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Knowledge generation using satellite earth observations to support sustainable development goals (SDG): A use case on Land degradation

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ABSTRACT

Land degradation is a critical issue globally requiring immediate actions for protecting biodiversity and associated services provided by ecosystems that are supporting human quality of life. The latest Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services Landmark Assessment Report highlighted that human activities are considerably degrading land and threating the well-being of approximately 3.2 billion people.

In order to reduce and ideally reverse this prevailing situation, national capacities should be strengthened to enable effective assessments and mapping of their degraded lands as recommended by the United Nations Sustainable Development Goals (SDGs). The indicator 15.3.1 ("proportion of land that is degraded over total land area") requires regular data production by countries to inform and assess it through space and time. Earth Observations (EO) can play an important role both for generating the indicator in countries where it is missing, as well complementing or enhancing national official data sources.

In response to this issue, this paper presents an innovative, scalable and flexible approach to monitor land degradation at various scales (e.g., national, regional, global) using various components of the Global Earth Observation System of Systems (GEOSS) platform to leverage EO resources for informing SDG 15.3.1. The proposed approach follows the Data-Information-Knowledge pattern using the Trends.Earth model (http://trends.earth) and various data sources to generate the indicator. It also implements additional components for model execution and orchestration, knowledge management, and visualization.

The proposed approach has been successfully applied at global, regional and national scales and advances the vision of (1) establishing data analytics platforms that can potentially support countries to discover, access and use the necessary datasets to assess land degradation; and (2) developing new capacities to effectively and efficiently use EO-based resources.

1. Introduction

Most countries are aiming at becoming more sustainable while at the same time being attractive business locations with a high quality of life (Selomane et al., 2019). This ambitious objective is challenged by a number of trends such as: climate change, population growth, increasing mobility, energy demand, high consumption of resources, urbanization, loss of biodiversity and associated ecosystem services, and digitalization of society. These trends have an important impact on the environment and are placing unprecedented demands on land. Land is a limited resource and there will be an ever-increasing demand to control land resources and capitalize on the flow of goods and services from the land (Verburg et al., 2015), (Wood et al., 2018). This can potentially lead to social and political instability, intensifying poverty, conflict and migration.

In its last report, the Intergovernmental Panel for Climate Change (IPCC) has highlighted the fact that land is a critical resource essential for climate change adaptation and mitigation, land degradation and

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food security (IPCC, 2019). Without sustainable land management, the goals of the Paris Agreement will not be reached and cannot limit global warming to 1.5 degrees. During the last 50 years, it is estimated that human activities have affected globally about 70 % of the terrestrial land surfaces, undermining the well-being of at least 3.2 billion people (IPBES, 2018). Settlement and urban areas have grown, agricultural areas have been lost, forests have disappeared, desertification has increased and glaciers have receded (UNCCD, 2017a). Land Cover (LC) and Land Use (LU) changes are considered as major visible indicators of the human footprint (Giuliani et al., 2017a). Consequently, avoiding, reducing and reversing land degradation is an urgent action to protect biodiversity and ecosystem services as well as ensuring human well-being (IPBES, 2018).

Unsustainable land use management strategies (e.g., ecosystem destruction for crop or grazing lands) are recognized as the main drivers of land degradation caused by high-consumption lifestyles of developed countries and the increasing consumption in emerging economies (IPBES, 2018), (Cowie et al., 2018), (Ghebrezgabher et al., 2019). Associated with population growth, this leads to unsustainable pathways of agricultural expansion, natural resource and mineral extraction, as well as urbanization, which have great impacts on degrading land (Ivits and Cherlet, 2013). Consequently, there is a critical need to strengthen national capacities to quantitively assess land degradation as required by the United Nations Sustainable Development Goals (SDGs) (Sims et al., 2019), and adopt Land Degradation Neutrality (LDN) targets as proposed by the United Nations Convention to Combat Desertification (UNCCD) (Cowie et al., 2018), (Chasek et al., 2019; Gilbey et al., 2019; Metternicht et al., 2019). LDN is defined as "*A state whereby the amount and quality of land resources, necessary to support ecosystem functions and services and enhance food security, remains stable or increases within specified temporal and spatial scales and ecosystems"* (Cowie et al., 2018), (Chasek et al., 2019). This approach represents a paradigm shift in land management and planning policies. It aims at counterbalancing the loss of productive land with the restauration of degraded areas by developing conservation measures and sustainable land management practices (Gilbey et al., 2019).

Remotely-sensed Earth Observations (EO) acquired by satellites can be a reliable source for gathering effective Land Degradation (LD) information (Dubovyk, 2017). Indeed, the increasing availability of EO data together with improved computing and storage capacities allow monitoring, mapping, and assessing LD and its change over time on large areas in a consistent and robust manner (Gibbs and Salmon, 2015). However, currently no mechanisms are routinely generating accurate, consistent and regular LD information. The large volumes of freely and openly available EO data are still underutilized and not effectively used for national environmental monitoring. Therefore, mapping and monitoring LD changes remains a challenge that is not adequately addressed at the national scale.

To address this sustainability challenge, timely and reliable access to environmental data and information is fundamental (Giuliani et al., 2017a). It provides the necessary basis for reliable and accountable scientific understanding and knowledge to support informed decisions and evidence-based policy advices (Nativi et al., 2019). Therefore, reaching the goal of sustainable development requires the integration of different datasets describing the three dimensions of sustainability to adequately characterize a given location (Lehmann et al., 2017). This allows monitoring and assessing environmental conditions at different scales (e.g. national, regional, global); understanding interactions between various systems (e.g. atmosphere, hydrosphere, biosphere), and model future changes (Costanza et al., 2016). Consequently, Information Technology can play a significant role (i.e., Digital Transformation) to leverage modern analytics and modelling technologies (e.g., Big Data, Artificial Intelligence) and generate the required knowledge for decision-makers (Nativi et al., 2019).

To this end, a change of paradigm is required, moving from traditional data-centric approach to more information and knowledge centric approaches (Nativi et al., 2019). Recognizing that environmental data are a fundamental resource for environmental and sustainability research, monitoring and assessment, it is essential to organize actions (i.e., data acquisition to knowledge generation) in coherent and coordinated workflows also known as data value chains (Giuliani et al., 2017b). Data value chain is defined as an information flow that describes a series of steps required to generate value and useful insights from data (European Commission, 2014), (Curry, 2016). To fully realize the value chain of EO data, the Data-Information-Knowledge-Wisdom (DIKW) paradigm can facilitate evidence-based decision-making processes and informs about the limits of our planet (Ackoff, 1999), (Rowley, 2007). In DIKW, *data* is considered as a collection of facts/measurements in a raw or unorganized form (e.g., numbers); *information* is generated from data that has been cleaned of errors and further processed in a form that makes it easier to visualize, analyze and interpret for a specific purpose (e.g., relation with physical and/or social phenomena). In turn, *knowledge* is generated when information is not only perceived as a description of collected and organized facts (e.g., contextualization), but also when one understands how to apply it to achieve certain objectives (i.e., elaborating valuable patterns). Finally, *wisdom* is when knowledge is applied to action to explore future scenarios and answer question such as "what is the best" or "why do something" (Ackoff, 1999), (Rowley, 2007).

To reach the objective of a sustainable development, it is critical to support decision/policy-makers with proper knowledge on quantitative targets, at various spatial scales and across disciplines, in order to support evidence-based policy making (Rockström et al., 2018). Informed governance can strengthen policies and planning developments supported by best practices for sustainable development (Griggs et al., 2013). Selecting and gathering the necessary EO to inform environmental policy indicators is a scientific challenge. In order to fulfil this task, essential variables have been defined for climate, biodiversity, water, and oceans to describe the natural Earth system, and are now being developed also for socio-economic variables (Lehmann et al., 2019a).

This is exemplified by one of the objectives of the SDGs defined in the Agenda 2030 for Sustainable Development (United Nations, 2015). The SDG indicator 15.3.1 ("proportion of land that is degraded over total land area") is aiming to define such a quantifiable target to monitor and assess degraded land nationwide. It is presumed that UNCCD will collect, review and analyze, every four years, data reported by countries through their national reporting process. However, there are currently several drawbacks:

(1) This indicator was classified in Tier 2 (and since December 2019 is now a Tier 1 indicator), meaning that the that the indicator is conceptually understandable, has an internationally agreed methodology but data are not regularly produced by countries (Anderson et al., 2017),
(2) Lack of capacities at the country level in obtaining, using and validating EO data for UNCCD national reports,
(3) Limited data are currently officially provided by the United Nations Global SDG Database (https://unstats.un.org/sdgs/indicators/database/) for SDG15.3.1,
(4) Having the indicator value is an important information, but to support efficient and effective decision-making, knowledge is required.

Consequently, the aim of this paper is to provide an initial overview of an innovative and scalable approach to monitor land degradation at various scales (e.g., national, regional, global) in compliance with the SDG15.3.1 indicator UN guidance, and generate knowledge using EO data to support SDGs.

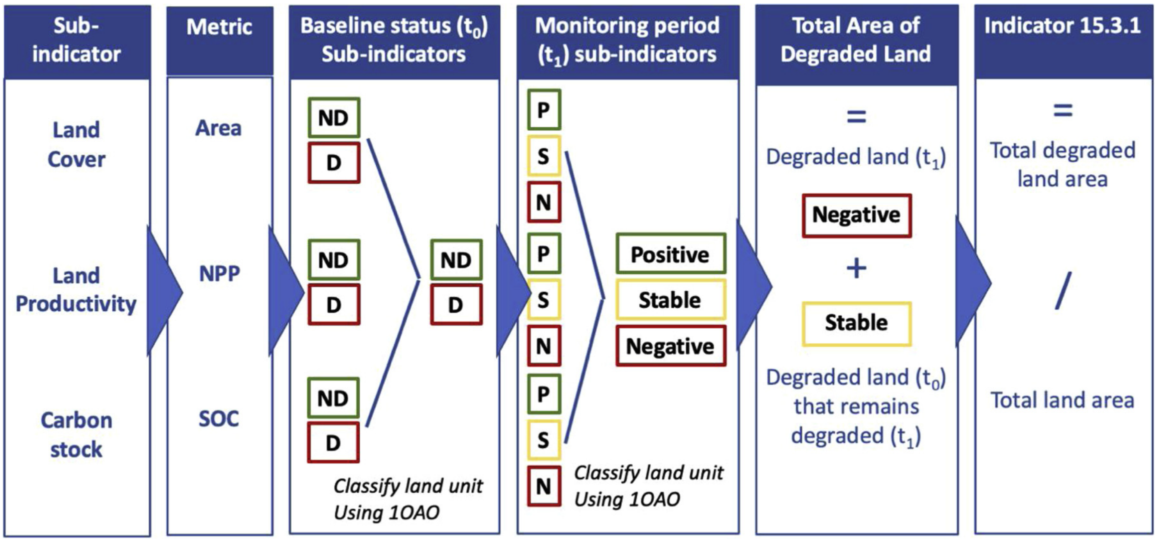

Fig. 1. Schematic representation of the methodology for generating the sub-indicators and calculating the SDG15.3.1 indicator (adapted from United Nations Statistical Division 2018).

2. Methodology

The proposed methodology follows the Data-Information-Knowledge-Wisdom (DIKW) (Rowley, 2007) pattern to organize the different components into a coherent workflow to enhance scalability (e.g., different scales from national to global) and flexibility (e.g., different data sources, processing platforms) for effective environmental monitoring. It applies the official UN SDG indicator framework (United Nations Statistical Division, 2018) and the guidance for implementation proposed by UNCCD, the custodian agency for the SDG indicator 15.3.1 (UNCCD, 2017b). One of the objectives is to use EO data to enhance quality, coverage and availability of the information required to generate a SDG indicator. The following characteristics of EO data can bring major benefits to support directly or indirectly 72 targets and 30 indicators of the SDG framework (CEOS, 2018), (Group on Earth Observations, 2017):

1 *Spatial resolution:* capacity to provide information, potentially for every 10 m x 10 m.
2 *Temporal resolution:* capacity to capture data at different frequencies of revisit (e.g., 5 days for Sentinel-2, 16 days for Landsat).
3 *Scale:* capacity to provide information for scales ranging from local up to global.
4 *Time-series:* capacity to provide continuous data starting from 1972 (e.g., Landsat).
5 *Multi-spectral:* provides measurement in different wavelengths (e.g., visible, thermal near-infrared) to capture different information on various environmental components (e.g., land, water).
6 *Consistency:* gives the ability to compare generated information in a consistent manner at various scales.
7 *Complementarity:* data can be validated using additional sources such as sensors or crowd-sourced data.

2.1. SDG15.3.1 definition and calculation

Land degradation is defined by the United Nations 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 is the total country area without considering inland waters surfaces (e.g., major rivers and lakes). It is expressed in hectares or km^2. The indicator represents the portion, in percentage, of degraded land over total land area, derived from a binary classification of land condition (i.e., degraded or not degraded) measures by three sub-indicators:

(1) *land cover and land cover changes*, to determine the possible diminution of ecosystem services that are valuable in a local or national context (Burkhard et al., 2009, Ban et al., 2015; Andrew et al., 2014).
(2) *land productivity trends*, to assess land productive capacity and health changes. It can indicate changes in ecosystem functioning and decreasing trends can suggest that land is degrading (Cowie et al., 2018), (Oehri et al., 2017).
(3) *carbon stocks (above and below ground) trends*, to evaluate soil quality associated with nutrient cycling and its 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 (Stumpf et al., 2018), (Hengl et al., 2017).

The quantification of the indicator is based on the evaluation of changes in the sub-indicators to derive the proportion of land that is degraded. The three sub-indicators are complementary and responsive to different degradation elements. To determine whether a given land unit is degrading, stable or improving the One Out, All Out (1OAO) principle is used.

If one of the values of sub-indicators is negative, then the land unit is considered as degraded. This is a precautionary rule considering that stable or improved land condition in any sub-indicators cannot counterbalance the degradation effects in the others (Fig. 1).

Land degradation is generally context-specific and therefore makes it difficult for a single indicator to capture the full complexity of land state and condition (Gilbey et al., 2019). However, the sub-indicators are sufficiently robust to address changes in different relevant ways such as understanding relatively fast changes with 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 for monitoring 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 et al., 2014), (Pereira et al., 2013). The indicator should be derived generally from standardized and comparable national official data sources. However, due to their nature, these sub-indicators can be derived from satellite EO as well as geospatial data from regional and global data repositories and can replace, complement or enhance national official data sources after validation by national authorities (UNCCD, 2017b).

2.2. System architecture and implementation

Currently, the reference implementation to help countries monitoring degraded land is Trends.Earth (Gonzalez-Roglich et al., 2019). It is a QGIS plugin working in combination with the Google Earth Engine (GEE) to facilitate data preparation, processing and visualization for generating both the sub-indicators and the final SDG indicator 15.3.1 (Meyer and Riechert, 2019), (Gorelick et al., 2017). The objective of this model is to help countries in analyzing data and preparing their reporting (e.g., plot time-series of sub-indicators, maps, graphics) in a format that is directly aligned with the UNCCD's Performance Review and Assessment of Implementation System (PRAIS), which is the reporting portal of LDN.. The default datasets provided with Trends.Earth are indeed coarse in scale, but they are also among the most consistent globally, and this tool is desgined to use any dataset at any scale. Even if this tool greatly facilitates the production of the SDG indicator, it has some shortcomings:

(1) it mostly relies on regional and global datasets derives from EO data. However, it lacks greater spatial and longer temporal resolution to better capture the dynamics of land degradation at national scale (Pasquarella et al., 2016), (Pettorelli et al., 2018). This limits the scalability (e.g., different scales from national to global) of the model.
(2) it is largely dependent on the GEE platform. Therefore, enhancing flexibility can be valuable allowing access to different data sources and different processing platforms.
(3) Finally, it translates EO data into useful information. However, it does not provide any knowledge. Having a possibility to create some knowledge would be valuable.

Consequently, to tackle these issues, it is interesting to develop workflows to address the need for trusted sources of data, essential variables and information to monitor the progresses made on environmental conditions towards policy targets (Lehmann et al., 2019b).

To facilitate access and integration of scientific models and their outputs, it has been decided to use a Model Web approach (Nativi et al., 2013) suggesting four architectural and policy principals for implementation (Mazzetti et al., 2016):

(1) *Open Access:* notably to support the documentation, publication, and sharing of models and algorithms.
(2) *Low entry barrier:* reduce entry barriers for both resources' providers and users.
(3) *Service-driven approach:* in particular, models and algorithms access are provided by online services to enhance machine-to-machine interoperability.
(4) *Scalability:* facilitates the use of increasingly large volume and variety of data –i.e. Big Data requirements.

In addition, and closely related to these principles, an important pattern to be applied is the *separation of concerns* –i.e. separating a computing process into distinct sections, so that each section addresses a separate concern. By adopting the principles and the implementation pattern, the software components (along with their services) dealing with Data, Information, and Knowledge scopes were separated carrying out three sub-systems that generate, respectively: the sub-indicators, the SDG composed indicator, and the online services to access results together with the visualization tools to explore them as maps and graphs (Fig. 2).

Applying the separation-of-concern pattern brought a set of benefits, including: (a) the Trends.Earth model is now published as a Model Web service; (b) presently, the sub-indicators can be generated by using different data sources and processing platforms; (c) scalability and flexibility of the entire value-chain was improved, introducing, for example, the possibility to parallelize the model execution and address important challenges raised by Big Data. This implementation scheme allows users to compute each sub-indicator separately in a spatially explicit manner under the form of raster maps that is than integrated into a final indicator map, producing at the same time a table with results reporting areas potentially improved, stable or degraded over the area of interest. This enables the use of different data sources, such as the Copernicus Open Access Hub (previously known as Sentinels Scientific Data Hub) and/or the Copernicus data and Information Access Services (DIAS), the Global Earth Observation System of Systems (GEOSS), or national data infrastructures such as Data Cubes (European Commission, 2018; Craglia et al., 2017; Asmaryan et al., 2019; Giuliani et al., 2017c) (Fig. 3).

The value-chain is composed of three business processes, which are described in the next sub-sections.

2.2.1. Data - sub-indicators generation

Following Trends.Earth methodology (Gonzalez-Roglich et al., 2019) to compute the three sub-indicators, in accordance with UNCCD best practice guidance document (UNCCD, 2017b), a series of Python scripts were written. They were designed to be sufficiently generic to be executed (with some limited adaptation) on different processing platforms and using different data sources. Currently, they can be used on: (1) Google Earth Engine using MODIS and AVHRR data (this is the native mode of Trends.Earth); (2) Earth Observation Data Cube using Landsat, to enable higher spatial and temporal resolution (Giuliani et al., 2019a) ; (3) the Copernicus DIAS platforms (European Commission, 2018) (e.g., ONDA, Creodias, Sobloo) to demonstrate the use of European data and computing resources; and finally (4) the Global Earth Observation System of Systems (GEOSS) (Provenzale and Nativi, 2017), to provide access to datasets that can be directly used as sub-indicators.

The sub-indicators are using a set of Essential Climate Variables (e.g., NDVI, Soil moisture, Precipitation, evapotranspiration, land cover) and are computed as follows:

Land productivity measures land's biological productive capacity, an important resource supporting many human activities (United Nations Statistical Division, 2018). To assess land productivity, remotely-sensed proxies are commonly used to derive information on Net Primary Production (NPP) (Paruelo et al., 2016). Different methods or datasets can be used to estimate land productivity such as the Land Productivity Dynamics using phenological metrics derived from time-series of vegetation index (Ivits and Cherlet, 2013). Alternatively, the Normalized Difference Vegetation Index (NDVI) annual mean time-series can be used to determine three measures of change (Pettorelli et al., 2005): 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) (Gonzalez-Roglich et al., 2019), (Easdale et al., 2019). These measures are then aggregated in a 3-class (improvement; stable; degradation) land productivity sub-indicator.

Land Cover changes are assessed using land cover data over a given area for defined baseline and target years. To enable consistent and accurate comparison, Trends.Earth 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 et al., 2017). 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). Then a land cover transition analysis is applied to evaluate 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

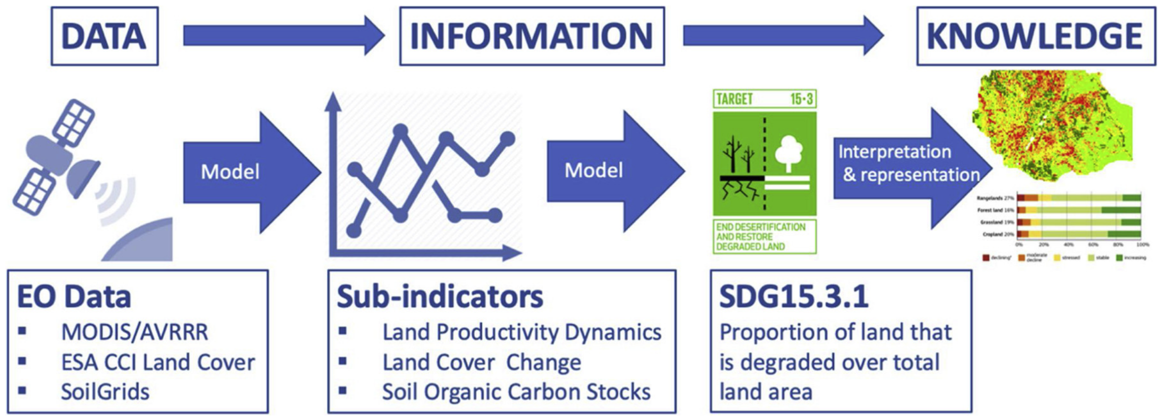

Fig. 2. Products and services generated by the proposed workflow.

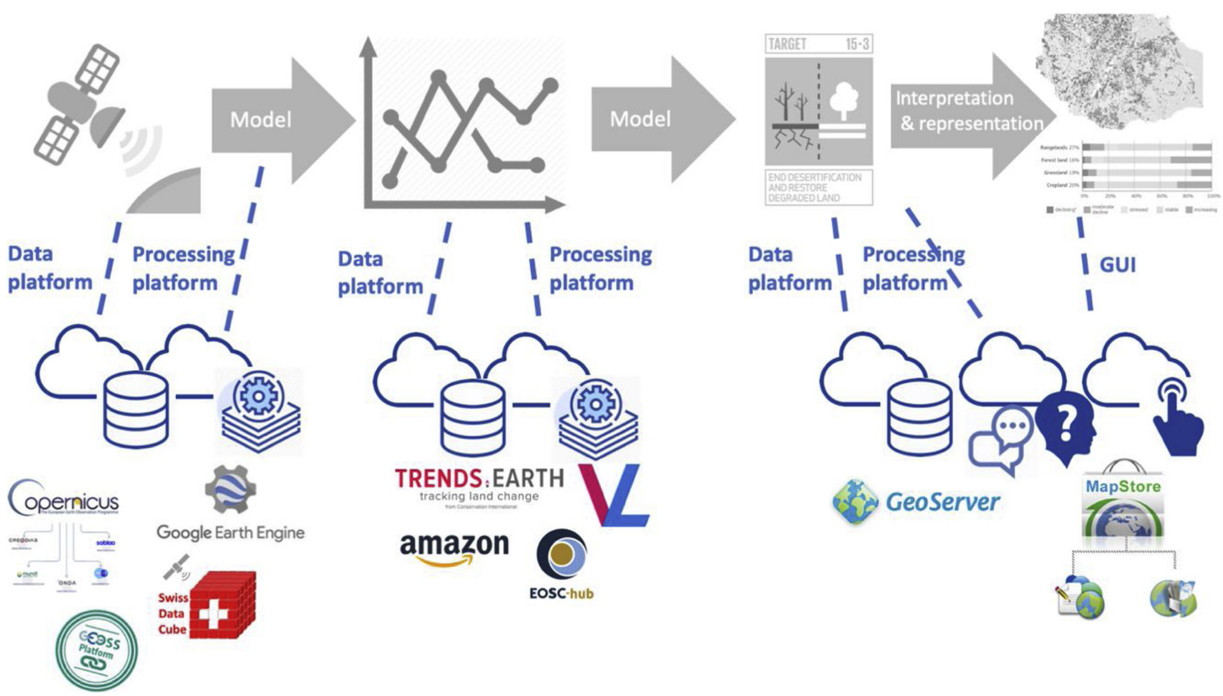

Fig. 3. The proposed value-chain process.

sub-indicator.

Carbon Stocks, above and below ground cannot be generated using satellite EO data and it is particularly difficult to assess for different reasons (e.g., spatial variability of soils, lack of consistent time-series data) (Stumpf et al., 2018). Consequently, Soil Organic Carbon (SOC) changes estimation is used as a proxy combining land cover and SOC data. A SOC reference value is defined using the SoilGrids carbon stocks at 250 m resolution (Hengl et al., 2017). The 7-class land cover map used for the second sub-indicator is also used to evaluate the changes in carbon stocks for the reporting period using conversion factors for changes in land use. Then finally the SOC changes are computed between 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.

Once computed, the sub-indicators serve has inputs (e.g., custom datasets) in the Trends.Earth model exposed in the VLab, to generate the SDG15.3.1 indicator.

2.2.2. From information to SDG indicator calculation

Recently, there has been a growing interest for informed decision-making processes supporting international agreements and policy targets at various scales. The assessment of objectives as well as the definition of achievable actions, and last but not least, the communication of such actions to the general public require the support of an evidence-based decision-making process at different levels. Consequently, policy-makers are increasingly requesting scientists to provide the required knowledge to establish effective decision-making process based on scientific evidence (Nativi et al., 2019), (Lehmann et al., 2019b).

To answer these questions, scientists need to develop scientific workflows generating the necessary knowledge that decision-makers need. A scientific workflow is a well-documented process for generating knowledge from observation/simulation data and scientific models. It can be as simple as a single scientific model using predefined datasets, or as complex as an integration of models working on multiple datasets. Therefore, to develop scientific workflows, scientists need to handle various resources such as datasets (e.g., satellite, in-situ), programming languages (e.g., Python, R), algorithms or modelling tools.

The Virtual Laboratory Platform (VLab), inspired by the GEO Model Web vision (Santoro et al., 2016), (Santoro et al., 2019), is aiming to support the needs of scientists and modelers, facilitating the generation of knowledge for evidence-based decision-making. It allows:

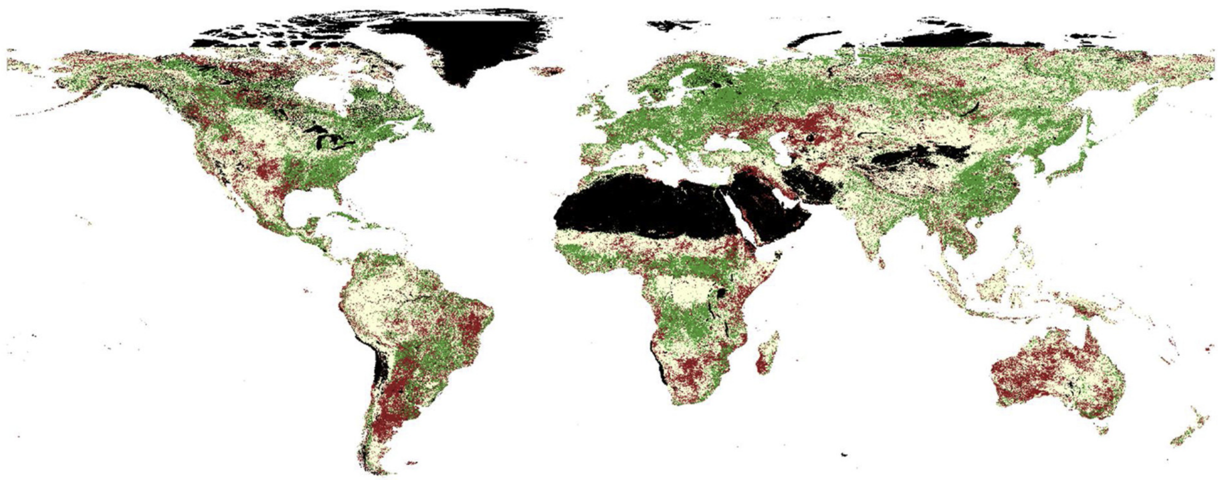

Fig. 4. Global Model of Land Degradation for SDG15.3.1 showing degraded (red), stable (yellow), improved (green) or no data (black) areas (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

- Harmonized discovery of and access to heterogeneous resources (e.g. data) from different systems
- Publication of scientific workflows connecting data and models
- Execution of scientific workflows based on data, essential variables and models developed with different programming languages and simulation frameworks
- Publication of workflow results

All the functionalities are made available through Application Programming Interfaces (APIs) enabling distributed systems integration and end-user's applications development.

The typical VLab users are:

- *Modelers* who have developed a scientific model or a full scientific workflow for generating knowledge, and who would like to make it discoverable and runnable by other users.
- *Application developers* who would like to build desktop and mobile apps for end-users (e.g. decision-makers) on top of available VLab workflows.
- *Scientists or policymakers* who want to access knowledge through the VLab enabled applications

In order to publish the Trends.Earth model on VLab, the Python source code available on GitHub was utilized (https://github.com/ConservationInternational/trends.earth). The code implements a plugin for the QGIS desktop application. After installation, the plugin calculates Land Degradation Indicator utilizing user-provided sub-indicators. If no sub-indicator is available, it is possible to define and launch GEE (Google Earth Engine) scripts for the calculation of the sub-indicators.

The publication of Trends.Earth on VLab focused on the possibility to calculate Land Degradation Indicator from existing sub-indicator datasets. Essentially, this task required only a slight modification to Python code of Trends.Earth to cope with the need to run the plugin without the user interface.

2.2.3. From knowledge to visualization and representation

Model outputs are then published using GeoServer (https://geoserver.org), an open source web server designed to publish geospatial data using widely adopted standards (e.g., Web Map Service (WMS), Web Coverage Service WCS)) advanced by the Open Geospatial Consortium (OGC) (Giuliani et al., 2011). It allows users to share, access, and use data in an interoperable and standardized way, facilitating data access, exchange, and integration.

Results are then organized in a Dashboard environment that allows users visualizing and exploring model outputs in a concise and comprehensible way. Dashboards are currently gaining a lot of interest as a tool for facilitating users' interaction with complex sets of data and information (van Ginkel Kees et al., 2018) and can potentially help decision-makers or practitioners to better understand an issue (Fegraus et al., 2012).

To create a dashboard, MapStore (https://mapstore.geo-solutions.it) was selected because it is an open source web-based application conceived to produce, manage and securely share maps, mashups, and dashboards using resources published following OGC standards. It provides users with common standard geoportal functionalities (e.g., map visualization, data discovery, spatial analysis) allowing users to find, view and query geospatial data and integrate multiple data sources into a single map. In addition, it allows the creation of dashboards using widgets such as maps, statistical charts, tables, and text boxes.

3. Results

In order to validate the technical feasibility, identify the possible issues and determine the potential of such an approach for generating knowledge using EO data to monitor land degradation at various scales, a proof-of-concept workflow has been developed. To enhance the scalability and flexibility of Trends.Earth to use various EO data sources and processing capabilities for generating the SDG 15.3.1 indicator at different spatial scale and resolutions. It enables also the use of components for model execution and orchestration (e.g., Virtual Laboratory), knowledge management (e.g., Knowledge Base), and visualization (e.g., Dashboard). To demonstrate the scalability and flexibility of the proposed approach, four different use case have been implemented:

(1) *Global model* using the Google Earth Engine and MODIS data (Fig. 4),
(2) *European model* using Copernicus DIAS platforms with Sentinel-2 data,
(3) *National model* using the Swiss Data Cube with Landsat data,
(4) *Generic model* using the GEOSS platform to access relevant data sources that can be used as sub-indicators.

The main output of these models is pixel-based over the entire landscape showing areas that are considered either degraded, stable or improved according to the SDG15.3.1 indicator. This output can be then aggregated at various administrative levels including the national level. Furthermore, all this information is integrated into a dashboard providing a consistent and comprehensible one-(web)page document

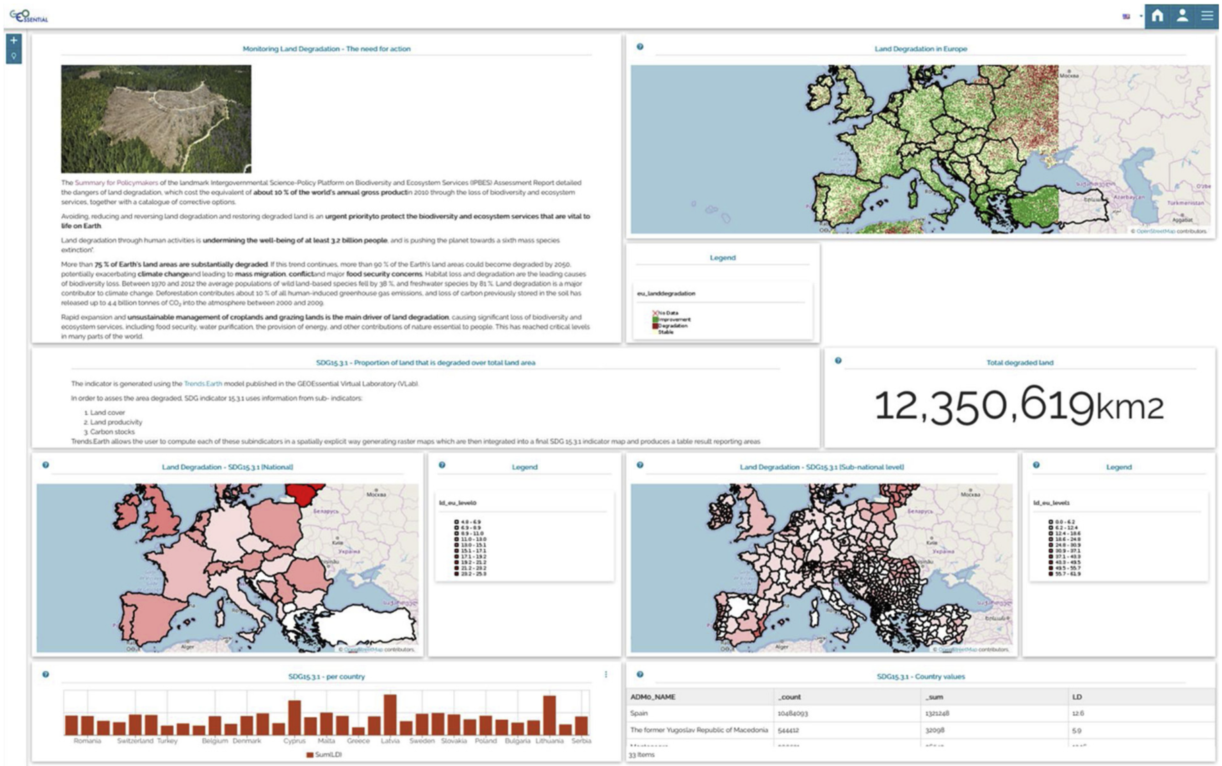

Fig. 5. SDG15.3.1 dashboard at European scale (https://geoessential.unepgrid.ch/mapstore/#/dashboard/4).

allowing examination of the issue. This is exemplified by the following example (Fig. 5):

This dashboard enables dynamically exploring the pixel-based map as well as aggregated indicators at national and sub-national levels. Maps, graph, table, and counters are synchronized and dynamically updated according to the zoom level. It allows visualizing only the information on countries that are visible in the current zoom level. Additionally, some text is provided to explain the issue of land degradation and how the indicator is calculated. The dashboard aggregates and provides a possible interpretation of the generated information: i.e. the current status and the temporal changes of the land degradation index. Providing context to the calculated information, the process generates knowledge.

Through the dashboard, users access the knowledge on land degradation status directly provided by the value of the index. They also access further knowledge through the generation of aggregated indices and through visual analysis of spatial distribution through the visualized maps.

All the generated information and knowledge are exposed with well-recognized interfaces such as OGC standards for efficient discovery, access and use. This makes data Findable, Accessible, Interoperable and Reusable (FAIR) (Stall et al., 2019), (Wilkinson et al., 2016) and greatly facilitate the sharing of data, information and knowledge and contributing to major initiative like GEOSS. One of the objectives of the Group on Earth Observation (GEO) is to provide full and open access to EO data, information and knowledge required to address unprecedented social, economic and environmental challenges (Anderson et al., 2017). GEO is an intergovernmental organization aiming to improve and coordinate global EO systems and promote broad, open data sharing. The GEO community is building GEOSS to improve observing systems integration and data sharing by interconnecting existing infrastructures using widely accepted standards (Giuliani et al., 2016). The GEOSS portal (https://www.geoportal.org) is the single web-based discovery and access point of EO resources from various providers all over the world through GEOSS. It is aiming not only to facilitate data and information accessibility but also help users to generate and discover knowledge. To demonstrate the facilitated access and integration of the model and outputs and the separation of concerns proposed by the Model Web approach, the different components of the workflow have been integrated into the GEOSS platform. The following use scenarios have been defined:

1 An end-user wants to know what the situation of land degradation in Europe is.
2 In the GEOSS portal and a for "Land degradation" is performed.
3 The user obtains a number of resources that matches his search criteria.
4 Under the Knowledge tab, a description about the SDG15.3.1 indicator is provided (Fig. 6). The user can then navigate deeper into the knowledge.
5 The user discovers that four models are available: Global, European, National, and Generic.
6 By selecting the *European* model, he finds that there are some data available for visualization and download (Fig. 7) and an external link to the dashboard previously mentioned.
7 He can discover three resource layers that can be loaded on the map: indicators at national level; sub-national level, or at the pixel level (1 km resolution). He selects the national data and his able to visualize it (Fig. 8).
8 He realizes that there is a *Service* associated to this model. The GEOSS Platform associates the model to the actual processing services that enable its computation, which the user can access and run in a user-friendly way. In particular, he can inspect the process workflow and search and select data as input to the service. In addition, he/she has the capability to choose a Cloud computing platform of preference among the available (these include all the DIAS Platforms and Amazon Web Services).
9 The user can now start the computation on the selected infrastructure and wait for the results (Fig. 9).

Fig. 6. Knowledge discovery in the GEOSS platform (https://www.geoportal.org).

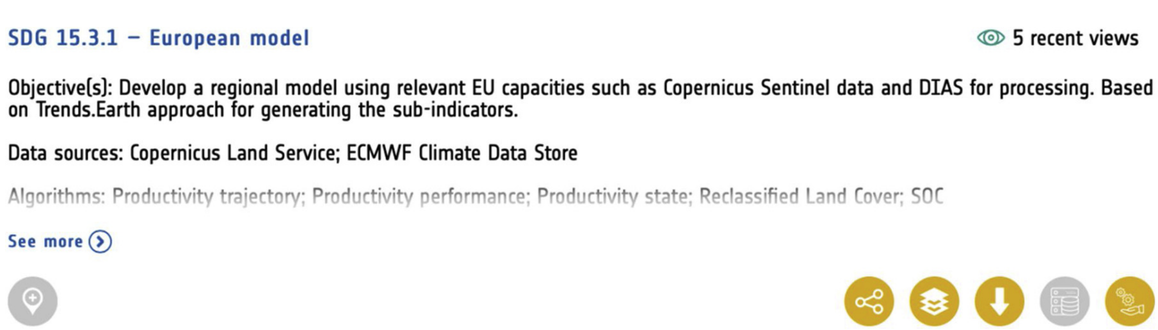

Fig. 7. Details on the European model with links to data download, visualization and dashboard.

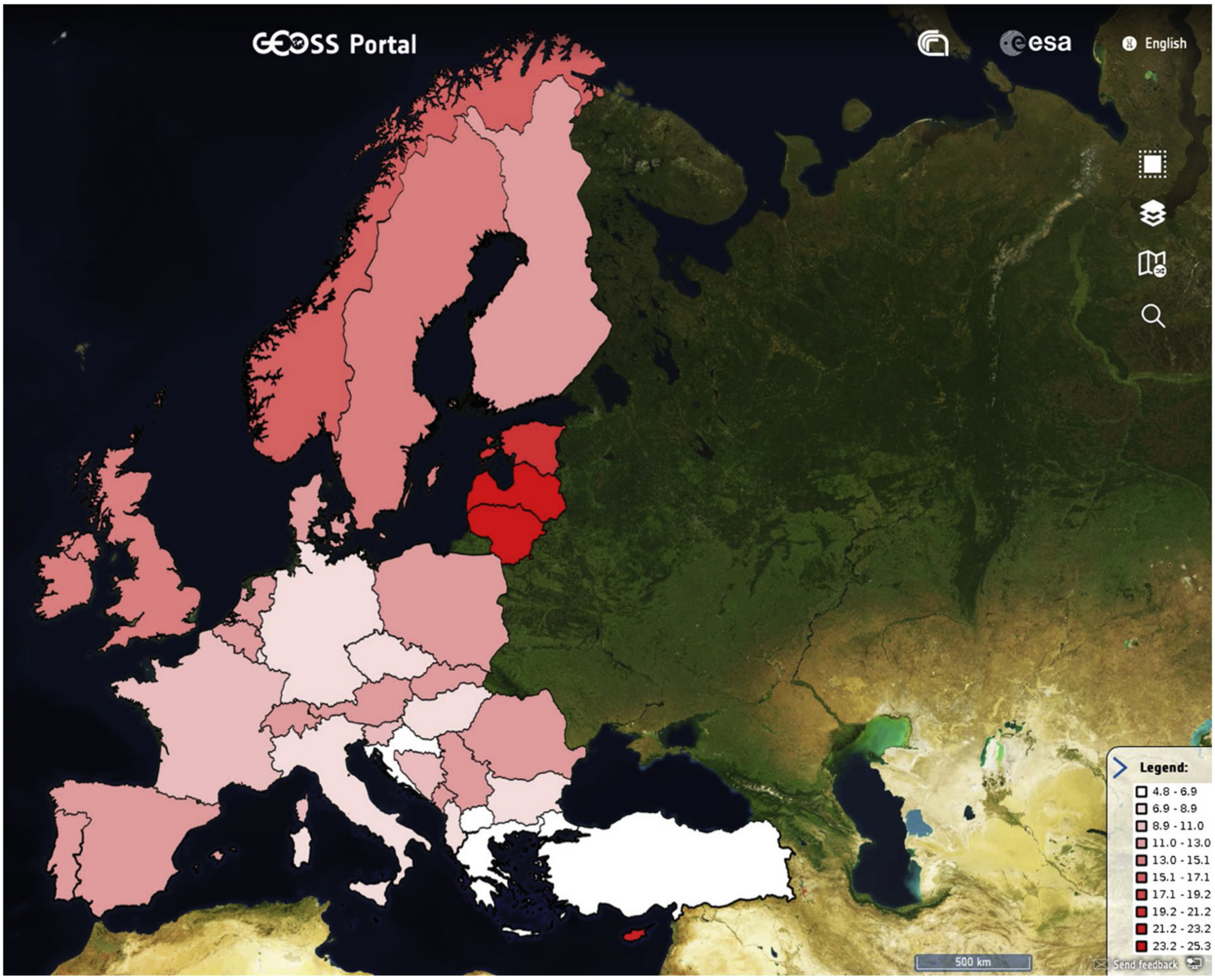

Fig. 8. SDG15.3.1 indicator at national level visualized in the GEOSS platform (https://www.geoportal.org).

The GEOSS Platform, version Data and Knowledge, is a next step in the implementation of a result-oriented GEOSS responding to the user need to access not only Earth Observation data but as well knowledge and services, in support of scientific research as well as of decision and policy making processes.

4. Discussion

The proposed approach is, to the knowledge of the authors, the first attempts to provide a scalable and flexible framework to monitor land degradation at different geographical scales in compliance with the SDG15.3.1 indicator UN guidance and generate knowledge using EO data to support SDGs. The proposed implementation was developed as a proof-of-concept. Initial results indicate that using the DIKW model has helped building a consistent and coherent data value chain to assess land degradation. The implementation was successful and demonstrated benefits, limitations and needs for further developments to consolidate the approach.

Concerning the evidenced benefits, the approach has proven the scalability (e.g., models at different geographical scales), flexibility (e.g., different data sources, spatial and temporal resolutions, processing platforms) and reproducibility and exhaustivity (compared to national statistics). This enables more effective and efficient analysis of EO data of various spatial and temporal dimensions. In particular, the implemented workflow can be executed every year, creating a time-series of land degradation information, and consequently creating the basis of land monitoring service. The long-term monitoring capability provided by Landsat and Copernicus programs is an additional benefit capturing the evolution of LD since 1972 and envisioning a continuous monitoring for the next 20 years. The implemented solution has also demonstrated the potential of building data value chains following the DIKW model and provides a solution for supporting decisions and policy makers to obtain the required knowledge. This is a fundamental pre-requisite to efficiently embed science into decision-making and avoid the dissemination of fake information in a post-truth world. Openness and transparency are essential to support more open and reproducible science (Giuliani et al., 2019b). Finally, having the model output disaggregated at the pixel-level can be a good complement to traditional national statistics. Indeed, usually SDG indicators are monitored from an economic perspective and are reported to the UN at the country level meaning that users obtain one value per country. However, from a sustainable development perspective, including environmental and societal aspects, it is necessary to have more spatial information. Indeed, without disaggregated indicators it is not possible to capture spatial and temporal dynamics of environmental changes (Anderson et al., 2017), (CEOS, 2018). The proposed solution can help users exploring those dimensions and answering questions such as: How many? Where? When? that are essential to support efficient and effective land management. These identified benefits illustrate, more generally, how EO data play an insightful role in monitoring SDGs and can complement official statistics provided by countries. In particular, it shows the importance of focusing on Tier 2 applications because they have accepted methodologies whereas Tier 3 likely needs more fundamental research before looking into EO opportunities.

The current implementation has some limitations since it was developed as a proof-of-concept, and is not yet readily usable for decision-

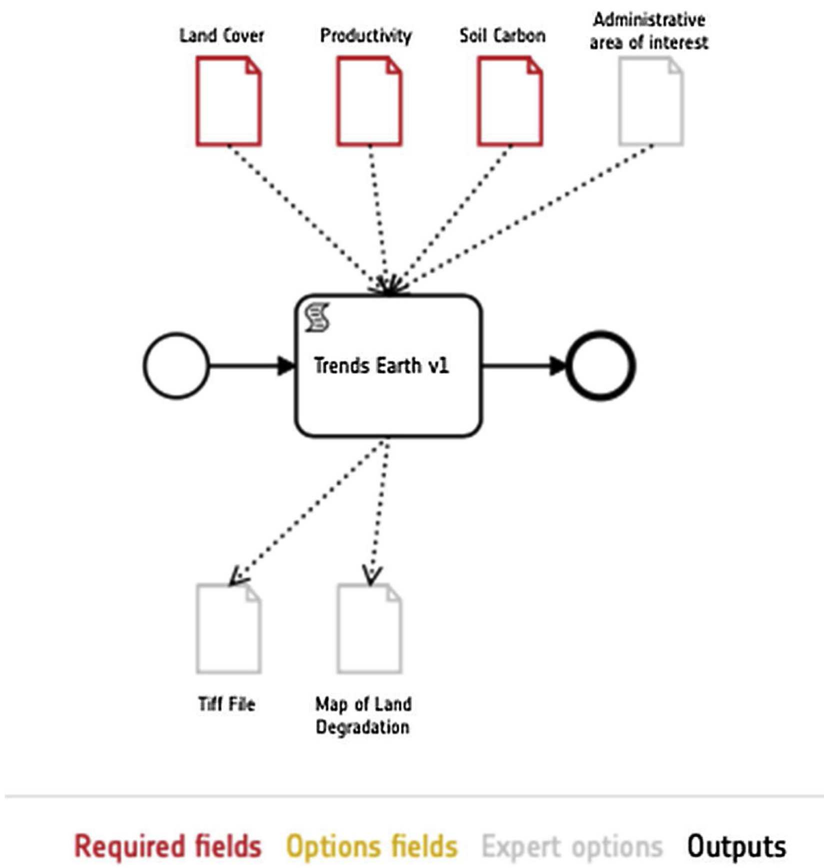

Fig. 9. Trends.Earth model exposed in the VLab (https://vlab.geodab.org) and accessible/executable through the GEOSS platform (https://www.geoportal.org).

making. In terms of input data for the Trends.Earth model, currently it is not possible to benefit from Sentinel-2 data because the time-series is not sufficiently long for consistent analysis. Only Landsat can provide an acceptable time-series to obtain reliable results. However, data fusion approaches can enable defining harmonized Landsat and Sentinel-2 surface reflectance time-series (Claverie et al., 2018). Another limitation lays in the validation of the model outputs. Currently, depending on the spatial scale, methodologies are often restricted to visual comparison to identify areas that are known to be degraded. When possible, results obtained with the Trends.Earth model can be also compared with authoritative data sources.

In terms of perspective, the emergence of continental scale data cubes such as Digital Earth Africa (DEA – http://digitalearthafrica.org) allows envisioning the possibility to develop high resolution land degradation models at the regional scale using the proposed solution. Indeed, the African continent is one of the regions in the World that is severely affected by land degradation, and therefore providing timely information and knowledge on degraded land and their evolution is vital for ensuring the provision of ecosystem services (Wolff et al., 2018). Land Cover Change and Carbon Stocks indicators can be improved using newly available models and enhanced dataset. The EO Data for Ecosystem Monitoring (EODESM) model facilitates regular classification according to the Food and Agricultural Organization – Land Cover Classification System (FAO – LCCS) and also includes change detection and the production of maps revealing causes and consequences (Lucas et al., 2018), (Lucas and Mitchell, 2017). Concerning the Carbon Stocks sub-indicator, the SoilGrids database is subject to large differences in estimates (Tifafi et al., 2018). Consequently, we should consider using the Global Soil Organic Database that may provide improved information to generate this sub-indicator. Finally, one of the great challenges of land degradation is the range of models and datasets available and the possible bias to present different perspectives of degradation. Harmonizing models' outputs and datasets is therefore of primary importance. The proposed approach can be seen as an initial step towards this objective giving the possibility to use different data sources and possibly different models using the VLab. The system can be also extended to link climate models, planning data and the sub-indicators to derive a probability of future degradation and ultimately operate as an early-warning system.

To stop land degradation progression, it is important to improve capacities at national level to map their degraded lands and support effective assessment mechanisms. The proposed approach can contribute in such capacity development efforts. This can at the same time ensure national ownership while retaining 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 aiming at supporting countries with readily available EO datasets and 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 presented approach can contribute to the objectives of this initiative.

To improve understanding and knowledge on drivers and impacts of land degradation, the results of the models should be related to socio-economic and other environmental data. This can possibly further help decision-makers to identify the most adapted response. The developed solution is contributing to the SDG indicators framework. However, it can also contribute to other policy framework such as the Aichi targets (Petrou et al., 2015). The flexibility provided by the implemented framework can therefore also facilitate contributions to multiple monitoring programs.

The discussed solution applies a co-designed and co-creation (i.e. collaborative) approach. In particular, the development starts from a clear policy need and coordinates the products and services offered by many to address such a need. Contributions are connected according to a well-defined and loosely coupled value chain in three main value-adding stages: (1) information generation from data; (2) knowledge-generation from information, and (3) actionable knowledge provision to users. The presented solution can be seen as a possible template for other collaborative efforts, addressing policy implementation (e.g. SDG indicators generation), at various scales. It can help bringing together different organizations to address national or regional policy needs and then contribute to global assessment. From a governance perspective, organization such as GEO and the linked Regional GEOs can help connecting and facilitating the utilization of existing developments for ICT and EO cross-fertilization. Finally, from a scientific perspective, the proposed approach enhances reproducible science demonstrating the benefits of open data, open source applications and algorithms, and the use of FAIR data principles (Stall et al., 2019), (Wilkinson et al., 2016).

5. Conclusions

Land degradation is an important issue and land should be carefully managed to reduce climate change, biodiversity loss, while at the same time ensuring food security and sufficient provision of ecosystem services. To achieve the objective of a stable functioning of the ecosystem, it is critical to produce reliable knowledge on measurable targets, at various scales and across disciplines, in order to efficiently support evidence-based policymaking.

The proposed solution extends the Trends.Earth model to make it more flexible and scalable (e.g., various data and processing platforms) for building efficient data value chains following the Data-Information-Knowledge-Wisdom framework in order to support effective decision-making processes and informs about the limits of our planet. The initial implementation has demonstrated that it is technically feasible to implement a scalable and flexible approach to help monitoring land degradation, in accordance to the UN SDG framework, and at various geographical scales. It strengthens capacities to use EO data and can complement existing reporting and statistical systems by making information more comprehensive and comparable. From a technical perspective, the introduction of a model execution and orchestration engine (e.g., VLab) together with a visualization tool (e.g. dashboard) can support the generation of effective knowledge. Finally, from a scientific perspective, the presented approach is a step towards more open and reproducible science. This is essential to adequately embed science into the decision-making process.

CRediT authorship contribution statement

Gregory Giuliani: Supervision, Conceptualization, Methodology, Writing - original draft. **Paolo Mazzetti:** Conceptualization, Methodology, Writing - review & editing. **Mattia Santoro:** Methodology, Writing - review & editing. **Stefano Nativi:** Conceptualization, Writing - review & editing. **Joost Van Bemmelen:** Writing - review & editing, Methodology. **Guido Colangeli:** Writing - review & editing, Methodology. **Anthony Lehmann:** Writing - review & editing.

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.

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