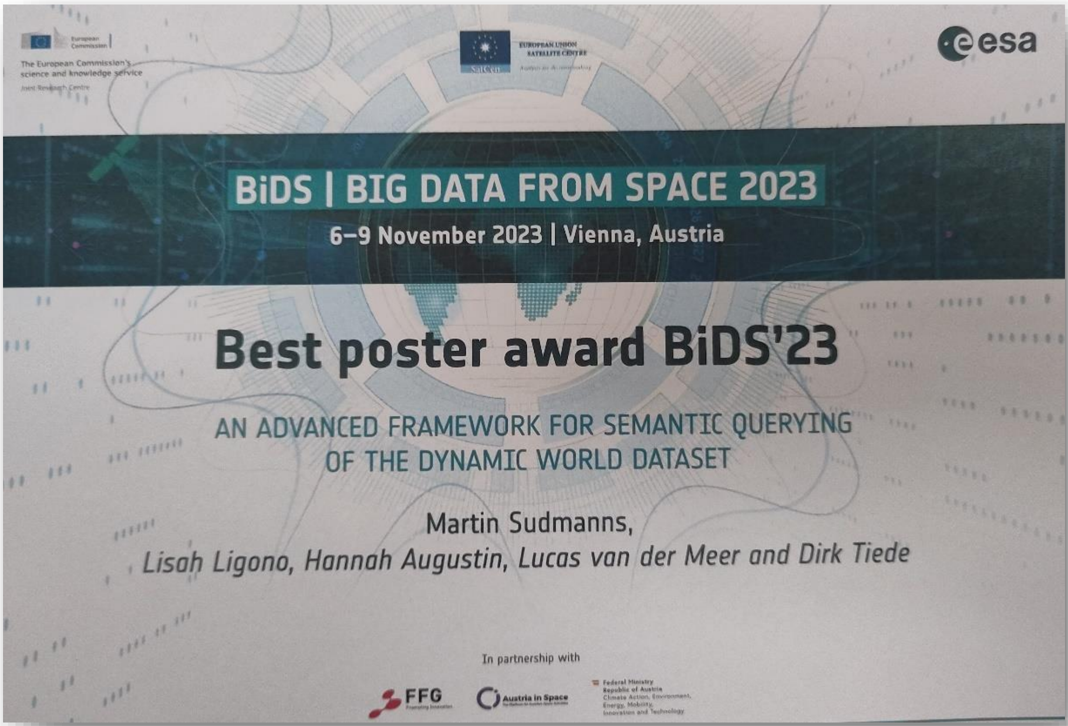

FIGURE 1-2: BEST POSTER AWARD FOR THE SCIENTIFIC POSTER SUBMITTED BY PLUS ("AN ADVANCED FRAMEWORK FOR SEMANTIC QUERYING OF THE DYNAMIC WORLD DATASET") FOR THE ESA BIG DATA FROM SPACE CONFERENCE IN VIENNA, 2023

2. COLLECTION OF ABSTRACTS

In the following, the presented and published abstracts are embedded as printed.

2.1. SCIENTIFIC ABSTRACT I

AN ADVANCED FRAMEWORK FOR SEMANTIC QUERYING OF THE DYNAMIC WORLD DATASET

Martin Sudmanns, Lisah Ligono, Hannah Augustin, Lucas van der Meer, Dirk Tiede

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ABSTRACT

Within this contribution we show how the Dynamic World data by Google and the World Resources Institute can be semantically queried, using a methodology originally developed for use within semantic Earth observation (EO) data cubes. We demonstrate in a minimal working example how the Dynamic World dataset can be analyzed through space and time based on the given categories/classes but also on aggregated classes. This is beyond selecting the most occurring class (i.e., using the mode operator) and opens new possibilities for using this dataset and a new direction to unfold its potential.

Index Terms— Semantic Querying, Data Cubes, Dynamic World, Categorical Time Series Analysis, querying aggregated classes.

1. INTRODUCTION

Transforming reflectance values, which do not have inherent semantics, into categorical information, which can be understood by users, is an ongoing endeavor (e.g., for creating land cover maps, time series analysis). An approach that we developed is the semantic Earth observation (EO) data cube, which provides categories that users can combine on a case-by-case scenario in custom spatial and temporal ranges. A semantic EO data cube (i.e., semantics-enabled EO data cube) is defined as "a data cube, where for each observation at least one nominal (i.e., categorical) interpretation is available and can be queried in the same instance" [1]. Based on this definition, we developed a scalable architecture covering Austria, called Sen2Cube.at [2], utilizing a generic semantic enrichment of each available Sentinel-2 image. To facilitate semantic querying of the semantic EO data cube and analyzing categorical variables, we developed an inference engine, *semantique* (https://github.com/ZGIS/semantique) [3].
Google and the World Resources Institute pushed the boundaries for what is possible in the big (Earth) data era when they released the Dynamic World dataset because they do not provide a single, global product with a fixed legend. Instead, they have classified (and are continuously classifying) all Sentinel-2 images having less than 35% cloud cover according to their image-wide metadata [4]. This is a different approach compared to most land cover products that are generated and released every few years. Since this dataset is provided to Google Earth Engine (GEE) users, the users can create their own (land cover) maps by specifying temporal rules that are applied to the dataset, so-called reducers. While in their publication by Brown et. al 2022 they use the mode to reduce the temporal dimension of the dataset to select the most often occurring class, they argue that with "a more advanced decision framework […] it is possible to customize a discrete classification as is appropriate for a user's unique definitions or downstream task." [4]. We argue that this statement is in-line with the objectives of a semantic EO data cube architecture and to the best of our knowledge, such a decision framework has not been developed or proposed.
In this contribution, we show that our *semantique* inference engine can be such a decision framework for working with Dynamic World land cover classes. We use the classes as input for *semantique* and thus allow users to perform more complex operations than using only the mode. We demonstrate this approach by transferring our inference engine to Dynamic World classes using a minimal working example and argue for considering approaches that are inherently transferable to a variety of datasets and systems.

2. METHOD, DATA, AND IMPLEMENTATION

Our implementation uses the *semantique* Python package for semantic querying of the Dynamic World dataset. The Dynamic World dataset, available via GEE , is a near real-time global Sentinel-2 land use / land cover (LULC) mapping generated by a Fully Convolutional Neural Network (FCNN) [4]. The dataset provides nine classes, which can be accessed either per-pixel by probability or by directly obtaining the class with the highest probability (Figure 1). The classes were derived from level-1C data available since 2015 because Sentinel-2 level-2A data are systematically produced globally only after 2017.
semantique is an open-source Python package for semantic querying of EO data [3]. While it was originally developed for querying the spectral categories produced by the SIAM Software [5], it is designed to be generic and can be applied to any kind of image categorization. The abstraction levels of semantic querying using *semantique* consist of three elements referred to as the layout, mapping, and query recipe.

Fig. 1. Sample of the Dynamic World dataset of Lake Baringo and its environments from September 03, 2020. Note that this is a mono-temporal classification, while the entire Dynamic World dataset covers temporal stack of images that are typically reduced to a single map by using the mode operator (most often occurring class).

The **layout** is a human- and machine-readable description of the semantic EO data cube's content [6]. It defines the individual categories or classes of the semantic layers as well as the storage structure. For example, it specifies that categories 'A', 'B', and 'C' are stored in file 'X' and categories 'D', 'E', and 'F' in file 'Y'. Therefore, it allows connecting to different storage systems using the same content name and optimizes the storage system without affecting analysis.

The **mapping** is a human- and machine-readable connection between the available categories in semantic EO data cubes and the user's target classes. In the context of our original Sen2Cube.at implementation, it is used to bridge the high-level semantic domain (with vocabularies containing terms like "Forest") and the image domain (with vocabularies containing terms like "greenness above an index threshold"). This approach goes back to existing ideas of knowledge-based image interpretation [7]. The mapping can be either defined in a stable way or on a case-by-case, user-defined scenario. In the context of the Dynamic World dataset, the classes are already on a high semantic granularity; however, users may be still requiring referring to the (thematically) aggregated class "Vegetation" as a combination of "Trees", "Grass", "Crops", and "Shrub and scrub" or to the class "Surface Water" as a combination of "Water" and "Flooded Vegetation". References and – in this case – grouping of classes like these are defined in the mapping.

The **query recipe** is a set of high-level instructions where operations are defined and applied to the entities (i.e., classes in the case of the Dynamic World) specified in the mapping. Common examples are operations such as reduce, group, or extract.

While the layout defines what is available and storage parameters and the mapping connects categories to target semantic entities, the query recipe defines spatio-temporal operations for these entities when applied to a spatio-temporal subset of a data cube.

In our proof-of-concept implementation, we created a layout and a mapping using the Dynamic World classes and ad-hoc querying using the *semantique* API. In the example, we use the classes "Water" and "Flooded vegetation", respectively, with the aim to identify basic temporal dynamics of surface water. This type of analysis is similar to calculations using the Water Observations from Space (WOFS) algorithm [8] or the JRC Surface Water product [9].

3. EXAMPLE

To showcase our approach using semantic querying, we selected an area in Kenya covering several Dynamic World classes but focused on water dynamics of Lake Baringo (Figure 2). In this example, we want to demonstrate the added value of a more advanced querying framework instead of using only the mode as temporal reducer. Lake Baringo is a suitable test site for applying this approach because it has recently experienced an unusual increase in surface area extent due to rising water levels.

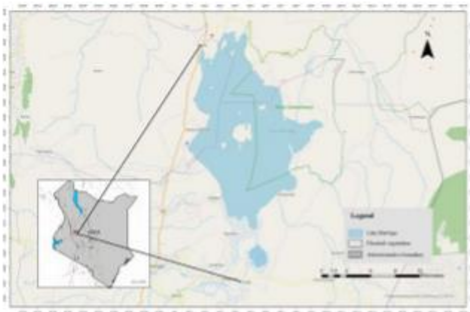
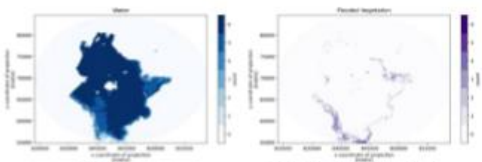


Fig. 2. Visualization of the test site, Lake Baringo which is a Great Rift Valley Lake. ©OpenStreetMap and contributors, CC-BY-SA.

Lake Baringo is a desert lake [10] located in the Great Rift Valley in Kenya (0.6667° N and 36.0667° E) with an elevation of about 970 meters above sea level. It covers an area of approximately 180 square kilometers, and as of 2020 is the second largest freshwater lake in Kenya. Its maximum depth reaches around ten meters, although these figures are seen to vary due to recent swelling of the Rift Valley lakes. The lake receives water primarily from two main rivers, the Molo and the Ol Arabel, as well as numerous small streams. It lacks any significant outlet, resulting in a relatively high mineral concentration due to evaporation. Nonetheless, it is still a freshwater lake [11].

In this minimal working example / proof of concept, we created a connection to GEE using the Python package wxee (https://wxee.readthedocs.io/en/latest/) to obtain the data directly as xarray. In this case, we used six different time steps between 2020 and 2022. After creating the layout for connecting the *semantique* package to the available classes of the Dynamic World dataset, we created the following mapping of the classes: a 1:1 mapping of the Dynamic World classes, extended with a mapping of the two water-related classes ("Water" and "Flooded Vegetation") into one semantically aggregated target class ("Surface Water"). As a result, we can directly conduct queries against these classes using the *semantique* API; in this case, we apply reducing operations over time and space.

The result of reducing over time by counting class occurrences is illustrated in two maps of Figure 3. In both maps, higher values indicate a higher occurrence of the class over time, from no observations up to six. In contrast to the mono-temporal selection or a mode operator, such a reducer is able to show temporal dynamics, which, in this example, are distinctly visible in the eastern, southern, and western part of the lake (Figure 3 – (a)). The map on the right side shows complementarily the flooded vegetation (Figure 3 – (b)). Both maps can already be used to visually identify areas with permanent surface water and areas that are occasionally dry as well as flooded.



(a) Water (b) Flooded Vegetation

Fig. 3. Visualized output of the query execution for 'Water' (a) and 'Flooded Vegetation' (b) on a six-timestamp date range between 2020-04-01 and 2022-08-31.

If users are not interested in the separated classes of "Water" and "Flooded Vegetation" but want to consider them both at the same time, it is possible to query them using the combined class specified in the mapping. Figure 4 shows the result of the same reducing operation of the combined class.

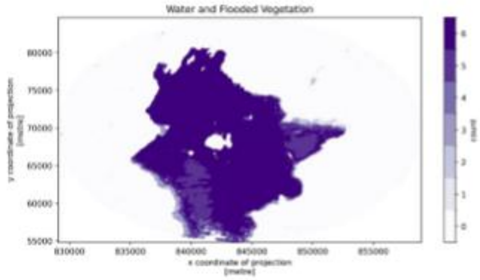


Fig. 4. Visualization of the analysis of the aggregated class "Surface Water", as a combined mapping of "Water" and "Flooded Vegetation".

Further, instead of reducing over time, it is also possible to reduce over space. The result of a reducing operation over space is not a map but a graph showing the aggregated values for each timestamp. In this case, it is the water count indicating the size of the lake and surrounding water areas (Figure 5).

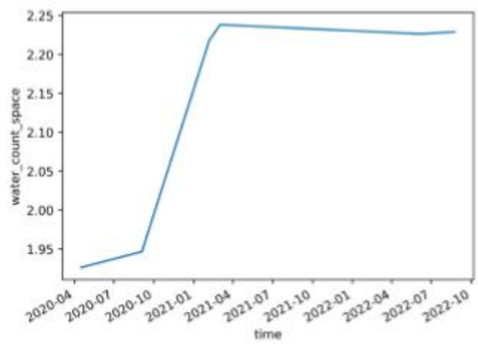


Fig. 5. The graph shows a steep rise in the observations of the class "Water" in October 2020 based on counted water pixels.

These examples use count as the aggregation function in both reducing operations. However, other functions are also possible and include aggregating or reducing based on the average, maximum, minimum, standard deviation, last, or first over time or space in the user-defined area of interest. It is the user's or developer's decision to choose the function and/or combine it with additional processing steps depending on their desired result, which is potentially much more sophisticated compared to the one in our example.

4. DISCUSSION

We demonstrated how our semantic querying and analysis approach can be extended and transferred to the Dynamic

World dataset. The semantic querying approach can be transferred to the Dynamic World dataset and individual query recipes can be generated and re-used due to the abstraction that semantic querying provides. The execution of the querying recipe is agnostic to the underlying dataset. For example, if other semantic enrichment approaches like the mentioned SIAM color names are mapped to the class surface water, the same querying can be applied.

While the algorithms and processing steps of the *semantique* package can be validated independently, the quality and validation of the overall result is dependent on the quality of the initial classification.

Instead of using the *semantique* Python package, it would be possible to develop such a querying and analysis framework directly in GEE's programming environment. A direct integration removes the necessity to download the data and process them locally. Instead, the processing would be done on GEE. There are other advantages of this approach as well such as good integration with existing scripts and workflows. However, has the main disadvantage of lacking transferability to other platforms. While the Dynamic World dataset is available in GEE and currently unique worldwide, we can expect that similar approaches will be developed and published soon.

5. CONCLUSIONS AND OUTLOOK

With continuous advancements in artificial intelligence and deep learning, land cover datasets that provide an interpretation of every available image, such as the Dynamic World, are possible. In contrast to other "fixed" processed land cover datasets, it does not provide a single layer of pre-calculated classes based on one or multiple years. Instead, it provides classes on a per-pixel level for all Sentinel-2 images and allows custom selection of spatio-temporal extents and classes. Hence, based on our work towards querying time series of categories to enable semantic queries, we argue that the *semantique* package can be one of the decision frameworks that the authors of Dynamic World dataset asked for in their publication.

To demonstrate the technical feasibility of connecting *semantique* to the Dynamic World dataset and the benefit of such a querying framework, we created an example for Lake Baringo in Kenya, which has had significant water dynamics in recent years.

Based on the promising results of the prototypical implementation and the experimental use cases, we conclude and argue that the full potential of datasets such as the Dynamic World unfolds when a semantic querying interface is available to users. Instead of reducing the dataset using a mode operator only, the spatio-temporal distribution of the classes and their occurrence can be analyzed in more detail. Therefore, a semantic querying interface could increase the dataset's uptake.

The example and technical implementation shown here can be considered the beginning, and there are several options for future developments. They include but are not limited to closer integration of such a querying framework into the GEE to be directly connected to the entire Dynamic World dataset, handling probabilities, and testing the dataset and approach in various applications.

REFERENCES

[1] H. Augustin, M. Sudmanns, D. Tiede, S. Lang, and A. Baraldi, "Semantic Earth observation data cubes," *Data*, vol. 4, no. 3, p. 102, 2019, doi: 10.3390/data4030102

[2] M. Sudmanns, H. Augustin, L. van der Meer, A. Baraldi, and D. Tiede, "The Austrian Semantic EO Data Cube Infrastructure," *Remote Sensing*, vol. 13, no. 23, p. 4807, 2021, doi: 10.3390/rs13234807.

[3] L. Van Der Meer, M. Sudmanns, H. Augustin, A. Baraldi, and D. Tiede, "Semantic querying in Earth observation data cubes," *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, vol. XLVIII-4/W1-2022, pp. 503–510, 2022, doi: 10.5194/isprs-archives-XLVIII-4-W1-2022-503-2022.

[4] C. F. Brown *et al.*, "Dynamic World, Near real-time global 10 m land use land cover mapping," *Sci Data*, vol. 9, no. 1, p. 251, 2022, doi: 10.1038/s41597-022-01307-4.

[5] A. Baraldi, L. Durieux, D. Simonetti, G. Conchedda, F. Holecz, and P. Blonda, "Automatic Spectral-Rule-Based Preliminary Classification of Radiometrically Calibrated SPOT-4/-5/IRS, AVHRR/MSG, AATSR, IKONOS/QuickBird/OrbView/GeoEye, and DMC/SPOT-1/-2 Imagery—Part I: System Design and Implementation," *IEEE Trans. Geosci. Remote Sensing*, vol. 48, no. 3, pp. 1299–1325, 2010, doi: 10.1109/TGRS.2009.2032457.

[6] M. Sudmanns, H. Augustin, L. van der Meer, C. Werner, A. Baraldi, and D. Tiede, "One GUI to Rule Them All: Accessing Multiple Semantic EO Data Cubes in One Graphical User Interface," *giforum*, vol. 1, pp. 53–59, 2021, doi: 10.1553/giscience2021_01_s53.

[7] S. Growe, "Knowledge based interpretation of multisensor and multitemporal remote sensing images," *Int. Arch. Photogramm. Remote Sens*, vol. 32, no. pt 7, pp. 4–3, 1999.

[8] N. Mueller *et al.*, "Water observations from space: Mapping surface water from 25 years of Landsat imagery across Australia," *Remote Sensing of Environment*, vol. 174, pp. 341–352, 2016, doi: 10.1016/j.rse.2015.11.003.

[9] J.-F. Pekel, A. Cottam, N. Gorelick, and A. S. Belward, "High-resolution mapping of global surface water and its long-term changes," *Nature*, vol. 540, no. 7633, pp. 418–422, 2016, doi: 10.1038/nature20584.

[10] C. O. Olilo, C. O. Odoli, M. O. Obiero, J. O. Malala, and C. H. Bironga, "Chapter 8 - Microbial ecology of desert Lakes Baringo and Turkana, Kenya, East Africa," in *Lakes of Africa*, M. El-Sheekh and H. E. Elsaied, Eds., Elsevier, 2023, pp. 247–268. doi: 10.1016/B978-0-323-95527-0.00016-6.

[11] E. O. Okech, N. Kitaka, S. Omondi, and D. Verschuren, "Water level fluctuations in Lake Baringo, Kenya, during the 19th and 20th centuries: Evidence from lake sediments," *African Journal of Aquatic Science*, vol. 44, no. 1, pp. 25–33, 2019, doi: 10.2989/16085914.2019.1583087.

2.2. SCIENTIFIC ABSTRACT II

Kröber et al

EARSeL Manchester 2024
Abstract
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Semantic World – A Novel Benchmark Dataset for Semi-Supervised Semantic Segmentation

Felix Kröber[1], Dirk Tiede[1], Andrea Baraldi[2], Sébastien Lefèvre[3]

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Keywords: Deep Learning, Supervised learning, Semi-supervised learning, Land cover, Sentinel-2

Challenge

Despite the increasing interest in deep learning models for remote sensing applications, large-scale data sets foundational to these models are still scarce. Data sets covering a range of biomes worldwide are of particular interest to train models generalisable across space. In this regard, the Dynamic World data set [1] represents an important milestone giving rise to the eponymous model [2] as well as the ESRI land cover product [3]. With these models global, continuously updatable land cover classifications have been produced for the first time. However, one factor that limits the accuracy and generalisability of the models is the availability of training data, based on a labour-intensive manual labelling process. Upscaling the training of such models requires an extension of the narrow view of supervised learning to semi-supervised learning, which enables the leveraging the much larger archive of unlabelled satellite scenes.

Methodology

This work utilises semantic enrichments of satellite data to develop the Dynamic World dataset into a more comprehensive dataset for semi-supervised semantic segmentation tasks. The use of the Dynamic World dataset as the basis for the Semantic World presented here enables corresponding benchmarking with the aforementioned models [2], [3].

The semantic enrichment is carried out using the Satellite Image Automatic Mapper (SIAM) [4]. SIAM is a physical model-based expert system capable of mapping, automatically and in near real-time, multi-spectral satellite imagery into a discrete and finite vocabulary of semi-symbolic spectral categories. Encoded as a decision tree, SIAM performs a deterministic, hyperparameter-free enrichment process translating reflectance values into a pre-classification. As an input, SIAM can employ any radiometrically calibrated multispectral image data, including Sentinel-2 L1C or L2A data. This allows to enhance the existing labelled Dynamic World patches by adding the pre-classifications as bands that can be used as input instead of or in combination with the original non-semantical reflectance values. Furthermore, adding pre-classifications for Sentinel-2 patches for which no land cover annotations are available enables to extend the dataset for purposes of semi-supervised learning. The data set designed in this way makes it possible to investigate the added value of knowledge-based, semantic enrichments in the context of various deep learning architectures.

Expected results

The data set produced comprises around 57.4K semantically enriched Sentinel-2 patches of 510 x 510 pixels – around 21.4K with and 36.0K without land cover annotations. The split between training and test data of 57.0K to 0.4K is based on the original split according to the Dynamic World dataset. The reflectance values of all 10m and 20m Sentinel-2 bands for both processing levels (i.e. L1C & L2A) are provided as input information. In addition to any land cover annotations, the SIAM categorisations in four different granularities (i.e. 18, 33, 48 & 96 categories) are always available. The automated scene classification (i.e. SCL layer of the S-2 L2A products) is also stored in the label stack of an Sentinel-2 patch for comparison purposes of the added value of the SIAM categorisation. The overall organisation of the data set is summarised in Figure 1.

The diversity and scope of the dataset is evident from Figure 2. Based on the Dynamic World dataset, the sample patches are distributed across a total of around 9K Sentinel-2 scenes from the years 2017 to 2019, which in their entirety cover all main biomes globally. This spatio-temporal diversity is accompanied by a corresponding diversity of the spectral profiles of the Sentinel-2 input data and a broad coverage of 9 different land covers classes.

Outlook for the future

Building on the performed technical validation of the created data set, basic model tests will be carried out in the next step. These are intended to demonstrate the use of the dataset under fully- and semi-supervised paradigms. Well-established backbones for semantic segmentation networks (such as U-Net) will be used to perform these initial assessments. In a next step model architectures will be tailored to the unique structure and information content of the Semantic World dataset. The scalability of the semantically enriched part of the dataset offers the potential to establish a novel foundation model specific to remote sensing data. Conditioning such a model on the knowledge-based spectral categorisations can provide stronger guiding for learning physically reasonable feature representations within such foundation models. The Semantic World dataset along with basic model tests will be released publicly enabling users to train and develop their own architectures.

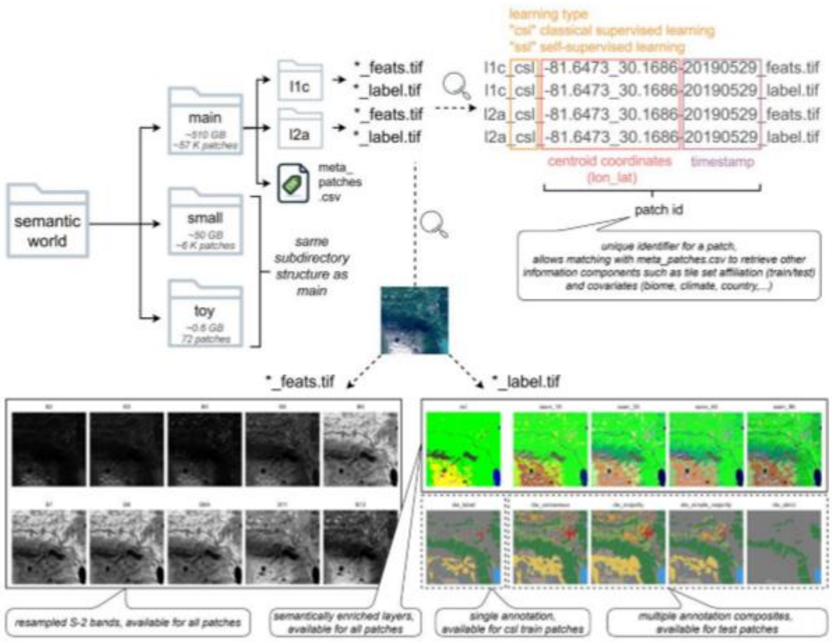

Figure 1 Structure of the Semantic World

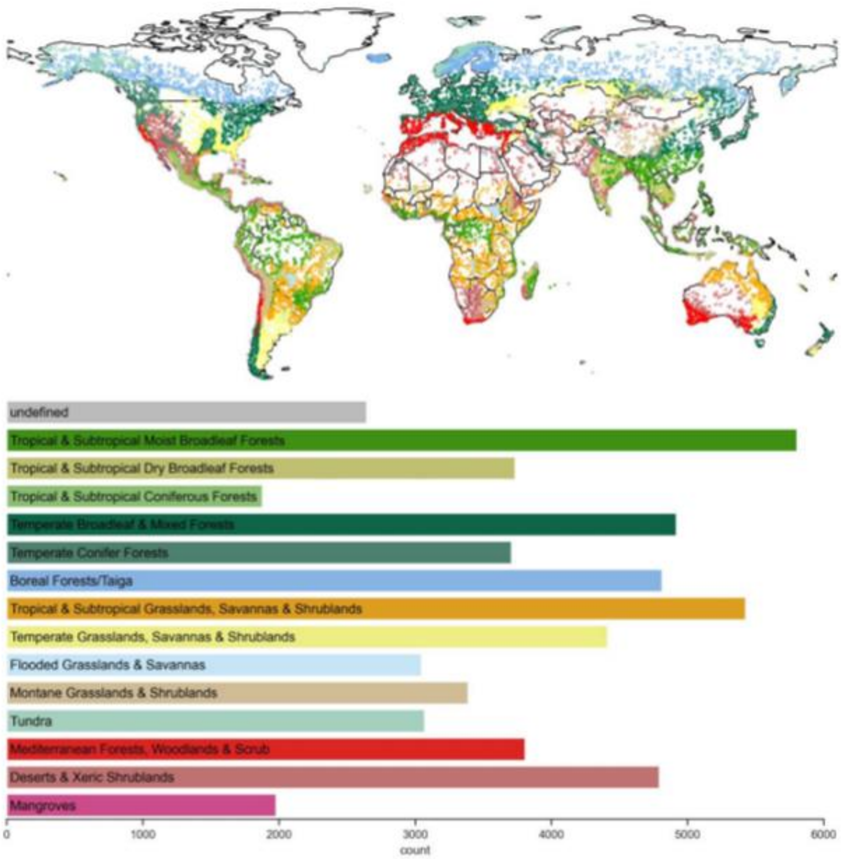

Figure 2 Spatial distribution of Semantic World patches with their relationship to global biomes

References

[1] A. M. Tait, S. P. Brumby, S. B. Hyde, J. Mazzariello, and M. Corcoran, 'Dynamic World training dataset for global land use and land cover categorization of satellite imagery'. PANGAEA, 2021. doi: 10.1594/PANGAEA.933475.

[2] C. F. Brown *et al.*, 'Dynamic World, Near real-time global 10 m land use land cover mapping', *Sci Data*, vol. 9, no. 1, p. 251, Jun. 2022, doi: 10.1038/s41597-022-01307-4.

[3] K. Karra, C. Kontgis, Z. Statman-Weil, J. C. Mazzariello, M. Mathis, and S. P. Brumby, 'Global land use / land cover with Sentinel 2 and deep learning', in *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, Brussels, Belgium: IEEE, Jul. 2021, pp. 4704–4707. doi: 10.1109/IGARSS47720.2021.9553499.

[4] A. Baraldi, M. L. Humber, D. Tiede, and S. Lang, 'GEO-CEOS stage 4 validation of the Satellite Image Automatic Mapper lightweight computer program for ESA Earth observation level 2 product generation - Part 1: Theory', *Cogent Geoscience*, vol. 4, no. 1, p. 1467357, Jan. 2018, doi: 10.1080/23312041.2018.1467357.

2.3. SCIENTIFIC ABSTRACT III

EARSeL Manchester 2024
Abstract
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An Approach for the Semantic Enrichment of Sentinel-1 Imagery Suitable for Large-scale Analysis

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Keywords (5): Earth Observation, Synthetic Aperture Radar (SAR), Big Earth Data, Land Use, Copernicus

Challenge

Synthetic Aperture Radar (SAR) Earth observation (EO) satellites have several advantages over their optical counterparts, such as being able to observe the Earth's surface at night, and through a wide variety of weather conditions. However, due to the nature of their sensors and mechanisms of capture, the resultant imagery is often difficult to interpret and use in downstream analyses. Several approaches exist for the semantic enrichment of optical data, such as the Satellite Imager Automatic Mapper (SIAM*), which, coupled with their use in EO data cubes, can greatly improve accessibility and use of the original data. A system offering similar benefits for SAR EO data could be highly beneficial, especially considering the potential to complement optical data. Designing such a system to permit analyses across differing geographic areas globally presents an additional challenge which we have also attempted to address in this work.

Methodology

We devised an approach for the semantic enrichment of dual-polar Sentinel-1 radiometric-terrain-corrected (RTC) backscatter imagery (VV and VH polarizations). We refer to this as *polarimetric categorization*. It consists of binning the parameter space of VV and VH backscatter according to the scattering properties of known surface types; the result is that each pixel is assigned a category according to the scattering type(s) exhibited, e.g., surface scattering, volume scattering, double-bounce. The categorization/binning is performed with a decision tree algorithm, with set (constant) thresholds. These thresholds were determined in a part knowledge-based, part data-driven process. Figure 1 shows our preliminary categorization scheme.

Our categorization processor was implemented as a Python package, with working title, *dpolcat* (dual-polarimetric categorizer). It depends on standard EO packages such as xarray† and a STAC client. Just-in-time (JIT) compiler Numba‡ was also utilized to improve computational performance.

Several trials were conducted in using categorized scenes generated by our algorithm in downstream analyses, such as flood mapping, burned-area delineation, and vegetation change mapping.

Expected results

* Baraldi, A., Humber, M. L., Tiede, D., & Lang, S. (2018). GEO-CEOS stage 4 validation of the Satellite Image Automatic Mapper lightweight computer program for ESA Earth observation Level 2 product generation – Part 1: Theory. Cogent Geoscience, 4, doi: 10.1080/23312041.2018.1467357

† https://xarray.dev/

‡ https://numba.pydata.org/

Our preliminary version of *dpolcat* has facilitated several downstream trial analyses using models constructed in Python scripts. The first was an automatic flood mapping task. Observing the grid cells newly changed into strong surface scatterers (category 1 as in Figure 1), a model was built. Some simple spatial filtering and thresholding were also applied. The model was applied to map the flooding event of Duisburg, Germany, July 2021. Validated against the Copernicus Emergency Mapping Service reference, an F1 score of 0.80 was achieved. The source, intermediate, and resultant imagery are shown in Figure 2.

Other tasks include burned-area delineation and vegetation change mapping. Quantitative validation of these is ongoing. But, in all cases, the models using polarimetric categories were quick and simple to design and implement, compared to those in similar analyses using non-enriched images – models can be implemented in minutes rather than hours.

In terms of computational performance, it takes approximately 4 minutes to process an entire Sentinel-1 scene with *dpolcat*, using an Intel Xeon Platinum 8272CL CPU @ 2.60GHz.

Outlook for the future

As the category thresholds are globally constant, the algorithm can be applied to any Sentinel-1 scene, or across an area spanning multiple scenes, without a learning step - this is in contrast with similar techniques such as polarimetric decomposition and clustering. Also, compared to learning-based techniques, the algorithm is simple enough such that the computational cost for processing a scene is relatively low. This lends itself well to its use in semantic EO data cubes[§], where there is often a requirement to semantically enrich large numbers of scenes as a pre-requisite for further analyses.

Our preliminary results have identified some limitations of the approach. In time series analysis, especially with vegetated and mixed-use areas, the category assigned to a given location can vary unexpectedly, i.e., where there is seemingly no change to the underlying land-cover type. We refer to this as categorical instability. This could be due to, for instance, signal values close to category thresholds; and, with noise (which radar is prone to), a pixel can 'flip' between categories over time. Furthermore, there is scope to refine the implementation and integrate *dpolcat* processing into existing EO data cubes. We aim to address these in future work.

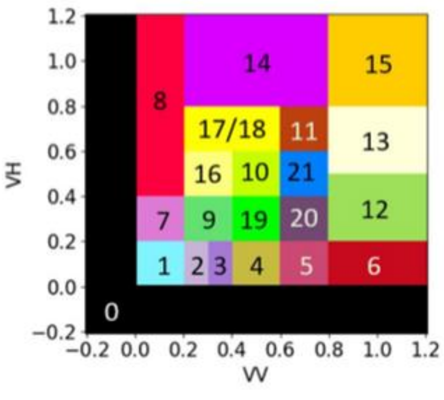

Figure 1 Division of the VV and VH parameter space into polarimetric categories: 1, 2, 3 and 4 represent mostly surface scattering; 9, 10, 16 and 19 represent mostly volume scattering; 8 is ill-defined (physically improbable); 0 is invalid or 'no data'; the remaining represent double-bounce and other phenomena.

[§] Augustin, H., Sudmanns, M., Tiede, D., Lang, S., Baraldi, A., 2019. Semantic Earth Observation Data Cubes. Data 4, 102. https://doi.org/10.3390/data4030102

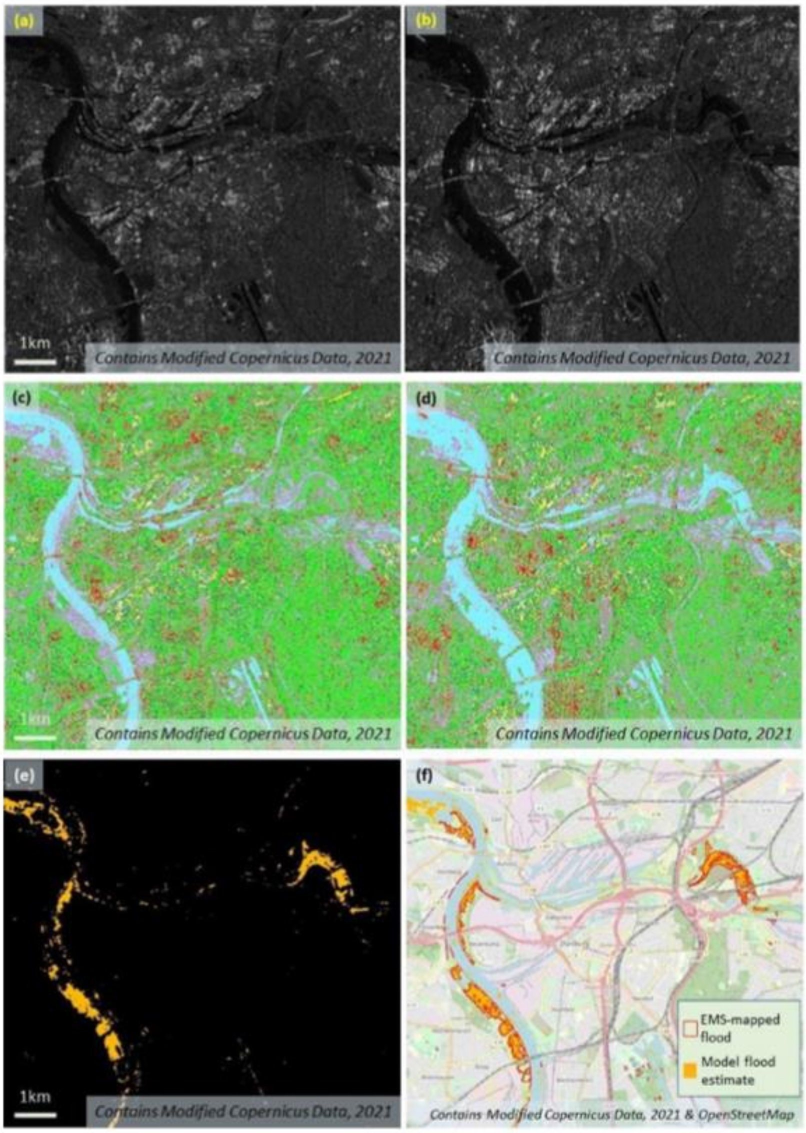

Figure 2 Example of using *dpolcat* in an automated flood mapping workflow – Duisburg, Germany, 13 July 2021 (pre-flood) to 16 July 2021 (in-flood). (a) Sentinel-1 VV backscatter, pre-flood. (b) Sentinel-1 VV backscatter, in-flood. (c) Pre-flood image categorized with *dpolcat*. (d) In-flood image categorized with *dpolcat*. (e) Flood map model output. (f) Flood map model output with Copernicus EMS reference**.

** Copernicus Emergency Mapping Service, product [EMSR517].

2.4. SCIENTIFIC ABSTRACT IV

EARSeL Manchester 2024
Abstract
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One-layer RGB representation of big EO data analyses for supporting the visual communication of multi-temporal change detection

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Keywords (5): Earth Observation, Big EO Data, Change analysis, Sentinel-2, Geovisualization

Challenge

Big EO data, such as provided by the European Copernicus programme, are a great opportunity for continuous temporally high-frequent global monitoring of the environment. Challenges exist not only in the processing of the big multitemporal data* but also in communicating results in a meaningful and useful manner, especially for non-EO experts.

We present an approach for big EO data analyses in a semantic EO data cube and communicate results using a single-layer RGB (red, green, blue) representation, where each colour represents one of three different user-defined time periods. We focus on change analysis of observed vegetation, but the approach can be used in other applications. The resulting RGB layer serves as an interpretable base map that can be integrated in any GIS or browser interface. Multi-temporal information is encoded in different colour combinations. An adaptable colour cube legend aids interpretation (see Figure 1).

Methodology

The big EO data analyses behind the multi-temp thematic RGB layer are conducted in semantic EO data cubes†, where for each observation at least one nominal (i.e. categorical) interpretation is available and can be queried in the same instance. Our implementation - Sen2Cube.at‡ - is a semantic EO data cube available for all of Austria, where every Sentinel-2 satellite image taken since 2015 and their semantic enrichment can be analysed in the cloud. Data cubes have the advantage that the spatial and temporal extent to be analysed can be dynamically selected. Semantic data cubes extend this flexibility with a semantic query option that allows analyses directly in the selected area. No programming knowledge or additional software is required - everything can be done via the web browser and integrated with other data sets.

This approach uses semantic enrichment to count the percentage of vegetation / non-vegetation observed for all Sentinel-2 images in a user defined analysis period (e.g. years or seasons). Different to index-based approaches using only NDVI, no thresholds need to be defined since the semantic classes

* Sudmanns, M., Tiede, D., Lang, S., Bergstedt, H., Trost, G., Augustin, H., Baraldi, A., Blaschke, T., 2020. Big Earth data: disruptive changes in Earth observation data management and analysis? International Journal of Digital Earth 13, 832–850. https://doi.org/10.1080/17538947.2019.1585976

† Augustin, H., Sudmanns, M., Tiede, D., Lang, S., Baraldi, A., 2019. Semantic Earth Observation Data Cubes. Data 4, 102. https://doi.org/10.3390/data4030102

‡ Sudmanns, M., Augustin, H., van der Meer, L., Baraldi, A., Tiede, D., 2021. The Austrian Semantic EO Data Cube Infrastructure. Remote Sensing 13, 4807. https://doi.org/10.3390/rs13234807

(here: spectral categories) also reflect cloud-like / bare-soil-like / vegetation- and water-like categories. All available imagery can be used without additional pre-processing to filter cloud contaminated data. This has the advantage that smaller cloud-free regions are used even in very cloudy images, increasing the number of valid, clear observations and therefore the statistical soundness.

Expected results

The current implementation focuses on vegetation / non-vegetation changes based on Sentinel-2 big EO data, which means at least one image every 5 days, and in higher latitudes and overlapping orbits even more. The definition of the three time periods can be interactively conducted in the Sen2Cube.at interface and every Sentinel-2 image in the defined period will be used for the analysis. Based on the semantic enrichment, the spectral categories to be analysed in any given period are summed up and calculated as a percentage of the analysed images.

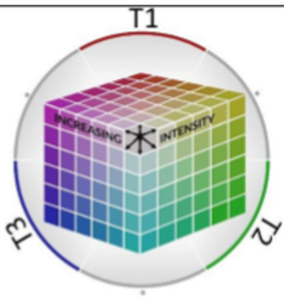
The RGB colour model is an additive colour model used to visualise the 3 different grayscale layers for each time period, each indicating the proportion of vegetation observed. The approach allows changes from 3 periods to be displayed on a map in one image using the different colour combinations. The interpretation of the colours can be drawn from the colour cube (Figure 1). The RGB colour palette and colour cube for the interpretation does not only communicate change, but also communicates changes in intensity and/or partly changed vegetation to non-vegetation and vice versa using main RGB colours and mixed colours plus their intensity (see Figure 2).

Outlook for the future

The single-layer representation is an approach to better communicate multi-temporal analyses to users (planning authorities, decision makers, non-EO scientists etc.). Our approach clearly indicates where changes happened and provides information on change intensity. This is different from base maps heavily used in GIS-based decision support systems, where often only mono-temporal information serve as background layers, such as static maps or aerial/satellite image mosaics with unclear observation dates. Application cases include supporting soil sealing monitoring, monitoring construction activity or natural disaster-based changes.

The layers can be accessed via WMS and soon also via STAC. Since the semantic EO data cube enables a spatio-temporal dynamic query, user-defined areas and time periods can be calculated on-demand at any time.

We will present different implementations for the Austrian federal states of Salzburg and Burgenland including different application scenarios.



- Black are areas: without vegetation for the whole-time span.
- White /bright coloured areas: highly vegetated in all time periods.
- Strong red means vegetation in T1, little to no vegetation in T2 and T3.
- Strong green means vegetation in 20T2, little to no vegetation in T1 and T3.
- Strong blue means vegetation in T3, little to no vegetation in T1 and T2.
- Mixed colours: Yellow shades are between T1 and T2 (a mixture of red and green) and mean vegetation in these years, but little to no vegetation in T3 (blue shade missing). Magenta: Colour mixture of red (T1) and blue (T3) - green shade missing, as little to no vegetation in T2 etc.

Figure 1 Example of the RGB legend and the colour coding in respect to the three time periods (T1-T3)

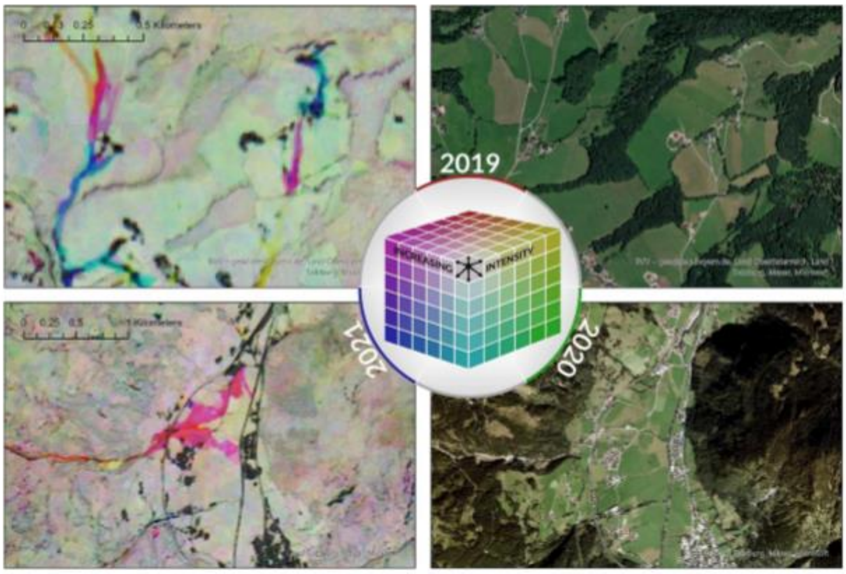


Figure 2 Example for a one-layer representation of the changes of observed vegetation counted from every Sentinel-2 image in the years 2019, 2020 and 2021 (can be adapted to any time period (e.g. different years or seasons)). Upper left: RGB layer representing changes in road construction based on vegetation change derived from all Sentinel-2 images, the colours represent the years when the changes occurred (removal of vegetation during construction, but also vegetation regrowth of parts of the area when the roads were finished). Upper right: VHR image of the same area taken after the changes happened (>2022). Lower left: RGB representation for a mudflow taken place in Bad Hofgastein, Austria, early July 2020. Since the vegetation was removed by the mudflow the colour changes to red (not vegetated parts of 2020 and 2021), for some parts to magenta, which indicates a regrowth of vegetation already in 2021. Lower right: VHR image of the same area taken after the changes happened (>2022)

3. CONCLUSIONS

During the initial phase of the LEONSEGS project, research and development activities were extensively published and presented at various scientific conferences. A notable achievement was the organization of a dedicated workshop on semantic and explainable big EO data analysis at the EARSeL symposium. This workshop showcased advancements in EO data analysis, particularly in semantic and explainable methodologies, within an international scientific context, fostering discussions among diverse research groups. The receipt of the Best Scientific Poster Award at the ESA BiDS conference further emphasized the scientific community's interest in semantic information extraction.

As the project moves into the second phase, the primary objective is to enhance the dissemination of LEONSEGS project outcomes. This will involve broader outreach efforts and the publication of results in high-impact scientific journals.

APPENDIX

The following poster has been awarded with the best poster award at ESA BiDS 2023 (Scientific Abstract No I):