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**How to cite**

GIULIANI, Gregory et al. Data Cube on Demand (DCoD): Generating an earth observation Data Cube anywhere in the world. In: International Journal of Applied Earth Observation and Geoinformation, 2020, vol. 87, n° 102035, p. 1–6. doi: 10.1016/j.jag.2019.102035

This publication URL: https://archive-ouverte.unige.ch/unige:128161
Publication DOI: 10.1016/j.jag.2019.102035

Int J Appl Earth Obs Geoinformation 87 (2020) 102035

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

# Data Cube on Demand (DCoD): Generating an earth observation Data Cube anywhere in the world

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ARTICLE INFO

*Keywords:*
Open Data Cube
Landsat
Sentinel-2
Remote sensing
Satellite imagery
Docker
MapX

ABSTRACT

To tackle Big Data challenges such as Volume, Variety, and Velocity, the Earth Observations Data Cube (EODC) concept has emerged as a solution for lowering barriers and offering new possibilities to harness the information power of satellite EO data. However, installing, configuring, and managing an EODC instance is still difficult requiring specific knowledge and capabilities. Consequently, facilitating and automating the generation and provision of EODC given specific user's requirements can be beneficial.

In response to this issue, this paper presents the Data Cube on Demand (DCoD) approach, a proof-of-concept that aims at facilitating the generation and use of an EODC instance virtually anywhere in the World. Users are only required to specify an area of interest; select the types of sensors between Landsat 5-7-8 and Sentinel-2; choose a desired temporal frame; and provide their email address to receive notifications. Then automatically an empty ODC instance is instantiated and desired data are ingested.

The proposed approach has been successfully tested in two sites in Bolivia and DRC in the field of environmental monitoring. It has lowered many complexity barriers of such a new technology; greatly facilitated the generation and use of the Data Cube technology; enhanced data sovereignty; and ultimately can help reaching large adoption and acceptance.

## 1. Introduction

Since 2008, with the emergence of the free and open data access policy for Landsat data (Ryan, 2016; Woodcock et al., 2008; Wulder et al., 2012), many governments and space agencies have opened their archives making large collections of satellite Earth Observations (EO) data available to everyone (Appel et al., 2018). This abundance of remotely-sensed data enhances scientists understanding and knowledge on environmental changes (e.g., climate change, urbanization, deforestation, pollution, land cover change) at all scales (e.g., from local to global) (Giuliani et al., 2017b). One of the major possibilities, is that, it has enabled time-series analysis and not only diachronic comparison of a couple of images through time.

However, the amount of data that is generated on a given portion of the Earth surface makes it almost impossible to manually search, download, preprocess and organize as files (Maso et al., 2019). To tackle Big Data challenges such as Volume, Variety, and Velocity, the Data Cube (DC) concept has emerged as a solution for lowering barriers and offering new possibilities to harness Big Data at low cost and effort (Giuliani et al., 2017a). It strengthens connections between data, applications and users, facilitating management, access and use of Analysis Ready Data (ARD) (Dwyer et al., 2018; Frantz, 2019). It requires installing and configuring a suite of software to pre-process, ingest, store, analyze and visualize EO data. In this category we can find the Open Data Cube (ODC), RasDaMan/EarthServer (Baumann et al., 1997, 2016), or Pangeo (Signell and Pothina, 2019) software. Another approach is based on libraries that allow getting spatio-temporal data from data providers directly from analytical desktop client. This is the case of gdalcubes (Appel and Pebesma, 2019) or dtwSat (Maus et al., 2019) that allows accessing and analyzing time-series data using the R software. Finally, we can have cloud-based processing facilities such the Google Earth Engine (GEE) (Gorelick et al., 2017) or the Copernicus Data and Information Access Services (DIAS)(European Commission, 2018). These platforms allow users to interact with EO data without investing in computing and data management infrastructures. However, they may lock users into a platform with well-known challenges such as sustainability of the platform; limited time and scale for analyses; cloud-based only (i.e., no options for local computing solution); limited data interoperability; data often not at ARD level (Giuliani et al., 2019). This variety of approaches also reflects the variety of interests and

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https://doi.org/10.1016/j.jag.2019.102035
Received 25 September 2019; Received in revised form 9 December 2019; Accepted 16 December 2019

needs from users.

The EODC approach is probably the solution that can offer most control, flexibility and scalability to users, as it allows: (1) installing on their own infrastructure a set of software components; (2) storing different types of data (e.g., Landsat, Sentinels, aerial photos, drone imagery); (3) increased sense of ownership; (4) sharing of code, tools, and algorithms. This explains why cloud-based providers are considering offering EODC services to users (Nativi et al., 2017; Strobl et al., 2017).

Among the different EODC implementations, the ODC is currently the most widely adopted solution with 4 operational data cubes, 11 in development and 28 having expressed interest (Killough, 2018). Even if installing, configuring and managing an ODC instance is becoming easier, there are still barriers (e.g., IT and remote sensing knowledge required to understand what data is needed, computing and storage resources; data sources and algorithms for ARD generation) that remain when one desire to start working with an EODC. Therefore, there is a clear interest/need to facilitate the generation and provision of EODC given specific users requirements in terms of localization, sensor types, and temporal frame. To our knowledge the only attempt, is the Cube In a Box (https://www.opendatacube.org/ciab), developed by Geoscience Australia, that allows indexing Landsat 8 data in an ODC instance. This is an interesting first step, but users still require having some technical knowledge and need to grab path/row index of Landsat scenes; define various parameters with command line; furthermore, this technology is restricted to Landsat 8 data.

Based on these considerations, the objective of this paper is to present the Data Cube on Demand (DCoD) approach, that aims at facilitating the generation and use of an ODC instance virtually anywhere in the World. Users are only required to specify an area of interest; select the types of sensors between Landsat 5-7-8 and Sentinel-2; choose a desired temporal frame; and provide their email address to receive notifications. Then automatically an empty ODC instance is instantiated and desired data are ingested. This can lower many complexity barriers of such new technology and can further help to facilitate generation and use of the Data Cube technology and ultimately reach large adoption and acceptance on this new technology.

## 2. Methodology and implementation

The main objective of DCoD is to automate the generation of an Open Data Cube instance. The entire process of installing the required software as well as selecting, ordering, downloading and ingesting Analysis Ready Data (ARD) is complex, requires several steps and necessitate particular skills. Most of these steps can be automated and the intention of the proposed approach is to reduce human interventions to a minimum and facilitates the use of a custom Data Cube. DCoD follows the generic principles of the Live Monitoring of Earth Surface (LiMES) methodology enhancing it with the Data Cube technology (Giuliani et al., 2017b). It is designed to meet the following two requirements: (1) Create and/or (2) Update an ODC instance.

When creating a new Data Cube, users have to provide the following information to the DCoD Application Programming Interface (API):

- Spatial extent of the Area Of Interest (AOI),
- Temporal extent,
- Selection of sensors between Landsat 5, 7, 8 and Sentinel-2,
- An email address.

When the process is launched, a multi-container Docker application is started, containing a fresh ODC including Jupyter Notebook and a PostgreSQL database; configuration files are generated and used for the DC initialisation; then required data are identified, downloaded, converted into ARD and ingested in the ODC. As the resolution of ingested Landsat and Sentinel 2 differ (respectively 30 m for Landsat and 10, 20, 60 m for Sentinel-2 in WGS 84 coordinate system) all Sentinel-2 bands are resampled at 10 m and the AOI is extended in order to guarantee a perfect overlap of 9 Sentinel-2 pixel (and tiles) with a single Landsat pixel (and tile). This enhances data interoperability allowing to use seamlessly data from both sensors in the same data collection and therefore facilitates data fusion. Once ready, the user receives an email with an URL to connect to the Jupyter instance of the ODC. Optionally, users can update an already instantiated ODC by providing some requirements (time frame, sensor type and email address) via the DCoD API (Fig. 1).

In term of data sources, DCoD uses:

- Level 2 Landsat 5,7, 8 Surface Reflectance processed with the Landsat Ecosystem Disturbance Adaptive Processing System (LEDPAS) (Schmidt et al., 2013) and automatically ordered and retrieved from USGS using the Bulk Ordering API[1] .
- Level 1 Sentinel-2 downloaded from Google Cloud[2] using gsutil[3] and converted into Level 2 Surface Reflectance using Sen2Cor[4] .

The implementation of DCoD is based on the following technical components:

- Docker for container management
- Docker Compose to manage multi-container Docker application
- Express server in Node.js to provide users an API to create and update an ODC instance
- Python and R scripts for scenes identification; data order + download; conversion into ARD and data ingestion
- MapX frontend to interact with the DCoD API (Lacroix et al., 2019) (Fig. 2)
- Jupyter notebook is used as processing interface to interactively interact with the created DC and analysis data using Python programming language (Rapiński et al., 2019).

A custom Dockerfile was developed from the opendatacube/datacube-core:1.7[5] image to run the ODC with Jupyter and all dependencies required to run the Python and R scripts. Docker Compose is used to run PostgreSQL along the ODC and offers easy management of containers and environmental variables. The DCoD API is a web server in Express a web framework for Node.js. It has three routes allowing users to access the API documentation (GET - */), to create a new instance of an ODC (POST - */create) or/and to update an already instantiated ODC (POST - */update). The server can run Docker Compose using the docker-compose package in Node.js[6] . Input parameters provided by users are validated using the joi[7] package before executing Docker Compose commands to avoid issues during creation/update process.

## 3. Results

To validate the technical feasibility, identify possible issues and determine the potential of such approach, DCoD has been tested in two specific areas known for their mining activities and visible land cover changes (Table 1). The first use case is located in southern Bolivia, in the central Altiplano of the Andes. The Salar the Uyuni is the world's largest lithium reserve on Earth. Globally, there is an increasing demand for this element that has various usage (e.g., batteries,). The second use case, the Tenke Fungurme mine, is located the south-eastern part of the Democratic Republic of Congo (DRC). It is one of the largest

[1] https://espa.cr.usgs.gov/
[2] https://cloud.google.com/storage/docs/public-datasets/sentinel-2
[3] https://cloud.google.com/storage/docs/gsutil
[4] https://step.esa.int/main/third-party-plugins-2/sen2cor
[5] https://hub.docker.com/r/opendatacube/datacube-core
[6] https://github.com/PDMLab/docker-compose
[7] https://github.com/hapijs/joi

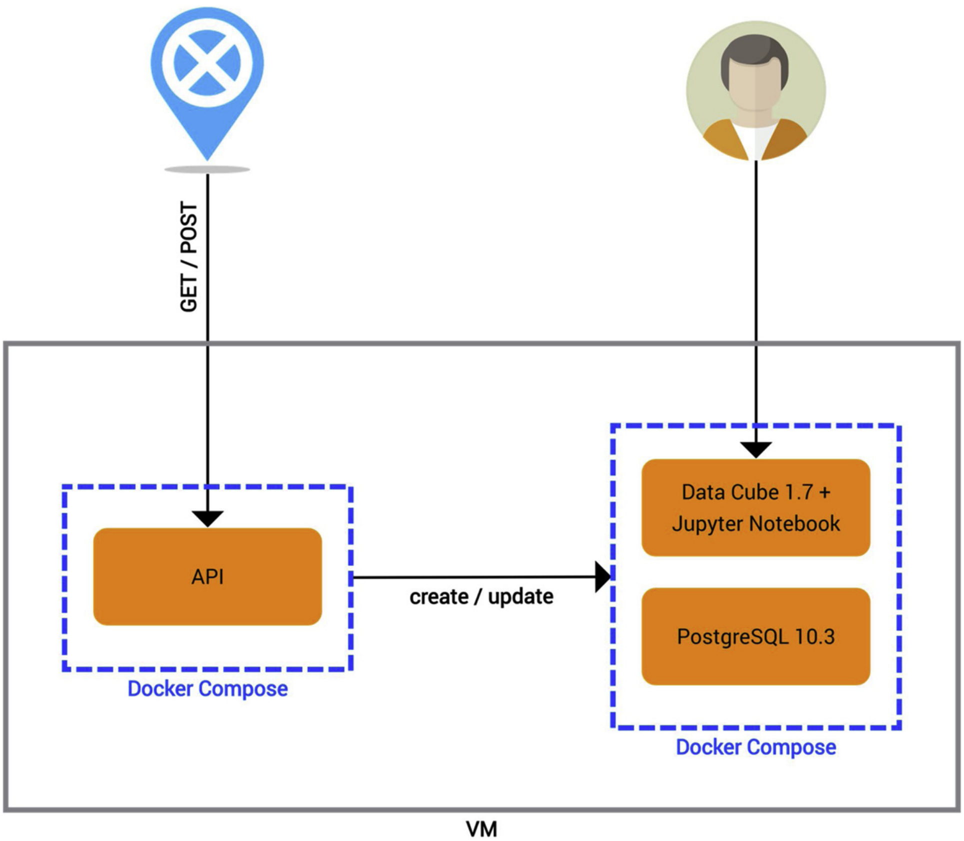


**Fig. 1.** Implementation schema of the DCoD methodology.

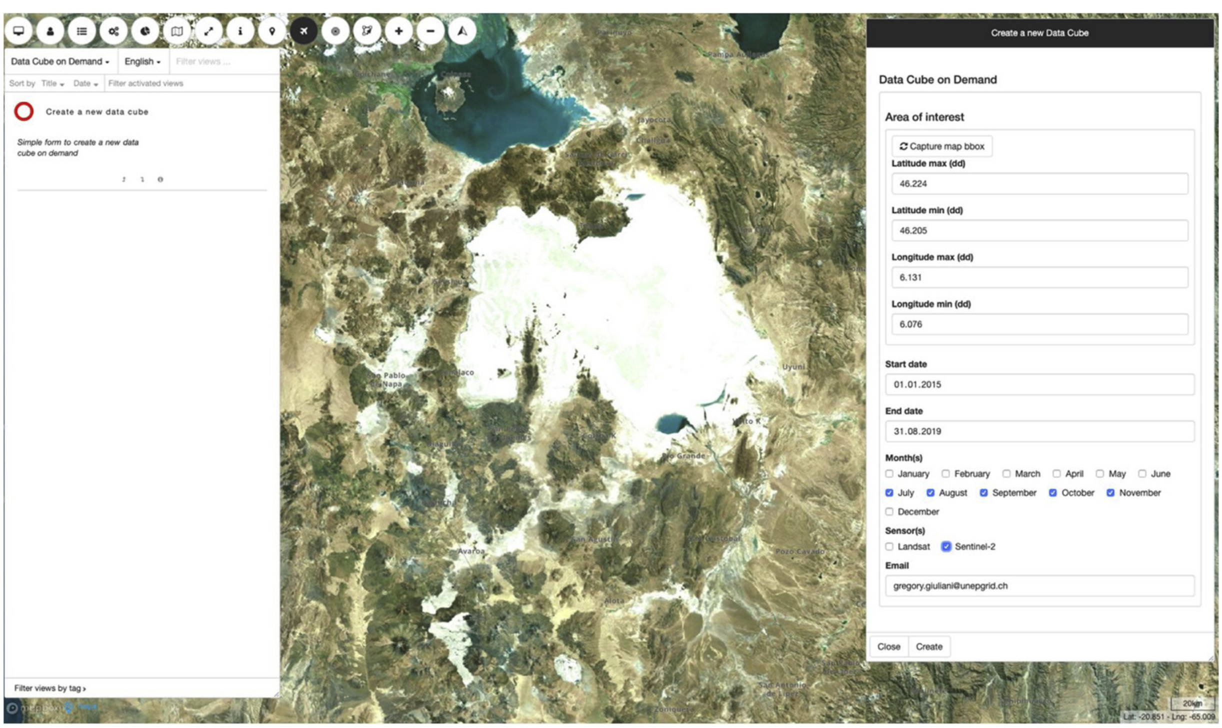


**Fig. 2.** Data Cube creation process through the MapX frontend. Users can select sensor, time frame and location (AOI) directly from a dedicated view in MapX then a POST request containing all parameters is sent to the DCoD API to instantiate a fresh ODC.

copper producers in DRC, and one of the world's largest known copper and high-grade cobalt deposits. The DRC has the second-largest tropical rainforest in the world, second after the Amazon rainforest and mining activities are considered as one of the principal causes of deforestation in that region.

The DC have been created on a Linux Debian Strech server with 8 CPUs at 2.9 GHz and 48GB of RAM. Once the DC were instantiated, it has been possible for users to access the content through the Jupyter

**Table 1**
Summary of the two use cases with the number of scenes ingested per sensor type, time to generate the DC, and total data volume.

| Site | Number of scenes ingested | Time to generate the DC | Data Volume |
|---|---|---|---|
| Salar de Uyuni [Bolivia] | Landsat: 292 Sentinel: 41 | Landsat: 10 h, Sentinel-2: 12 h | Landsat: 32GB Sentinel-2: 49GB |
| Tenke Fungurume [DRC] | Landsat: 551 | 33 hours | 43 GB |

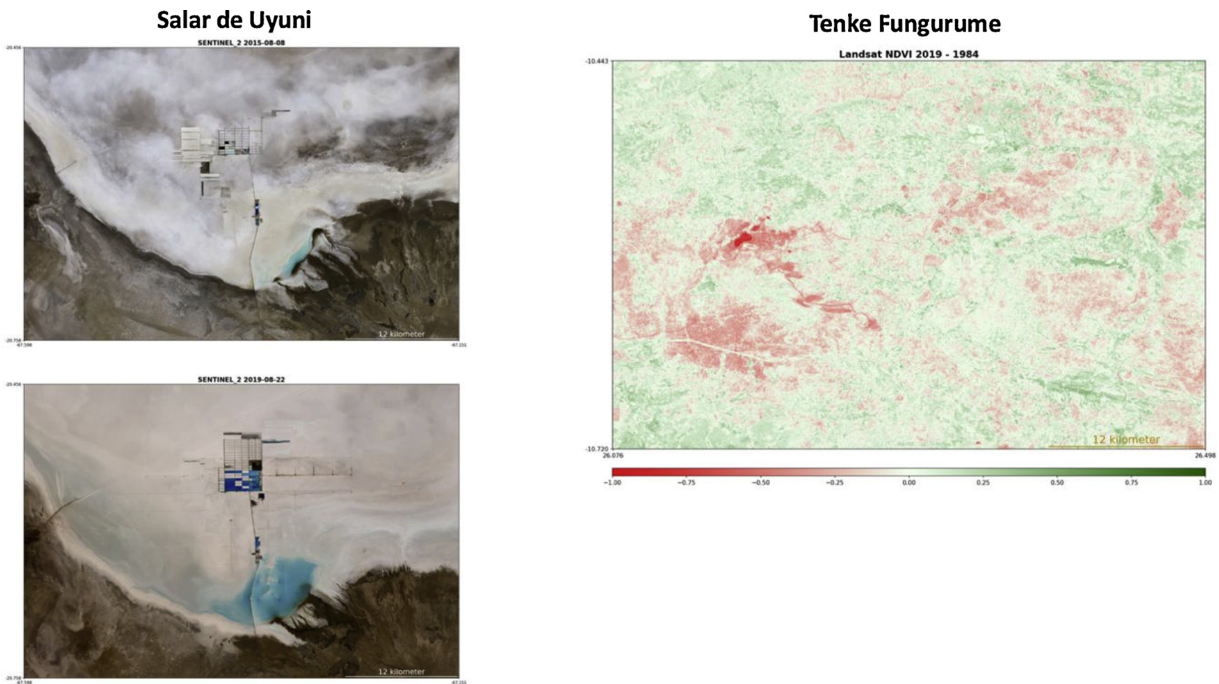


**Fig. 3.** Example of analysis output from the Data Cube generated in Bolivia and DRC using DCoD. Left: Salar de Uyuni Sentinel-2 NIRGB composite for 08.08.2015 (top) and 22.08.2019 (bottom); Right: Landsat annual NDVI Difference (1984–2019) in Tenke Funguurme showing important deforestation (in dark red).

Notebook interface and start analysing available data with custom Python scripts such as comparing the evolution of exploitation in the Salar of Uyuni with false colour composite Sentinel-2 data at different dates and an NDVI difference for the Tenke Fungurume mine (Fig. 3).

## 4. Discussion

Initial results show that the proposed solution works seamlessly, and two local data cubes have been generated on demand over the southern part of the Uyuni salt flat and over the Tenke Fungurume mine in DRC. We demonstrate that it is technically feasible to instantiate and populate an ODC instance on demand based on simple user requirements. Similar to the Analysis Ready Data concept that has significantly lowered the barrier of data preparation, the On-Demand approach has the potential to considerably reduce the burden of software installation, configuration and data ingestion. With a solution like DCoD users can benefit from having their own selection on ARD stored in their own ODC instance.

Another important benefit of this approach is that it enhances data sovereignty. Indeed, compared to cloud-based processing facilities, the DCoD solution provides an improved control, more flexibility and scalability in term of usage, and a strengthened sense of ownership. Users can share not only data but also code, tools and algorithms they developed. They can also fine tune the ARD processing and handle other sensors such as the Satellite Pour l'Observation de la Terre (SPOT) or the China-Brazil Earth Resources Satellite programme (CBERS) that are currently not available in Amazon or Google.

Other advantages of the proposed solution are: (1) the possibility to download the data content; (2) the capacity for users to operate the Data Cube on their own premises (once sufficient knowledge is acquired) and provide services for accessing and using EO data; and (3) the possibility to improve the code of DCoD as this is an open-source project; and (4) the possibility to interface the DCoD API with different frontend.

The main identified challenge concerns the computing power required to run many potential ODC instances. This approach has been tested on the cloud-based High-Performance Computing (HPC) infrastructure of the University of Geneva. This infrastructure is restricted to research usage and obviously does not have the capabilities of private clouds such as Google or Amazon. Therefore, in term of scalability, it would be beneficial to test such approach on a private cloud infrastructure. ODC instances are already running on the Amazon Cloud (Rizvi et al., 2018) therefore it should be possible to deploy the DCoD approach on this type of infrastructure.

Compared to cloud processing platforms like the Google Earth Engine, the DCoD approach provides enhanced flexibility and scalability; the possibility to add additional libraries (e.g., machine learning, data visualization); and the possibility to interact with other programming languages. On the other hand, cloud platforms have greater computing performances but at the same time they do not provide all data to users (Giuliani et al., 2017b).

Since Analysis Ready Data is becoming increasingly available by data providers, these datasets would avoid the need for any pre-processing other than reprojection and definition of the space and time bounds, further facilitating the generation of Data Cubes. Indeed, USGS plans to release, in early 2020, Landsat Collection 2 global ARD products for Landsat 8 Operational Land Imager (OLI) /Thermal Infrared Sensor (TIRS), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 4–5 Thematic Mapper (TM). Similarly, since December 2018, Sentinel-2 ARD products are available on the Amazon Cloud. However, it is not year clear is the entire Sentine-2 archive will be back-processed for data before December 2018. If a user requires data from 2015 to late 2018, then the implemented pre-processing procedure remains valuable.

These first results are encouraging and prove the feasibility of generating a Data Cube on Demand. However, further work is required to democratize the approach and extend it to other types of data analysis than the ones presented in this paper. First of all, it is necessary to test the approach in different contexts (e.g., type of users, environmental context) to better match with user requirements. Second, processing capabilities need to be enhanced in order to facilitate data processing. Third, the approach has to be tested on large spatial extents. Applying the approach at national level could help countries to fulfil their reporting obligations, e.g. to the sustainable development goals (SDGs) or the Aichi targets (Dhu et al., 2019). Fourth, implementing standardized interfaces could prevent that each generated Data Cube become silos of information (Giuliani et al., 2019). Fifth, to reduce data cube size and focus the data for specific users, one possibility is to complement the API with the option to select specific bands from each dataset. Finally, to reach large adoption, acceptance and commitment on EODC, capacity development is critical (Giuliani et al., 2016). The DCoD approach has the potential to increase and develop new capacities to access and use satellite EO data using the Data Cube technology.

## 5. Conclusions

EODC is a disruptive technology that is gaining a lot of interest and that can be applied in any part of the World and at different geographical scales (from local to national and regional scales) to harness the information power of satellite EO data. The proposed DCoD approach uses a chain of orchestrated scripts to enable the automatic generation of a data cube given some simple user requirements such as AOI, temporal frame and type of sensor. The proposed approach has been successfully tested in two sites in Bolivia and DRC in the field of environmental monitoring. It has proved to lower an important complexity barrier inherent to such new technology, allowing to seamlessly generate a Data Cube virtually on any place on Earth. With DCoD, it is the first time that the possibility is offered to users with limited technical knowledge to access and exploit analysis-ready time-series from different types of satellite imagery. Still some challenges need to be addressed, such as the need of reducing the installation/configuration burden and the necessity to scale up the solution in order to democratize its use.

## CRediT authorship contribution statement

**Gregory Giuliani:** Supervision, Conceptualization, Methodology, Writing - original draft. **Bruno Chatenoux:** Conceptualization, Software, Investigation, Validation. **Thomas Piller:** Conceptualization, Software, Investigation. **Frédéric Moser:** Software. **Pierre Lacroix:** Writing - review & editing, Conceptualization, Methodology.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

The views expressed in the paper are those of the authors and do not necessarily reflect the views of the institutions they belong to.

This research was funded by European Commission “Horizon 2020 Program” ERA-PLANET/GEOEssential project, grant number 689443.

We would like to thank Mr. Jean-Philippe Richard, IT administrator of GRID-Geneva, for its technical support on ODC and Docker.

Results of this publication are partly or fully relying on the Swiss Data Cube (http://www.swissdatacube.org), operated and maintained by UN Environment/GRID-Geneva, the University of Geneva, the University of Zurich and the Swiss Federal Institute for Forest, Snow and Landscape Research WSL.

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