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Monitoring land degradation at national level using satellite Earth Observation time-series data to support SDG15 – exploring the potential of data cube

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ABSTRACT

Avoiding, reducing, and reversing land degradation and restoring degraded land is an urgent priority to protect the biodiversity and ecosystem services that are vital to life on Earth. To halt and reverse the current trends in land degradation, there is an immediate need to enhance national capacities to undertake quantitative assessments and mapping of their degraded lands, as required by the Sustainable Development Goals (SDGs), in particular, the SDG indicator 15.3.1 (“proportion of land that is degraded over total land area”). Earth Observations (EO) can play an important role both for generating this indicator as well as complementing or enhancing national official data sources. Implementations like Trends.Earth to monitor land degradation in accordance with the SDG15.3.1 rely on default datasets of coarse spatial resolution provided by MODIS or AVHRR. Consequently, there is a need to develop methodologies to benefit from medium to high-resolution satellite EO data (e.g. Landsat or Sentinels). In response to this issue, this paper presents an initial overview of an innovative approach to monitor land degradation at the national scale in compliance with the SDG15.3.1 indicator using Landsat observations using a data cube but further work is required to improve the calculation of the three sub-indicators.

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1. Introduction

According to the summary for policymakers of the thematic assessment report on land degradation and restoration of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), avoiding, reducing, and reversing land degradation and restoring degraded land is an urgent action to protect biodiversity and ecosystem services vital to all forms of life on our planet and to ensure human well-being (IPBES, 2018). Currently, degradation of land through human activities is undermining the well-being of at least 3.2 billion people, pushing the planet towards a sixth mass extinction and costing more than 10 per cent of total Gross Domestic Product (GDP) (IPBES, 2018).

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At the global scale, the main drivers of land degradation are the high consumption lifestyles of the most developed economies, and the rising consumption in developing and emerging economies. This, combined with population growth, is driving unsustainable levels of agricultural expansion, natural resource and mineral extraction, and urbanization, which typically lead to greater levels of land degradation (Ivits & Cherlet, 2013). Consequently, timely action to avoid, reduce, and reverse land degradation can increase food and water security, can contribute substantially to the adaptation and mitigation of climate change and biodiversity loss, could reduce conflict and migration; and ultimately is essential for meeting many of the Sustainable Development Goals defined in the Agenda 2030 for Sustainable Development (IPBES, 2018; United Nations, 2015)

In order to halt and reverse the current trends in land degradation, there is an immediate need to enhance national capacities to undertake quantitative assessments and corresponding mapping of their degraded lands, as required by the Sustainable Development Goals (SDGs), in particular, the SDG indicator 15.3.1 (“proportion of land that is degraded over total land area”) (Sims et al., 2019), as well as by the adoption of Land Degradation Neutrality (LDN) targets under the auspices of the United Nations Convention to Combat Desertification (UNCCD) (Chasek et al., 2019; Cowie et al., 2018; Gilbey, Davies, Metternicht, & Magero, 2019; Metternicht, Akhtar-Schuster, & Castillo, 2019).

Remotely sensed Earth Observations (EO) acquired by satellites can be a reliable source for monitoring land cover change and biomass activity over long periods (Honeck et al., 2018; Vogelmann et al., 2017). They have been widely used for monitoring desertification dynamics (Ghebregabher, Yang, Yang, & Wang, 2019), forest degradation (Bullock, Woodcock, & Olofsson, 2018), or land cover change (Butson & Fraser, 2005). However, many countries, in particular from the developing world, have difficulties to access and/or generate the necessary information for monitoring land degradation from EO data (Group on Earth Observations, 2017). In 2015, UNCCD initiated an LDN target-setting pilot project with 14 countries to evaluate the utility of global data sets on Land Cover (LC) and Land Productivity Dynamics (LPD) derived from remotely sensed EO data. Countries were able to use global datasets in combination with their national data to set their targets (Anderson, Ryan, Sonntag, Kavvada, & Friedl, 2017). Although the selected global data sets (e.g. European Space Agency Climate Change Initiative (ESA CCI) – Land Cover, Joint Research Center – Land Productivity Dynamics (JRC LPD) and International Soil Reference and Information Centre – Soil Organic Carbon (ISRIC SOC)) (Hengl et al., 2017; Hollmann et al., 2013; Ivits & Cherlet, 2013) have been useful, the moderate to coarse spatial resolution (e.g. 250 m to 1 km) is an issue for adequately assessing land degradation, particularly in mountainous regions, small island states, and highly fragmented landscapes (Group on Earth Observations, 2017). Therefore, there is a need to develop methodologies for the production of increased spatial resolution indicators (e.g. 10–30 m) to assess land degradation.

The increasingly free and open availability of medium to high-resolution satellite EO data (e.g. Landsat or Sentinels) together with improved computing and storage capacities allow monitoring, mapping, and assessing land degradation and its evolution over time at national scale in an accurate, consistent and regular manner. 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, Zabala, Serral, & Pons, 2019). To tackle big Earth data challenges such as Volume, Variety, and Velocity

(Boulton, 2018), the data cube concept has emerged as a solution lowering barriers and offering new possibilities to handle large spatio-temporal EO data (Baumann, Misev, Merticariu, & Huu, 2019; Kopp, Becker, Abhijit Doshi, Wright, & Hong, 2019; Lewis et al., 2016). Data cubes are a time-series multi-dimensional (e.g. space, time, data type) stack of spatially aligned pixels used for efficient and effective access and analysis (Dhu et al., 2019). It strengthens connections between data, applications, and users facilitating management, access and use of Analysis Ready Data allowing different types of users to harness big Earth data at minimum cost and effort (Baumann, 2018; Giuliani, Masó, et al., 2019).

Consequently, the aim of this paper is to provide an initial overview of an innovative approach to monitor land degradation at the national scale in compliance with the SDG15.3.1 indicator using Landsat observations available in a data cube, enabling more effective and efficient analysis of EO data over their full spatial and temporal dimensions.

2. Methodology

The methodology follows the official UN SDG indicator framework (United Nations Statistical Division, 2018, p. 15) and its implementation as proposed by UNCCD Good Practice Guidance (GPG) document (UNCCD, 2017). UNCCD is the custodian agency for SDG indicator 15.3.1 to monitor progress towards achieving SDG target 15.3. UNCCD through its national reporting and review process should regularly collect, on a four-year basis, and analyze data on the proportion of land that is degraded over the total land area (Sims et al., 2019).

2.1. SDG15.3.1 definition and measurement

According to the UN SDG indicator framework, land degradation is defined as *“the reduction or loss of the biological or economic productivity and complexity of rain fed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from a combination of pressures, including land use and management practices”* (United Nations Statistical Division, 2018). Total land area, expressed in hectares or km², is the total surface area of a country less the area covered by inland waters, like major rivers and lakes. The indicator is expressed as the proportion (in percentage) of land that is degraded over the total land area. Currently, the indicator is classified in Tier 2, meaning that the indicator is conceptually clear, has an internationally established methodology but data are not regularly produced by countries (Anderson et al., 2017).

The indicator is derived from a binary classification of land condition (i.e. degraded or not degraded) of a harmonized set of three measurable sub-indicators:

- (1) *land cover and land cover changes*, to assess the possible loss of ecosystem services that are valuable in a local or national context (Andrew, Wulder, & Nelson, 2014; Ban, Gong, & Gini, 2015; Burkhard, Kroll, Müller, & Windhorst, 2009).
- (2) *land productivity trends*, to determine changes in health and productive capacity of the land. It usually reflects the net effects of changes in ecosystem functioning (e.g. plant and biomass growth) and declining trends can be a defining characteristic of land degradation (Cowie et al., 2018; Oehri, Schmid, Schaepman-Strub, & Niklaus, 2017).

- (3) *soil organic carbon trends*, to quantify overall soil quality associated with nutrient cycling and its aggregate stability and structure with direct implications for water infiltration, soil biodiversity, vulnerability to erosion, and ultimately the productivity of vegetation, and in agricultural contexts, yields (Hengl et al., 2014; Stumpf et al., 2018).

For each of the sub-indicators, countries can access a wide range of data source (e.g. EO and geospatial data), while at the same time ensuring national ownership (United Nations, 2015).

Quantifying the indicator is based on the evaluation of changes/trends in the sub-indicators in order to determine degraded land. The sub-indicators are few in number, complementary and non-additive components of land-based natural capital and sensitive to different degradation factors. The One Out, All Out (1OAO) principle is applied: if one of the sub-indicators is negative (or stable when degraded in the baseline or previous monitoring year) for a particular land unit, then that land unit would be considered as degraded subject to validation by national authorities. This rule is applied as a precautionary measure, because stability or improvements in the land condition in any of the three indicators cannot compensate for degradation in the others.

The quantification, monitoring, and assessment of land degradation are generally context-specific and therefore makes it difficult for a single indicator to capture the full complexity of land (e.g. state and condition) (Gilbey et al., 2019). The three sub-indicators are however sufficiently robust to address changes in different relevant ways such as apprehending relatively fast changes with a land cover or productivity trends while capturing slower changes through carbon stocks (Cowie et al., 2018; Gonzalez-Roglich et al., 2019). These sub-indicators are widely accepted to monitor major factors and driving variables reflecting the capacity to deliver valuable ecosystem services (Fu et al., 2015). Their definition and methodology for calculation are recognized as technically and economically feasible for systematic observation (Bojinski, Michel Verstraete, Peterson, Simmons, & Zemp, 2014; Pereira et al., 2013). The indicator should be derived principally from comparable and standardized national official data sources. However, due to their nature, these sub-indicators can be derived from satellite Earth Observations as well as geospatial data from regional and global data repositories but should be validated by national authorities (UNCCD, 2017). Currently, the reference implementation to help countries monitoring degraded land is Trends.Earth (Gonzalez-Roglich et al., 2019). It is a desktop and cloud-based system to generate the three sub-indicators, and to combine the sub-indicators to calculate Indicator 15.3.1. It uses QGIS as a data preparation and results visualization interface (Meyer & Riechert, 2019) and uses the Google Earth Engine (GEE) to process data (Gorelick et al., 2017). It supports countries in analyzing data and preparing their reporting commitments to UNCCD such as plot time series of sub-indicators, generate maps and other graphics. While regional and global datasets derived from remote sensing can play an important role, there is still a need for greater spatial and longer temporal resolution to better capture the dynamics of land degradation at a national scale (Pasquarella, Holden, Kaufman, & Woodcock, 2016; Pettorelli et al., 2018).

Therefore, to tackle this issue, it would be interesting to explore the potential of Earth Observations Data Cube (EODC) that may benefit from the large historical data archive from the USGS Landsat programme (Dwyer et al., 2018; Wulder et al., 2016) as well as the higher spatial and temporal resolution provided by ESA Sentinels (Addabbo, Focareta, Marcuccio, Votto, & Ullo, 2016; Malenovský et al., 2012) to generate the required sub-

indicators for calculating the SDG15.3.1 indicator. Moreover, the rapid diffusion and implementation of EODC in various countries (4 operational, 11 in development, 28 have expressed interest)(Killough, 2018) may facilitate replicating and enhancing the developed code as well as strengthening national capacities to use EO data for monitoring land degradation.

2.2. Implementation

Accessing and integrating scientific models is still a complex task with many different proposed approaches and solutions (Nativi, Mazzetti, & Geller, 2013; Santoro, Nativi, & Mazzetti, 2016). It has been decided to base the implementation on four principals of GEO Model Web (Mazzetti et al., 2016):

- (1) *Open Access*: facilitates the creation and sharing of models.
- (2) *Low entry barrier*: minimize entry barriers for both resources' providers and users.
- (3) *Service-driven approach*: access to model is provided by web-based services to enhance interoperability.
- (4) *Scalability*: facilitates the use of increasingly large volumes of data.

Following these principles, it has been decided to separate the generation of the three sub-indicators from the calculation of the SDG indicator. The Trends.Earth model will be published on the Virtual Laboratory (see Section 2.2.2) while the sub-indicators generation will be implemented in an EODC environment (Figure 1). This de-coupling has been intended to enhance the scalability and flexibility of the Trends.Earth model. Indeed, this model allows users to compute each sub-indicator separately in a spatially explicit manner under the form of raster maps that will be further integrated into a final indicator map and produces at the same time a table with results reporting areas potentially improved, stable, or degraded over the area of interest. This allows the use of different resources such as the Copernicus Data and Information Access Services (DIAS), the Global Earth Observation System of Systems (GEOSS) or national data infrastructures (Asmaryan et al., 2019; Craglia, Hradec, Nativi, & Santoro, 2017; European Commission, 2018).

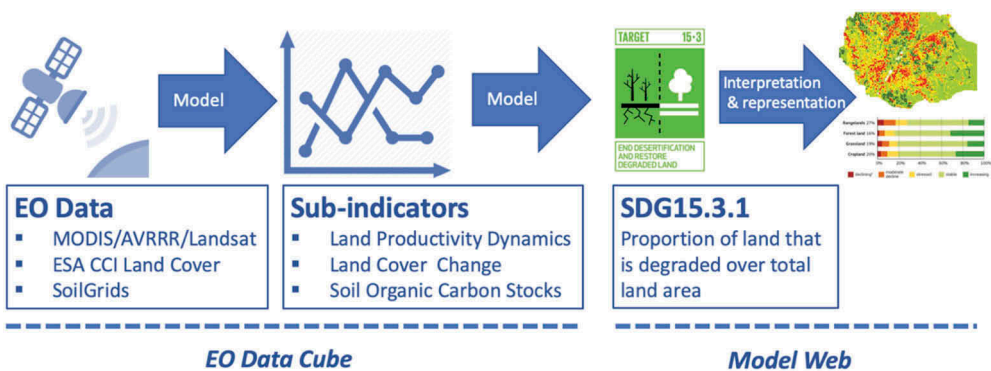


Figure 1. General representation of the implementation.

2.2.1. *Generating sub-indicators using an Earth Observations data cube*

Switzerland has a unique EO Analysis Ready Data Archive covering the entire territory. The Swiss Data Cube (SDC – <http://www.swissdatacube.ch>) is an innovative analytical cloud-computing platform allowing users the access, analysis, and visualization of 35 years of optical (e.g. Sentinel-2; Landsat 5, 7, 8) and radar (e.g. Sentinel-1) satellite Earth Observation (EO) Analysis Ready Data over the entire country (Giuliani et al., 2017; Giuliani, Chatenoux, Honeck, & Richard, 2018; Truckenbrodt et al., 2019). Importantly, the SDC minimizes the time and scientific knowledge required for national-scale analyses of large volumes of consistently calibrated and spatially aligned satellite observations. The SDC is an initiative supported by the Federal Office for the Environment (FOEN) and developed, implemented, and operated by the United Environment Program (UNEP)/GRID-Geneva in partnership with the University of Geneva (UNIGE), the University of Zurich (UZH), and the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL). The objective of the SDC is to support the Swiss government for environmental monitoring and reporting and enable Swiss scientific institutions to fully benefit from EO data for research and innovation. The SDC is based on the Open Data Cube (ODC) software stack which is an open source project providing a common analytical framework for processing satellite data (Killough, 2018; Rizvi, Killough, Cherry, & Gowda, 2018).

To fully benefit from the great wealth of data available, facilitate their analysis and develop tailored tools and application, the SDC has a Python Application Programming Interface (API) that allows users to program their own processing algorithms. Therefore, using this API can ease the production of yearly sub-indicators to track land degradation over Switzerland. Each of the three sub-indicators will be generated using a dedicated Python script with the result exposed in the Trends.Earth model as custom datasets. The implementation for the calculation of the sub-indicators strictly follows the approach documented by Trends.Earth (Gonzalez-Roglich et al., 2019) and replicate as closely as possible the source code available from Trends.Earth GitHub repository (<https://github.com/ConservationInternational/landdegradation/tree/master/landdegradation>) with the only exception to the correction of the climate effect for the computation of productivity trajectory that will be implemented in the next development iteration. UNCCD GPG recommends implementing Water Use Efficiency (WUE)(Ponce-Campos et al., 2013) to take into account the potential impacts of climate in time-series productivity analysis.

Land Cover (LC) changes are assessed using land cover data over the country for the baseline and target years. To enable valid comparison, LC data should be sufficiently consistent and accurate. Currently, the proposed and implemented approach relies on the European Space Agency (ESA) Climate Change Initiative (CCI) (<http://cci.esa.int>) Land Cover data (<https://www.esa-landcover-cci.org>) (Plummer, Lecomte, & Doherty, 2017). National or local data can be also used. Currently, the official source of Switzerland LC information, provided by the Federal Statistical Office (FSO) is produced every 6–12 years by visual interpretation of aerial photos and assigning an LC and an LU category to each sample point in a regular 100 m grid cell. Even if this data set is useful, thanks to its thematic richness, neither the reduced spatial resolution, nor the update frequency allows providing accurate and timely information to better understand the dynamic of LC/LU changes (e.g. spatial and temporal heterogeneities of the landscape features and values) and their impact across Switzerland. In the absence of a sufficiently precise LC map of Switzerland, it has been decided to rely on the default ESA CCI data. Following UNCCD

guidance, land cover data should be classified in 7-classes (forest, grassland – including shrub and sparsely vegetated areas, cropland, wetland, artificial area, bare land, and water). Landcover data are also employed in the calculation of the second sub-indicator through a land cover transition analysis to monitor whether a given pixel remains in the same land cover type or has changed. The resulting map is a 3-class (improvement; stable; degradation) land cover change sub-indicator.

Land productivity is the biological productive capacity of the land, the source of all the food, fiber, and fuel that sustains humans (United Nations Statistical Division, 2018). To assess land productivity, Net Primary Production (NPP) is usually used. However, it is time-consuming and costly to estimate. Hence, remotely sensed proxies are commonly used to derive indicators of NPP (Paruelo et al., 2016; UNCCD, 2017). One of them is the Normalized Difference Vegetation Index (NDVI) (Pettoirelli et al., 2005). Mean annual NDVI time-series are computed allowing to assess three measures of change: productivity trajectory (i.e. rate of change in primary production over time), state (i.e. detection of changes in primary productivity as compared to a baseline period) and performance (i.e. local productivity relative to other areas that share a similar landcover type over the dedicated region) (Sims et al., 2019; UNCCD, 2017). The three measures are then aggregated resulting in a 3-class (improvement; stable; degradation) land productivity sub-indicator following UNCCD guidelines for reporting (UNCCD, 2017). First, the annual average NDVI values of each pixel in the study area are calculated using time series of Landsat surface reflectance data sets that are available in the SDC for the selected time frame over a given region. Then, the trajectory is measured by fitting a robust regression line across the entire baseline period, or the most recent 8 years of annual data for each reporting period and assessing the significance of the slope is tested using a Mann-Kendall test. The measure of productivity state is then defined by comparing the average annual NDVI calculated for a baseline period (historical period to which to compare recent primary productivity) with that calculated for a more recent period (e.g. target period). Finally, the performance of productivity is calculated by comparing the average NDVI value of the defined time frame with the maximum productivity of ecologically similar units calculated as the unique intersection of land cover and soil type (respectively, ESA CCI at 300 m resolution and SoilGrids USDA at 250 m resolution). The maximum productivity of each ecologically similar unit is defined by the 90th percentile of the frequency distribution of the annual NDVI values of each type of unit. Once trajectory, state, and performance sub-indicators have been generated they are combined into 3 or 5 classes (respectively, degradation, stable, improvement or declining, early sign of decline, stable but stressed, stable, improving). The 3 class combination follows GPG recommendation (UNCCD, 2017) whereas the 5 class aggregation is specific to Trends.Earth (Gonzalez-Roglich et al., 2019) and the World Atlas on Desertification (Cherlet et al., 2018).

The third and last sub-indicator as part of the SDG process requires quantifying changes in soil organic carbon (SOC). Unfortunately, this sub-indicator cannot be generated using satellite EO data and it is particularly difficult to assess for various reasons (e.g. spatial variability of soils, lack of consistent time-series data) (Stumpf et al., 2018). To estimate changes in SOC, the proposed methodology by Trends.Earth is to use a combination of land cover and SOC. This suggests determining the SOC reference values using the SoilGrids carbon stocks at 250 m resolution as the reference value (Hengl et al., 2017). Then, use the 7-class land cover maps previously employed to

evaluate the changes in carbon stocks for the reporting period using conversion factors for changes in land use. Finally, compute the changes in SOC between the baseline and target/reporting period. Areas that show SOC loss of 10% or more are considered as degraded, while areas experiencing a gain of 10% or more are showing improved conditions.

Finally, the three sub-indicators are combined according to an aggregation table based on the 10AO rule, meaning that an area is considered degraded in the final output if any of the sub-indicators identified the area as degraded (Figure 2).

2.2.2. Trends.earth on the virtual laboratory

In recent years, there has been an increasing demand for informed decision-making processes to address international agreement and policy goals at local, national, regional, and global scales. The assessment of targets, and the definition of possible actions towards their fulfilment require informed decision-making at different levels. Consequently, policy-makers are asking the scientific community to provide the necessary knowledge to enable an evidence-based decision-making process (Lehmann et al., 2019; Nativi, Santoro, Giuliani, & Mazzetti, 2019).

To answer these questions, scientists need to manage heterogeneous resources including satellite data, in-situ data, services, analysis and modelling tools, processing algorithms, models/workflows, and models results.

The Virtual Laboratory (VLab) is a cloud platform that aims to facilitate the execution of scientific workflows for the generation of knowledge (e.g. indicators, indices, Essential Variables, etc.) by scientists and modelers for evidence-based decision-making (Santoro, Mazzetti, & Nativi, 2019). A scientific workflow is a process for generating knowledge from observation/simulation data and scientific models. According to the GEO Model Web

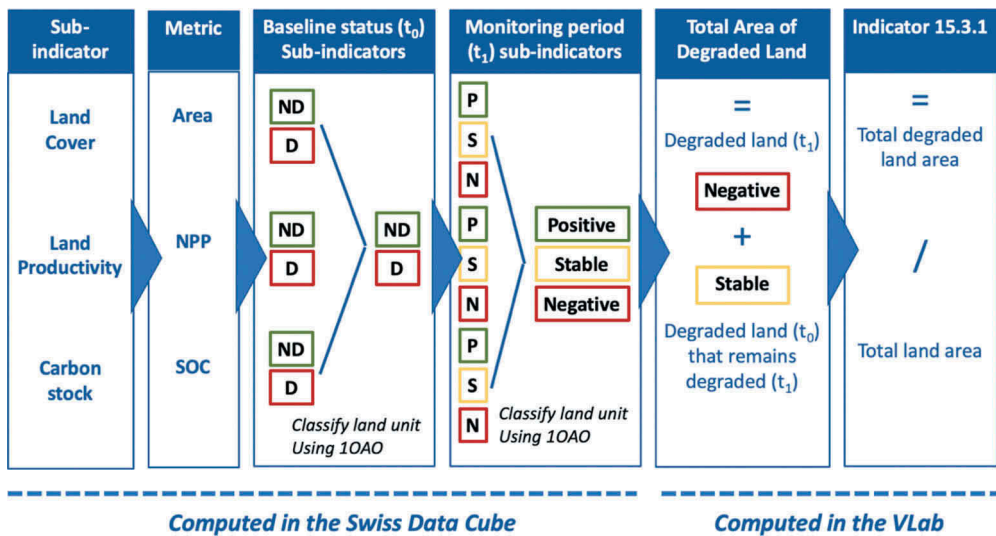


Figure 2. Schematic representation of the implementation for computing the sub-indicators and the aggregation for calculating the SDG15.3.1 indicator (adapted from United Nations Statistical Division, 2018).

principles, VLab aims to minimize as much as possible the interoperability requirements for publishing and sharing a scientific model. Figure 3 depicts a high-level schematic overview of VLab architecture. The main functionalities provided by VLab are:

- Harmonized discovery of and access to heterogeneous resources from multiple systems;
- Publication and sharing of scientific models developed on heterogeneous programming environments;
- Execution of scientific workflows developed on heterogeneous execution environments (e.g. different cloud platforms, different software libraries, etc.);
- Publication of execution results.

The connection to data systems is obtained by adopting brokering technology, already described in other manuscripts (Nativi, Craglia, & Pearlman, 2013; Nativi et al., 2015; Vaccari, Craglia, Fugazza, Nativi, & Santoro, 2012). VLab utilizes Git technology for scientific model source code sharing; while it is able to handle multiple programming languages and execution environments by utilizing a containerization approach, implemented using Docker technology.

VLab orchestrates the actions needed to implement the required workflow for model execution: (a) it accesses and ingests the required datasets into the execution environment; (b) it clones the model source code to the execution environment; (c) it launches the model execution; (d) it retrieves output datasets.

VLab functionalities are available through Web Application Programming Interfaces (APIs) for system integration and development of applications.

VLab addresses three types of users:

- Modelers who have developed a scientific model for generating knowledge, and who would like to make it discoverable and runnable by other users.

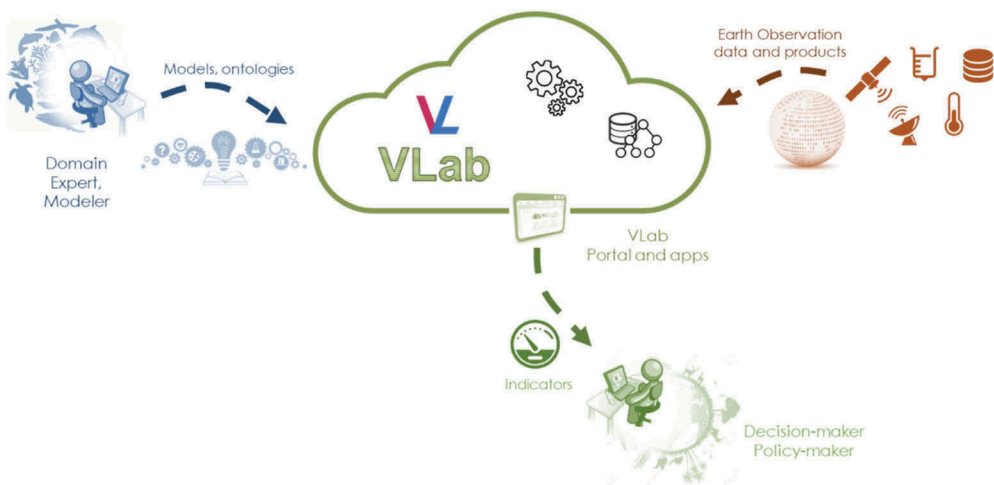


Figure 3. General concept of the VLab.

- Application developers who would like to build desktop and mobile apps for end-users (e.g. decision-maker) on top of VLab resources (data and workflows).
- End users (scientists or policy-makers) who want to access knowledge generated by thematic workflows directly or through a dedicated user-interface

Through the VLab, modelers can publish their existing scientific models developed in different programming environments (e.g. Python, Java, R, NetLogo) and make them seamlessly runnable from external users. Application developers can create applications, including dashboards, Decision-Support-Systems, mobile apps, etc. These can exploit VLab resources (data and models) and functionalities through different interfaces with different levels of complexity, including standard geospatial Web services, RESTful APIs, Javascript client libraries (Mazzetti, Santoro, & Nativi, 2018). Finally, end-users access the developed client applications to generate the needed products by running available workflows.

The original Trends.Earth model is made available as a plugin for QGIS desktop application. The plugin calculates a Land Degradation Indicator from user-defined sub-indicator datasets. Furthermore, if no sub-indicator is available, the plugin also allows the use of GEE (Google Earth Engine) scripts for the calculation of the sub-indicators. The publication of Trends.Earth on VLab emphasised the possibility of calculating a Land Degradation indicator from existing sub-indicator datasets. Essentially, this task required only a slight modification to the Python code of Trends.Earth to cope with the need to run the plugin without the user interface.

3. Results

In order to validate the technical feasibility, identify the possible issues and determine the potential of such an approach to monitor land degradation at the national scale in compliance with the SDG15.3.1 indicator guidance, a proof-of-concept workflow has been developed.

The code for generating each sub-indicator is made available as three dedicated python scripts that can be executed in Jupyter Notebook, an interactive web-based programming interface. The scripts are publicly available at <https://github.com/GRIDgva/SwissDataCube>. Similarly, the Trends.Earth model used to compute the SDG15.3.1 indicator is available on the VLab (<https://vlab.geodab.org>) after registration.

The three sub-indicators have been successfully computed at the national scale using the three Python scripts. Currently, only the Land Productivity sub-indicator has been fully implemented to make use of the content of an EODC while the Land Cover and Soil Carbon sub-indicators are currently still using GEE (Figure 4).

The indicator generated with the Swiss Data Cube shows much finer details providing improved information on the spatial patterns of land productivity. Trajectory, state, and performance indicators were compared from the Trends.Earth and SDC implementations (Figure 5). They show an accurate correlation indicating that the proposed implementation is suitable. However, it has been observed that annual average NDVI values can differ from time to time between those generated from GEE and SDC (e.g. negative values in GEE while positive in SDC). This difference can be caused by the fact that the SDC uses ARD data while GEE not. This can explain the highest variability in annual means observed

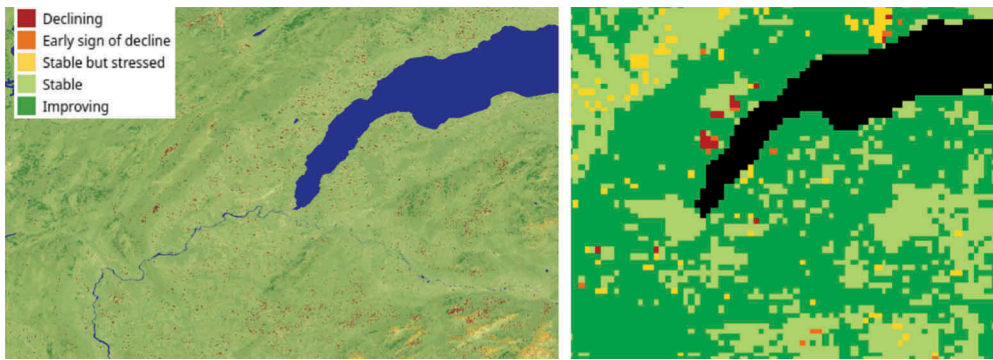


Figure 4. Land productivity indicator using landsat data for the greater Geneva area generated using the Swiss Data Cube (left) and Trends.Earth (right) (Baseline:2001–2012, Target:2013–2015).

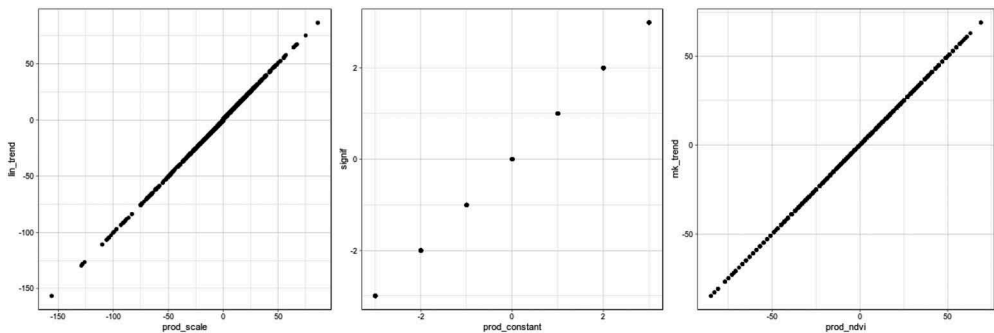


Figure 5. Comparison between trajectory (left), state (middle), and performance (right) indicators generated from Trends.Earth (X-axis) and the SDC (Y-axis) for the NDVI trend analysis.

with GEE data compared to the more reliable SDC values owing to the absence of atmospheric effects.

Once these three sub-indicators have been computed for the recommend period 2001–2015 by UNCCD in its GPG Document (UNCCD, 2017) they are then further used in the VLab to generate the SDG15.3.1 at the Swiss scale. The main output of the model is a pixel-based map over the entire country at a spatial resolution of 30 m. This gives the following information on the areas and their evolution for the period 2001–2015 (Table 1).

These results can be compared with the official indicator provided by the Monitoring Sustainable Development (MONET) indicator systems, a joint effort of the FSO, the Federal Office for the Environment (FOEN), the Federal Office for Spatial Development (ARE) and the Swiss Agency for Development and Cooperation (SDC) to measure progress towards sustainable development. Eighty-five indicators of MONET are included in the report “Switzerland implements the 2030 Agenda for Sustainable Development”, which has been approved by the Federal Council on 20 June 2018 (<https://www.eda.admin.ch/agenda2030/en/home/berichterstattung/nationale-berichterstattung.html>). The reported value for the indicator 15.3.1 is 4.7% (Swiss Confederation, 2018). In comparison, the value calculated using the proposed approach is 9.7% that is approximately twice higher than the official value (Table 1). This difference can be explained by the different definitions of

Table 1. Statistics of degraded, stable, and improved land area for the 2001–2015 period.

	Area (sq km)	Percent of total land area
Total land area	39'995.9	100.00%
Land area improved	13'351.3	33.38%
Land area stable	20'998.7	52.50%
Land area degraded	3'886.8	9.72%
Land area with no data	1'759.1	4.40%

land degradation used in Switzerland. Indeed, only sealed surfaces are considered as degraded land (<https://www.bfs.admin.ch/bfs/en/home/statistics/sustainable-development/2030-agenda-goals-monitoring/all-indicators/15-vie-terrestre/soil-sealing.html>). Sealed surfaces are impermeable built-up areas covered by hard surfaces (e.g. asphalt, concrete) causing a noticeable loss of natural soil function. However, this definition is extremely restrictive considering only anthropogenic factors and does not consider natural factors such as loss of soil fertility, loss of soil organic matter, or deterioration of soil structure (United Nations Statistical Division, 2018). This demonstrates the necessity of agreeing on a common definition to allow comparisons between countries. Otherwise, the indicator becomes too nationally specific and hinders effective comparison in opposition to the objective of global policy frameworks like the SDGs.

4. Discussion

The proposed approach is, to our knowledge, among the first attempts to provide a nation-wide consistent tool for monitoring land degradation in compliance with the UN SDG framework using an Earth Observations Data Cube. The proposed approach was developed as a proof-of-concept. The first results indicate that satellite EO data can be a good complement to traditional statistical measures by taking into account parameters that are not yet currently considered; by having the possibility to disaggregate the indicator at the pixel level, at high-resolution (30 m); by capturing both spatial (e.g. maps) and temporal (e.g. graphs) dynamics of land degradation; and finally by publishing the results of the analysis for decision-makers. The successful initial implementation showed benefits, limitations, and the need for further developments to strengthen this monitoring tool.

In terms of benefits, the proposed solution is paving the way for a national-scale monitoring service in compliance with the SDG15.3.1 indicator using satellite EO data. This enables a more effective and efficient analysis of EO data over their full spatial and temporal dimensions. Such a methodology can strengthen the national monitoring mechanism by complementing the current measurement of this indicator. It can enhance compliance with the official UN SDG reporting system and goes beyond the specific current national definition that only considers sealed surfaces as concerns Switzerland. Additionally, using the Swiss Data Cube benefitted from higher spatial resolution and longer time-series compared to MODIS which can potentially help to get an improved sense of the dynamics of land degradation across a country. Having the indicator generated at the pixel-level allows aggregation at different scales such as land unit or

various administrative units as well as generating the national value. Finally, the proposed approach can be easily replicated and further enhanced because of the Open Science approach relying on open data (e.g. Landsat), open software (e.g. Open Data Cube), and open algorithms (e.g. Jupyter Notebook, GitHub). This greatly facilitates reproducible science and considering then the trend of adoption of EODC at the global scale, this approach can be replicated and tested in various geographical and environmental contexts (Giuliani et al., 2019).

The current implementation has evidenced some limitations mostly concerning the data available in the Swiss Data Cube. Indeed, even if all the Sentinel-2 archive is available, the land degradation trend analysis is not possible with this dataset because the time-series is too short for efficient analysis. Only Landsat can provide a sufficiently long time-series to obtain reliable results. In the current implementation, the land productivity sub-indicator requires analysing at least 15 years of data. To tackle this issue and benefit from the increased spatial and temporal resolution of Sentinel-2 in conjunction with Landsat data, a possible solution is to apply the virtual constellation approach to facilitate data integration and fusion of different sensors (Wulder et al., 2015) allowing the creation of a harmonized Landsat and Sentinel-2 surface reflectance data set (Claverie et al., 2018).

Another limitation lies in the fact that Landsat 7 data has had data gaps (e.g. stripes) since June 2003 caused by the Scan Line Corrector (SLC) failure (Wulder, Ortley, White, & Maxwell, 2008) and only 78% of their pixels are working properly. To fill these gaps, various methods exist but one the most effective approach is based on the Neighbourhood Similar Pixel Interpolation (NSPI) (Chen, Xiaolin Zhu, Vogelmann, & Jin, 2011). Another possibility to consider to partially overcome this issue is to use only Landsat 5 and 8 sensors. However, for the year 2012, there will be a gap because only Landsat 7 was operational. Finally, the current implementation benefits from the EODC technology only for the land productivity sub-indicator.

Ideally, the sub-indicator on land cover change can also benefit from the Swiss Data Cube. However, this requires developing and implementing new methodologies for generating yearly land cover maps in an EODC. This issue has not been yet tackled but various possibilities can be explored such as advanced processing and classification algorithms such as Artificial Neural Networks (ANN), Support Vector Machine classifier (SVM) (Mountrakis, Im, & Ogole 2011), decision tree classifiers and Random Forest used in conjunction with time-series metrics, integration of ancillary data (e.g. Digital Elevation Model), and post-classification error reduction and accuracy assessment (Comber & Wulder, 2019; Dong, Metternicht, Hostert, Fensholt, & Chowdhury, 2019; Wulder, Coops, Roy, White, & Hermosilla, 2018).

Regarding, the land productivity sub-indicator, it currently does not allow seasonality to be taken into account in a dynamic way based on the variability of the NDVI values across year. The user can instead define a begin and end-month for each year in order to filter winter out but this does not allow filtering data for larger areas where seasons have different begin and end months or do the process in an automated way. To identify annual seasons for a productivity assessment, the GPG recommends the use of TimeSAT, a software package to investigate seasonality of time-series satellite data and their relationships with vegetation dynamics parameters (Eklundh and Per 2015; Jönsson & Eklundh, 2004). This can be implemented in the productivity assessment script using the provided pre-compiled Linux version of TimeSAT. Another possible improvement is to

correct the effects of climate (e.g. pluviometry) on land degradation to discriminate between human-induced degradation and regional change patterns in water availability (Wessels et al., 2007; Wessels, van den Bergh, & Scholes, 2012) using the Water Use Efficiency correction methods (Ponce-Campos et al., 2013) as recommended by the GPG.

The emergence of continental scale data cubes like Digital Earth Africa (DEA – <http://digitalearthafrica.org>) allows envisioning the possibility to develop high-resolution land degradation models at the regional scale using the presented solution. The same approach may be applied for any geographical scales at regional, national, and in principle even global scales. Given the global coverage of the Landsat program, any methods are geographically portable and consist of standardized data inputs, indicators algorithms generation, and accuracy assessment protocols. Of particular interest, is the possibility to generate a data cube anywhere in the World using the Data Cube on Demand (DCoD) approach (Giuliani, Chatenoux, Piller, Moser, & Lacroix, 2020). This can facilitate the creation of a data cube and then execute the three scripts to generate the sub-indicators on a given area. To overcome the issue of national yearly land cover maps, a valuable solution can be the use of the Earth Observation Data for Ecosystem Monitoring (EODESM) model (Lucas & Mitchell, 2017; Lucas, Mitchell, Manakos, & Blonda, 2018). It is currently under implementation in Digital Earth Australia (Lucas et al., 2019). This model facilitates regular classification according to the Food and Agricultural Organization – Land Cover Classification System (FAO – LCCS) as well as translations to other taxonomies like the General Habitat Classification. It also includes change detection and the production of maps indicating the causes and consequences of such changes. Concerning the SOC sub-indicator, the SoilGrids database is subject to large differences in estimates (Tifafi, Guenet, and Hatté, 2018). Consequently, we should consider using the Global Soil Organic Database that may provide improved information to generate this sub-indicator. Alternatively, national database such as the Swiss Soil Carbon Inventory can be investigated (Leifeld, Bassin, & Fuhrer, 2005).

To support countries in their measurement and assessment of Land Productivity, Land Cover, and SOC changes to evaluate land degradation, it is necessary to provide guidance and best practices. The proposed approach can contribute to such capacity development effort. This can at the same time ensure national ownership while preserving the flexibility for countries to use their national data. To enhance national capacities to process, interpret, and validate geospatial data and information on land degradation, the Group on Earth Observations (GEO) as launched in 2017 an initiative on Land Degradation Neutrality (<https://www.earthobservations.org/activity.php?id=149>). This initiative is aimed at supporting the rapid provision and deployment of EO datasets, country support, capacity development, together with EO tools and platforms to assist countries to efficiently and effectively monitor and report on SDG indicator 15.3.1 as well as sustaining the development of international standards, methodologies, and protocols for land degradation monitoring. The solution proposed in this manuscript can be considered as an early contribution towards the objectives of this initiative.

5. Conclusions

Even if at the national scale, various attempts have been done to use satellite imagery, currently, no mechanisms are routinely generating accurate, consistent, and regular land degradation data in accordance with the UN SDG indicator framework. The large volumes of

freely and openly available satellite EO data are still underutilized and not effectively used for national environmental monitoring. Therefore, mapping and monitoring degraded lands remain a challenge that is not adequately addressed at the national scale.

The proposed methodology extends the Trends.Earth approach by implementing it in an Earth Observations Data Cube environment. This provides the benefits of higher spatial resolution and longer time-series using Landsat data and therefore facilitates a solution for monitoring land degradation and providing information to the SDG framework in a consistent and comparable form.

This initial implementation has shown that it is technically feasible to implement in a data cube environment a methodology to monitor land degradation at the national scale in compliance with the UN SDG framework. It enabled a more effective and efficient analysis of EO data and benefited from the higher spatial and temporal resolutions provided by Landsat data. However, further work is needed to refine and strengthen the current implementation by improving the generation of the three sub-indicators. The rapid diffusion and implementation of EODC in various countries may facilitate the replication, testing in different geographical and environmental contexts and enhancement of the proposed methodology as well as strengthening of national capacities to use EO data for monitoring their degraded land and complementing existing national reporting systems by making information more comparable.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, [GG], upon reasonable request: <https://www.unige.ch/envirospace/people/giuliani/>.

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