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From a Vegetation Index to a Sustainable Development Goal Indicator: Forest Trend Monitoring Using Three Decades of Earth Observations across Switzerland

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Abstract: Forests represent important habitats for species and provide multiple ecosystem services for human well-being. Preserving forests and other terrestrial ecosystems has become crucial to halt desertification, land degradation, and biodiversity loss worldwide, and is also one of the Sustainable Development Goals (SDGs) to be achieved by 2030. Remote sensing could greatly contribute to measuring progress toward SDGs by providing consistent and repetitive coverage of large areas, as well as information in various wavelengths, which facilitates the monitoring of environmental trends at various scales. This paper focuses on SDG indicator 15.1.1—"Forest area as a percentage of total land area" to demonstrate the potential of Earth Observation Data Cubes for SDGs. The approach presented here uses Landsat Analysis Ready Data (ARD) stored in the Swiss Data Cube, and offers a complementary method to ground-based approaches to monitor Switzerland's forest extent based on the Normalized Difference Vegetation Index (NDVI). The proposed method performs time-series analyses to extract a forest/non-forest map and a graph representing the trend of SDG 15.1.1 indicator over time. Preliminary results suggest that this approach can identify similar forest extent and growth patterns to observed trends, and can therefore help monitor progress toward the selected SDG indicator more effectively.

Keywords: Sustainable Development Goals; Earth Observations; Landsat; Swiss Data Cube; forest monitoring

1. Introduction

The Sustainable Development Goals (SDGs), agreed by the international community in 2015, are an ensemble of 17 goals supported by 169 targets to address environmental and social economic challenges worldwide [1]. Following the Millennium Development Goals (MDGs), SDGs are complemented by additional goals and are to be achieved by 2030 by all member countries.

SDG indicators are classified into three tiers based on the level of data availability at global scale and established monitoring methodologies [2]. Measurements for SDGs are based on statistical data provided by member countries, which are required to regularly report their national progress towards each target. The joint United Nations Economic Commission for Europe (UNECE)/Eurostat/Organization for Economic Co-operation and Development (OECD) working group on statistics are working on identifying good practices to assist governments in the design of sustainable development indicators to be used at national level [3]. The metadata repository provides guidance for calculating statistics for SDG indicators. Nevertheless, specification for measuring some targets are still lacking and there are still major issues concerning comparability and scalability. For instance, the metadata for SDG 15.1.1 [2] does not specify any requirements for the type of data, but explains that all national data should be compiled and provided to the Food and Agriculture Organization (FAO) following their standard format for country reporting, which includes original data, descriptions of their use, and reference sources. Complementary approaches such as remote sensing could help improve the comparability and scalability of national progress measurements, but no alternatives are proposed in the SDG metadata.

The power of data, especially "big data", in powering economic activities is increasingly recognized. Yet, efforts to date have focused on using data about people, business, and objects (e.g., cars). The power of "big data" about our built and natural environment, so-called Earth Observation (EO) data, is only starting to acquire recognition [4]. Our ability to exploit big EO data to understand how our built and natural environments are changing, and to predict what impact different interventions (commercial, governmental, social) could have for better or worse, will be critical to achieving the SDGs. Only by using this data will we be able to target our limited resources to the areas, peoples, and challenges that need it most. Big EO data are collected from a range of sources: from satellites in space, to global observatory networks operated by governments on the ground, to data collected by citizens using their mobile phones. This data will be a powerful tool in addressing global environmental challenges [4,5]. EO data acquired by satellites deliver repetitive coverage of large areas, uniform dataset, comparable time-series, as well as multiple spectral bands at different wavelengths. This produces synoptic, consistent, spatially explicit, and sufficiently detailed information to help monitor environmental changes and capture anthropogenic impacts at national scale. EO could greatly contribute to measuring progress towards SDGs as they can provide long baselines required to determine trends, define current states, and inform future conditions [6].

Significant investment by governments and the private sector, major advances in technology including advanced manufacturing and miniaturization, the Internet of Things, and artificial intelligence have resulted in much more of this data being available to use. However, only a few countries are able to take full advantage of this data at this time, and this needs to change. Such big challenges require substantial efforts to address them (in terms of new data, technology, science, etc.), but also create opportunities for everyone to contribute and benefit from. Countries need to support each other to put Big Earth Observation Data to work for achieving Sustainable Development [7]. However, the full potential of EO data has not yet been realized and concrete examples of its potential within the SDG framework remain scarce. Despite the exponential increase in freely available satellite data, they are still underexploited due to their complexity and lack of processing capabilities, as the necessary data pre-processing often represents a major technical barrier for users. In fact, satellite images may differ in terms of observation conditions such as clouds, geometry, and atmospheric conditions, and can have different spatial, spectral, and radiometric resolution depending on individual sensors [8].

To alleviate these issues, Geoscience Australia along with the Committee on Earth Observation Satellites (CEOS) (http://ceos.org) launched the Open Data Cube initiative (www.opendatacube.org), which addresses the storage issue of increasing EO data, following the release of Landsat archives by the United States Geological Survey (USGS) in 2008 [9,10]. Open Data Cubes not only offer a novel solution for storing, organizing, managing, and analyzing (EO) data [8], it also provides adequate infrastructures to store and exploit the full potential of open source EO data by enabling access to multi-dimensional time-series in analysis-ready form [11]. As a result, satellite images have already gone through radiometric, geometric, solar, and atmospheric calibration, and thus they are ready to be used [8].

Switzerland is the second country in the world with a national-scale Earth Observation Data Cube (EODC). The Swiss Data Cube (SDC—http://www.swissdatacube.ch) is supported by the Federal Office for the Environment (FOEN) and was developed, implemented, and operated by the UN Environment (UNEP)/GRID-Geneva in partnership with the University of Geneva (UNIGE). Currently, the SDC contains 34 years of Landsat 5,7,8 (1984–2018) and 3 years of Sentinel-2 (2015–2018) Analysis-Ready Data over the whole country (total volume: 3TB; 110 billion observations).

As described in the Group on Earth Observations (GEO)'s document released in 2017, 71 targets and 29 indicators from 16 SDGs can be supported by Earth Observation (EO) [12]. The Swiss Data Cube has the potential to monitor a wide range of environmental phenomenon, such as urbanization, landslide risks, water, snow, and forest cover changes. For this paper, we chose the SDG 15 concerning the protection and restoration of terrestrial ecosystems and sustainable management of forests to halt land degradation, desertification, and biodiversity loss [2], to demonstrate how national data cubes could help countries report their progress towards SDG targets.

Forests not only represent vital habitats for biodiversity, they also contribute to human well-being in numerous ways, including carbon sequestration, erosion control, drought reduction, water retention and purification, protection against certain natural hazards, provision of wood, and recreational opportunities [13]. Investing in the preservation of healthy forest ecosystems is central for climate change mitigation and adaptation, as well as for the livelihood of forest-dependent communities. Therefore, forests are increasingly recognized as a key element for sustainable development, supporting multiple SDGs ranging from hunger and poverty alleviation, freshwater regulation, climate action, health and well-being, and biodiversity [14].

The Normalized Difference Vegetation Index (NDVI) is a commonly used vegetation index for analyzing vegetation with remote sensing due to its simplicity to perform rapid assessments. NDVI is directly related to photosynthesis and can inform on vegetation condition. It is calculated as:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

with NIR and Red standing for spectral reflectance measurements in the near-infrared and red areas respectively [15–17]. The indicator measures values between -1 and 1, with negative values usually corresponding to water, and values closer to 1 corresponding to areas with high photosynthetic activity. Values of NDVI for vegetation will generally fluctuate during the year and according to the vegetation's health, with some exceptions for non-deciduous species for instance. Despite the slight lack of precision compared to other existing approaches such as machine learning based methods, the NDVI offers a complementary and fast method to derive forest area coverage with higher periodicity.

Trend analyses are increasingly used to explore long data records generated by the opening of historic data archives such as Landsat [18]. Vegetation indices, especially NDVI, are commonly used for the spatial monitoring of vegetation state at multiple scales [19]. The algorithm presented in this paper is based on time-series NDVI analyses, which are used in various contexts to detect trends and land cover change, such as vegetation dynamics, forest disturbance [18], land degradation, and agriculture intensification [20,21].

This paper focuses on SDG 15—"Life on Land" and presents an alternative approach to ground-based measurements for monitoring target 15.1–indicator 15.1.1—forest area as a percentage of total land area—using the Swiss Data Cube. Forests cover 31.3% of Switzerland and have increased by 3.1% during the period of 1985 to 2009 [22]. Since 1983, the National Forest Inventory (NFI) is responsible for generating a forest inventory using a 1.4 km grid combined with aerial photography interpretation in a 500 m grid [23]. Although the NFI's method produces very precise maps, the sampling frequency does not reveal yearly or seasonal fluctuations. The approach proposed here offers a faster and complementary method to monitor Switzerland's forest extent by remote sensing, using time-series analysis based on the Normalized Difference Vegetation Index (NDVI). This paper presents a first attempt to measure SDG indicator 15.1.1 for Switzerland and lays the foundation for future improvements of the accuracy of the method.

2. Materials and Methods

2.1. The SDG Indicator

According to the UN metadata repository [2], the SDG indicator 15.1.1 must be generated as:

$$SDG_{15.1.1} = \frac{Forest\ area\ \left(\mathrm{km}^2,\ for\ selected\ year\right)}{Land\ area\ \left(\mathrm{km}^2,\ in\ 2015\right)} \times 100$$

Regional and global estimates are the result of the sum of country values. "Forest" is based on FAO's definition of land larger than 0.5 hectares with trees able to reach higher than 5 m and a canopy coverage greater than 10%, excluding agricultural and urban land [24]. Although all data from country reports undergo a rigorous process by the FAO in order to review reference sources and the forest estimation methods, the indicator's metadata does not specify any further details on monitoring methodology, which may complicate comparisons between countries. Through the Swiss Data Cube framework, we demonstrate how EO data in analysis-ready form can contribute to more detailed measurements by providing consistent time-series to derive trends, and better harmonize SDG indicators without requiring any additional reporting by countries.

2.2. Algorithm Implementation

The analytical framework used to implement the processing algorithm is based on Python 3.6 (http://docs.python.org/3/) language and Jupyter notebooks (http://jupyter.org/), an interactive, web-based, and open-source software allowing interactive computing with over 40 different programming languages [25]. Geographic Information System (GIS) specific software such as QGIS (http://qgis.org/), ArcMap (http://arcgis.com/), and GDAL (http://gdal.osgeo.org/) libraries are also used to manipulate and extract information contained in spatial layers. The script is available on a public GitHub repository (https://goo.gl/bdhzuv).

The algorithm is expected to detect the evolution of forest coverage within the Swiss boundaries with time-series extracted from the SDC. The script consists of three major steps: configuration of inputs, running of the algorithm on a *mini* data cube with dimensions corresponding to the specified longitude and latitude ranges, and visualization of results (Figure 1).

In this first version, the user can choose the extent of the region of interest with geographic coordinates but can also delimit the analysis within specific borders such as cantons. The aim of this procedure is to derive a customizable mask of the area of interest, providing the exact extent of the total surface (i.e., the total number of pixels), which is one of the inputs required in the calculation of the SDG indicator. For this, a binary raster mask must be prepared and uploaded beforehand. The downloaded image is converted to TIF format to facilitate treatment in QGIS or ArcMap software. Figure 2 visualizes the steps towards the creation of the binary raster mask for the area of interest using specific tools of QGIS, like clip and raster calculator. As the script is sensitive to the alignment of pixels between the mask and image scene from the SDC, the binary mask must have the same extent as the selected data array. The mask is based on an image of the area of interest from the SDC in Network Common Data Form (NetCDF) format. This will ensure that the extents are identical, and pixels will be aligned with SDC images.

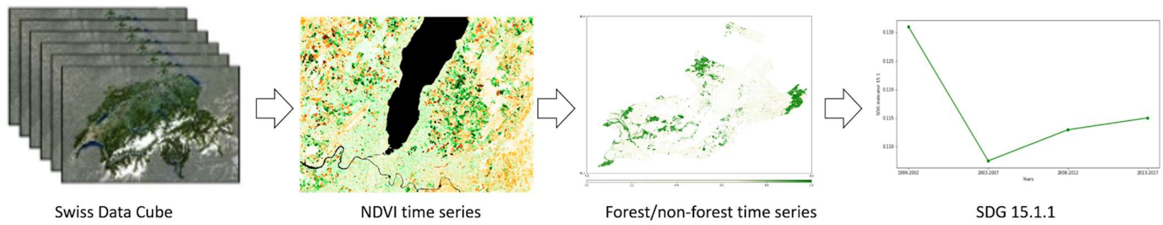


Figure 1. General overview of the analysis workflow.

The input parameters of the script are listed and available for any adaptation by the user. They include: choice of satellite's platform and product (Landsat-5/7/8, Sentinel-2), geographic coordinates, time boundaries (start and end dates of the series), time granularity, months selection for the analysis, mask for land categories to exclude from the computation (clouds, cloud shadows, snow and no data pixels), single pixel resolution in km^2, and imported binary raster mask to define the precise boundaries within the selected extent. A calibrated NDVI threshold for discriminating densely vegetated areas must also be indicated by the user, as well as a threshold indicating the required percentage of time scenes in which a single pixel has been flagged as being in the forest category. The script uses these inputs to query to the SDC database and create a mini data cube with dimensions corresponding to the specified latitude and longitude ranges and depth defined by the number of scenes available for each group of consecutive years. For large extents, chunks can first be created then assembled as a mosaic to bypass hardware limitations and reduce computing time.

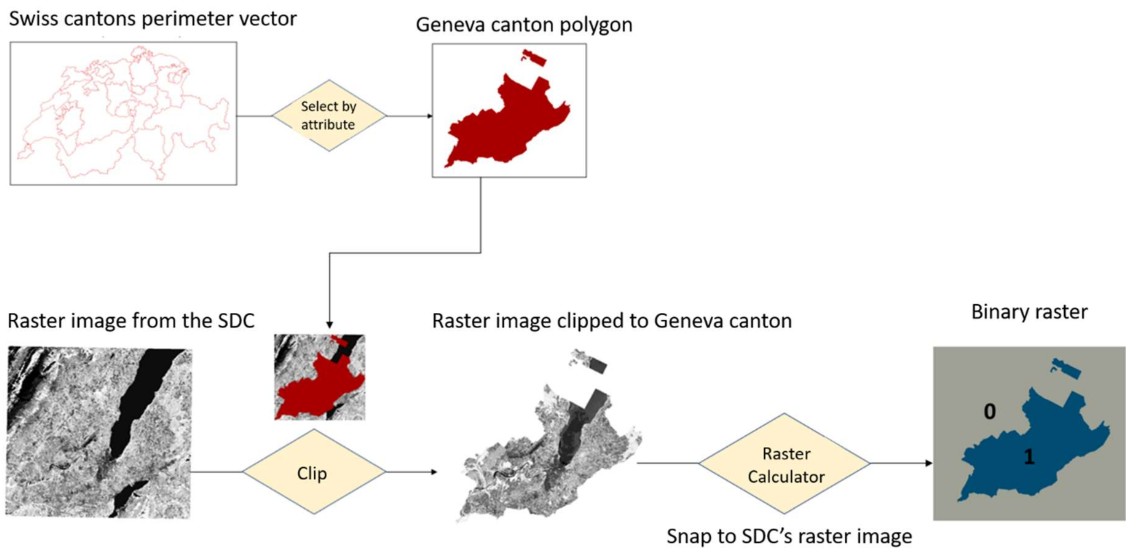


Figure 2. Creation of a binary raster mask.

The algorithm performs loops along the depth of the 3D datasets (corresponding to each time period defined in the time granularity). Each loop computes an NDVI index for each pixel of the dataset and stores it into the original dataset as a raw value (between −1.0 and +1.0) and as a binary value (0 or 1). The binary output depends on the computed NDVI index reaching the predefined threshold of 0.8, calibrated on a specific area of the Geneva canton. Next, a time filter (selected months) is applied together with the spatial mask and the pixel category mask to remove non-useful pixels. Subsequently, a time-series analysis is performed on the specified band (NDVI). For each pixel, the frequency of clean (no clouds, snow, water, etc.) and flagged as forest (non-null value for the binary NDVI index) over the available scenes in the mini data cube is computed. A percentage threshold on this frequency (>45%) is then used to filter out non-forest pixels from the densely vegetated category (percentage of times the same pixel must have an NDVI value above the chosen threshold in the analyzed scenes).

This provides the ability to distinguish agricultural areas which do not have a high NDVI value during the same period as forests due to crop rotations.

Finally, the algorithm converts the number of candidate forest pixels into forest area (in km^2) using the pixel spatial resolution and generates output values in the form of the ratio of forest area over the total land area within the spatial–temporal dimensions specified by the user in order to match the SDG 15.1.1 indicator definition. The results are displayed as a map of forest area for each time period and a graph representing the trend over time of the SDG indicator. Alternatively, the user can also visualize the output maps as an animated GIF and download them in NetCDF. The flow chart of the method is summarized in Figure 3.

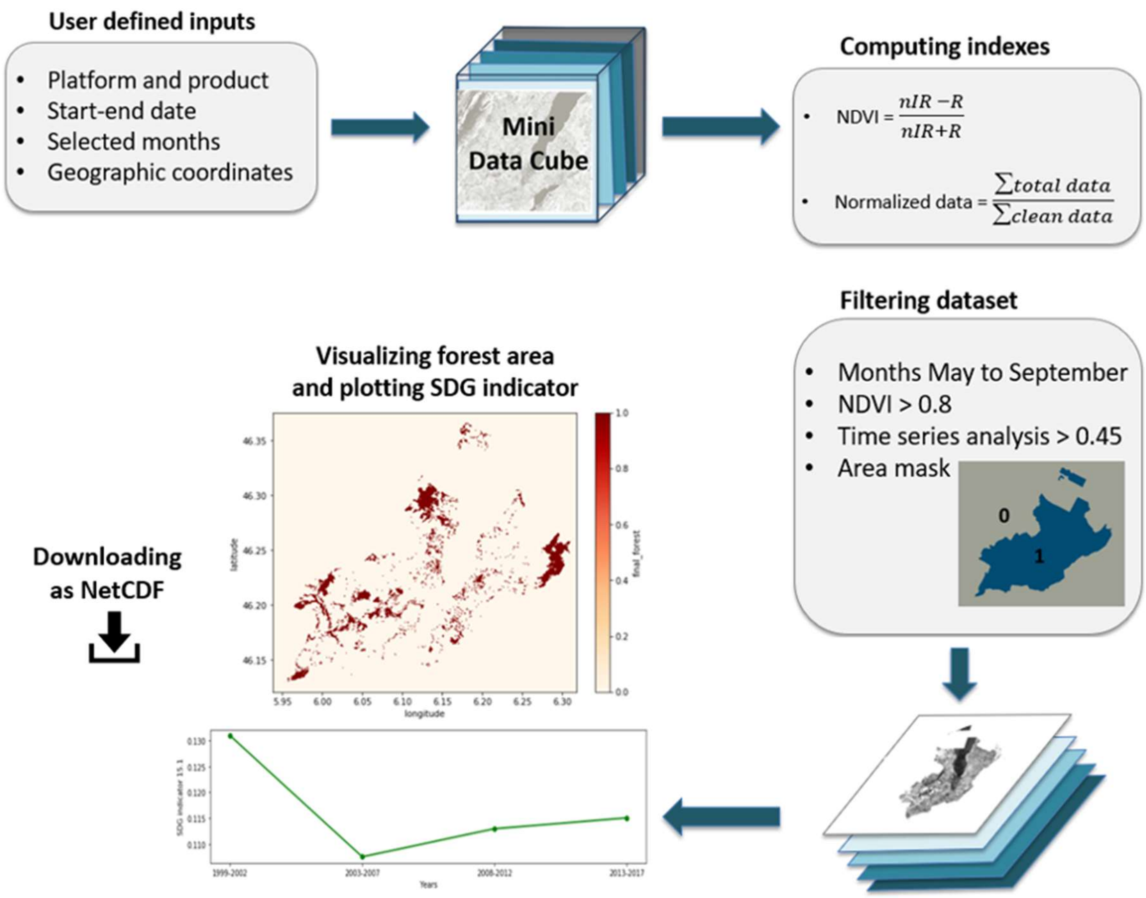
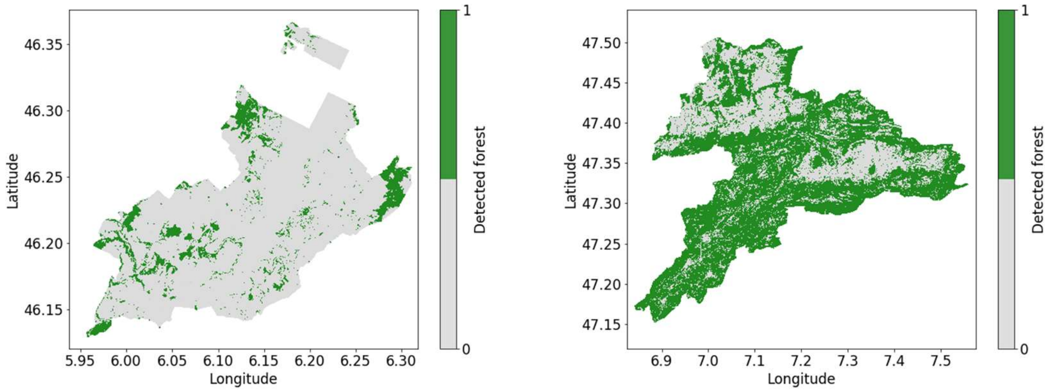


Figure 3. Forest detection algorithm workflow.

3. Results

The algorithm is applied at regional level in Switzerland, measuring the forest trend for the canton of Geneva (longitude range: 5.93771–6.31743; latitude range 46.12089–46.37531) and for the canton of Jura (longitude range: 6.82540–7.57596; latitude range: 47.11959–47.54011). Results were compared with official measurements from federal offices. The analysis is performed with images from Landsat 7 platform extracted from the SDC, including only the months from May to September. The NDVI and time-series analysis values have been calibrated to 0.8 and 0.45, respectively, to match the official forest extent in the canton of Geneva. The same values have been used for the canton of Jura. This means that the algorithm identifies forests as pixels having an NDVI > 0.8 for at least 45% of the time during the period of May through September. The results obtained by applying these thresholds in the algorithm for the period of 2013–2017 are shown in Figure 4.

The algorithm was able to capture the general trend of forest surface in Switzerland which has been increasing at a rate of approximately 3% since 1985 [22]. Pressures on forests remain high in the Plateau where it is the most urbanized, and forests have progressed over agricultural and alpine pastures that are no longer exploited in the Alpine arc and Southern Alps [26]. According to official numbers, forests occupy 30 km^2 or 12% of the canton of Geneva [27], and 370 km^2 or 46% of the canton of Jura [28]. The total amount of forest estimated with this algorithm was found to be on average 32 km^2 for the canton of Geneva and 508 km^2 for the canton of Jura. The values are in line with official values for the canton of Geneva (overestimation by 6%) but are overestimated for the canton of Jura by 37%. This can be ascribed to the different geographic configuration of this mountainous canton and indicates the necessity of calibration of the NDVI and time-series analysis threshold to different biogeographical areas.



(**a**) (**b**)

Figure 4. Forest coverage in the canton of Geneva (**a**) and canton of Jura (**b**) estimated by the forest detection algorithm. The time period refers to the years 2013–2017.

The error matrix in Table 1 quantifies the performance of our forest classifier. The model has an overall accuracy of 93%, defined as the ratio of correctly predicted observations (forest and non-forest pixels) over the total observations. Furthermore, the probability of the reference sample to be correctly classified, hereby referred to as "producer's accuracy", together with the probability that a classified sample belongs to the same category in the reference sample, hereby referred to as "user's accuracy", are also reported [29]. Further development of the algorithm will allow to eliminate patches of land that are too small to be considered forests, and account for altitude in the calculation of forest extent.

Table 1. Confusion matrix for assessing the percentage classification accuracy of the forest detection algorithm. Values in the table refer to the number of pixels for each class.

		Reference		
		Non-Forest	**Forest**	**Total**
Classified	**Non-Forest**	370416	25465	395881
	Forest	7831	43622	51453
	Total	378247	69087	447334
		Overall accuracy 414038/447334 = 93%		

	Producer's Accuracy		**User's Accuracy**	
	Non-Forest	370416/378247 = 98%	**Non-Forest**	370416/395881 = 94%
	Forest	43622/69087 = 63%	**Forest**	43622/51453 = 85%

The trend for SDG indicator 15.1.1 for the canton of Geneva is reported in Figure 5 and Tables 2 and 3. The positive increase of forest area after 2002 are in line with official statistics [27]. The sudden drop between the first two time periods could be explained by the data gap in Landsat scenes availability [11], and by the fact that this approach also detects densely vegetated areas such as parks which are not officially considered forests. This is noticeable when overlaying the map generated by the algorithm with the forest area layer from SITG (Système d'Information du Territoire Genevois) (Figure 6) [30]. A closer look at the area near Jussy, canton of Geneva, reveals how using time-series analysis can identify forest boundaries precisely while exclude agricultural areas which fluctuate between bare soil and dense vegetation with crop rotations (Figure 6).

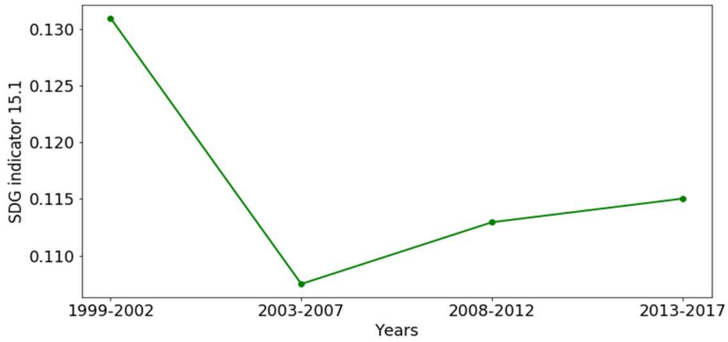


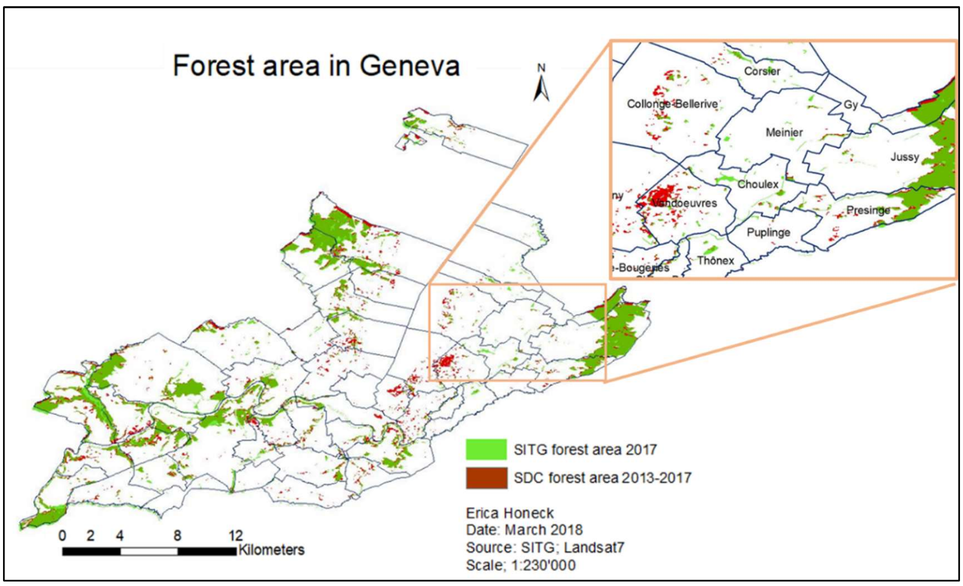
Figure 5. Forest area trend for indicator 15.1.1 in the canton of Geneva, estimated by the forest detection algorithm from 1999 to 2017.

Table 2. Forest surface absolute values for the canton of Geneva.

	Forest Surface (km^2)	Forest Pixels (nr.)	Forest Percentage (%)
1999–2002	36.61	58572	13.09
2003–2007	30.05	48088	10.75
2008–2012	31.58	50522	11.29
2013–2017	32.16	51453	11.50

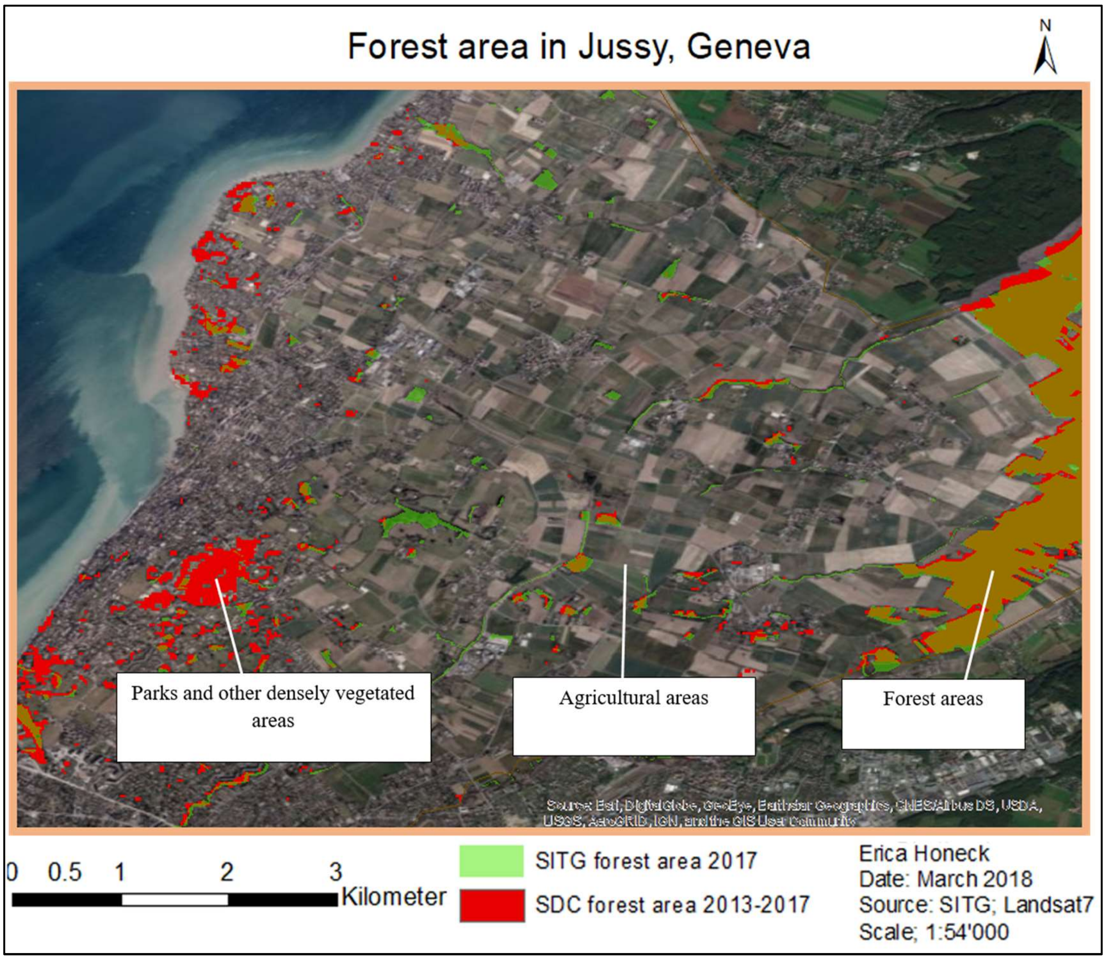
Table 3. Relative variations (percentage of loss and gains) of forest cover in the canton of Geneva. The variations are computed with respect to the older year's intervals.

Relative Variation (%)	1999–2002	2003–2007	2008–2012	2013–2017
1999–2002		−17.92	−13.74	−12.16
2003–2007			5.09	7.02
2008–2012				1.84



(**a**)

Figure 6. *Cont.*



(**b**)

Figure 6. Overlay of forest area estimated with the SDC and the official forest area layer (**a**) (above) and a zoomed area of the overlay with a base map (**b**) (below). The overlap between the red and green layers appears brown. (created with ArcMap 2018).

4. Discussion

This paper presents a first attempt to explore a methodology to monitor forest cover trends in Switzerland using the Open Data Cube framework. We demonstrated how analysis ready data stored in the Swiss Data Cubes make Earth Observation data more accessible to a wider public and facilitate the monitoring of SDG indicators at national scale.

The SDG 15.1.1 is a Tier 1 indicator, thus should be "conceptually clear, has an internationally established methodology and standards are available, and data are regularly produced by countries for at least 50 per cent of countries and of the population in every region where the indicator is relevant" [2]. However, it is consensus based and the metadata does not detail the methodology to collect data for measuring the relative extent of the forest as the percentage of total land. The SDG framework does not provide any specific accuracy requirements either [2]. Yet, the indicator would only be relevant to achieve target 15 if the methodology is harmonized and results are comparable among reporting countries. In fact, we must reflect on the feasibility of indicator measurements across the globe, with regard to different geographical, technological, and institutional dimensions between countries, as forest monitoring may prove to be difficult for countries lacking some form of national forest inventory [31,32].

To this extent, EO and the data cube approach offer multiple benefits for monitoring SDGs. Traditional environmental data has long suffered from data breaks, due to changes in reporting methods and from data gaps. As for satellite data, the same measurements are conducted globally at regular intervals, which provides a timely source of data that is commensurable across countries, regions, and cities, and enables consistent and comparable time-series analysis that can be automatically updated. In addition, earth observation data can be combined with other geo-referenced socio-demographic, economic, and public administration data to make indicators and analysis more relevant and targeted. This can help harmonize international reporting on natural resources and ecosystems and it offers a cost-effective approach without having to require additional reporting from countries.

Although remote sensing has numerous benefits, it does not replace in situ measurements. It rather offers a complementary approach to ground-based data, which are generally more precise but with few measuring points. In fact, results obtained from the Data Cube are suited to monitor environmental trends and analyze changes over time for broad areas, but the interpretation of exact values should be done with some caution. For instance, forest surface estimated by the algorithm presented here does not consider the topography. Another element this algorithm does not show us is the level of fragmentation of forests. Although the total surface of forest in Switzerland has remained somewhat constant over the last century, the fragmentation of forests and other natural habitats have increased, threatening natural habitats for biodiversity. In fact, forests are increasingly pressured by climate warming, introduced parasites, increasing periods of dryness, agricultural pollutants (nitrogen), atmospheric pollutants from transports, forest clearings, and other human activities, particularly in the Plateau region of Switzerland [26].

The forest detection tool provides rapid assessment of forest change through time. High-resolution time-series analysis is a complementary approach to ground-based measurements and is scalable at different spatial scales. The algorithm was developed for the entire country of Switzerland but could not be implemented on the whole country due to limited memory and computer power. Tests on other cantons have shown that NDVI and time-series analysis percentage should be calibrated to different biogeographical regions. Enough scenes are also necessary to produce coherent results, as many of them are masked by clouds and cloud shadows [33]. Although remotely sensed vegetation indexes including NDVI provide valuable qualitative and quantitative information regarding the biophysical properties of vegetation, they also present important limitations as their accuracy can be affected by factors such as canopy architecture, leaf water content, soil background and brightness, and canopy architecture [34]. Other studies using NDVI to study vegetation dynamics confirm this and recommend combining remote sensing techniques with ground-based measurements, using change indicators to enhance the comprehensiveness of forest analyses. For instance, NDVI has been shown to be most positively correlated with temperature among other climatic factors [35], which should be considered in NDVI time-series analyses. Other studies using NDVI in Switzerland have determined the day of the year with the highest values of NDVI as an indicator for the peak growing season in order to normalize NDVI time-series and the ground-based records [36]. In addition, Landsat 5 and 8 datasets differ in accuracy, which is likely to show abrupt changes in NDVI time-series [37]. Therefore, studies based on Landsat 5 must take into account possible underestimations of the NDVI. In our case, the large error observed in the canton of Jura is mainly due to the spatial–temporal heterogeneity in the NDVI time-series, which can influence the accuracy of the results [38]. In some cases, NDVI data and ground information from forest inventories can be very close [39]. However, NDVI can show nonlinearity over partially vegetated surfaces in areas with shadows or dark soil backgrounds [40], which is the case in mountainous areas with high topographic heterogeneity.

Next steps regarding the forest detection algorithm include refining the algorithm with machine learning and automatic image recognition to derive more precise values and distinguish between deciduous and non-deciduous vegetation, calibrate it with local data for different biogeographical regions and run it for the whole country, adapt and test it with Sentinel-2 data [41], and create or insert the framework in a web-based interactive user interface. The framework should also be replicated with other SDG indicators that can be measured with remote sensing techniques as listed in the European

Space Agency's report "Satellite Earth Observations in support of the Sustainable Development Goals" [42].

5. Conclusions

Increasing pressures on natural resources have generated the need for rapid and cost-effective ecosystem monitoring techniques to inform progress towards global environmental targets. Earth Observation Data Cubes represent a promising tool to process and analyze Earth Observation data for various environmental assessments. The high spatial and temporal resolution of data ingested in the Swiss Data Cubes (SDC) in analysis-ready form offers a great advantage to facilitate the interrogation of satellite data and will play a key role as an evidence base for advising the Swiss government and other decision-makers to design and implement well-informed policies, land planning and resource management.

This paper presented a novel methodology to monitor forest cover trends using the Open Data Cube framework with Switzerland as a case study. SDG indicator 15.1.1—forest area as a percentage of total land area—is a tier I indicator and for which data and established methodology should be available. However, consistent and accurate measurement may be difficult to perform in some countries lacking a national forest inventory. In addition, specification for measuring some targets are still lacking and there are still major issues concerning scalability of the measuring approaches and comparability of the results. In fact, traditional environmental data has long suffered from data breaks due to changes in reporting methods and data gaps.

Through the development of a forest detection tool within the Swiss Data Cube framework, we demonstrated how EO could provide consistent time-series to derive environmental trends, contribute to more detailed measurements and better harmonize SDG indicators without necessitating additional reporting from member countries. Although using Landsat based NDVI may lack precision compared to other approaches such as aerial photography interpretation, it offers a simple, replicable, and rapid alternative to derive forest area time-series with higher periodicity. Combined with other geo-referenced socio-demographic, economic, and public administration data, the developed algorithm could make indicators more relevant and targeted, and offer a cost-effective, synoptic, and scalable approach without having to require additional reporting from countries.

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References

1. United Nations Statistics Division (UNSD). *Sustainable Development Goals Report*; UNSD: Washington, DC, USA, 2016.
2. United Nations. SDG Indicators. 2018. Available online: https://unstats.un.org (accessed on 13 June 2018).
3. UNECE. Joint UNECE/Eurostat/OECD Working Group on Statistics on Sustainable Development. Available online: https://www.unece.org/stats/groups/wgssd.tor.html (accessed on 10 October 2018).
4. Guo, H.; Liu, Z.; Jiang, H.; Wang, C.; Liu, J.; Liang, D. Big Earth Data: A new challenge and opportunity for Digital Earth's development. *Int. J. Digit. Earth* **2017**, *10*, 1–12. [CrossRef]

5. Boulton, G. The challenges of a Big Data Earth. *Big Earth Data* **2018**, *2*, 1–7. [CrossRef]
6. Giuliani, G.; Dao, H.; De Bono, A.; Chatenoux, B.; Allenbach, K.; De Laborie, P.; Rodila, D.; Alexandris, N.; Peduzzi, P. Live monitoring of earth surface (LiMES): A framework for monitoring environmental changes from earth observations. *Remote Sens. Environ.* **2017**, *202*, 222–233. [CrossRef]
7. Anderson, K.; Ryan, B.; Sonntag, W.; Kavvada, A.; Friedl, L. Earth observation in service of the 2030 Agenda for Sustainable Development. *Geo-Spat. Inf. Sci.* **2017**, *20*, 77–96. [CrossRef]
8. Lewis, A.; Lymburner, L.; Purss, M.B.; Brooke, B.; Evans, B.; Ip, A.; Dekker, A.G.; Irons, J.R.; Minchin, S.; Mueller, N.; et al. Rapid, high-resolution detection of environmental change over continental scales from satellite data—The Earth Observation Data Cube. *Int. J. Digit. Earth* **2016**, *9*, 106–111. [CrossRef]
9. Purss, M.B.; Lewis, A.; Oliver, S.; Ip, A.; Sixsmith, J.; Evans, B.; Edberg, R.; Frankish, G.; Hurst, L.; Chan, T. Unlocking the Australian Landsat Archive—From dark data to High Performance Data infrastructures. *GeoResJ* **2015**, *6* (Suppl. C), 135–140. [CrossRef]
10. Woodcock, C.E.; Allen, R.; Anderson, M.; Belward, A.; Bindschadler, R.; Cohen, W.; Gao, F.; Goward, S.N.; Helder, D.; Helmer, E.; et al. Free Access to Landsat Imagery. *Science* **2008**, *320*, 1011. [CrossRef] [PubMed]
11. Giuliani, G.; Chatenoux, B.; De Bono, A.; Rodila, D.; Richard, J.P.; Allenbach, K.; Dao, H.; Peduzzi, P. Building an Earth Observations Data Cube: lessons learned from the Swiss Data Cube (SDC) on generating Analysis Ready Data (ARD). *Big Earth Data* **2017**, *1*, 100–117. [CrossRef]
12. Group on Earth Observations (GEO). *Earth Observations in Support of the 2030 Agenda for Sustainable Development*; Japan Aerospace Exploration Agency (JAXA) on Behalf of GEO under the EO4SDG Initiative: Tokyo, Japan, 2017.
13. Ouyang, Z.; Zheng, H.; Xiao, Y.; Polasky, S.; Liu, J.; Xu, W.; Wang, Q.; Zhang, L.; Xiao, Y.; Rao, E.; et al. Improvements in ecosystem services from investments in natural capital. *Science* **2016**, *352*, 1455–1459. [CrossRef] [PubMed]
14. World Resources Institute. Forests and SDGs: Taking a Second Look | World Resources Institute. Available online: https://www.wri.org/blog/2017/09/forests-and-sdgs-taking-second-look (accessed on 9 October 2018).
15. Yengoh, G.T.; Dent, D.; Olsson, L.; Tengberg, A.E.; Tucker, C.J. *The Use of the Normalized Difference Vegetation Index (NDVI) to Assess Land Degradation at Multiple Scales: A Review of the Current Status, Future Trends, and Practical Considerations*; Lund University Center for Sustainability Studies (LUCSUS) and the Scientific and Technical Advisory Panel of the Global Environment Facility (STAP/GEF): Lund, Sweden, 2014.
16. Rouse, J.W., Jr. *Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation*; NASA: College Station, TX, USA, 1972.
17. Rouse, J., Jr.; Haas, R.H.; Schell, J.A.; Deering, D.W. *Monitoring Vegetation Systems in the Great Plains with ERTS*; NASA: College Station, TX, USA, 1974.
18. RColditz, R.; Ressl, R.A.; Bonilla-Moheno, M. Trends in 15-year MODIS NDVI time series for Mexico. In Proceedings of the 8th International Workshop on the Analysis of Multitemporal Remote Sensing Images (Multi-Temp), Annecy, France, 22–24 July 2015; pp. 1–4.
19. Ceroni, M.; Achkar, M.; Gazzano, I.; Burgueño, J. Study of the NDVI with multi-scale and time-series analysis using SPOT imagery during the period 1998–2012 in Uruguay. *Rev. Teledetec.* **2015**, 31–42. [CrossRef]
20. Picoli, M.C.; Camara, G.; Sanches, I.; Simões, R.; Carvalho, A.; Maciel, A.; Coutinho, A.; Esquerdo, J.; Antunes, J.; Begotti, R.A.; et al. Big earth observation time series analysis for monitoring Brazilian agriculture. *ISPRS J. Photogramm. Remote Sens.* **2018**, *145*, 328–339. [CrossRef]
21. Eckert, S.; Hüsler, F.; Liniger, H.; Hodel, E. Trend analysis of MODIS NDVI time series for detecting land degradation and regeneration in Mongolia. *J. Arid Environ.* **2015**, *113*, 16–28. [CrossRef]
22. Schubarth, C.; IC Infraconsult AG; Weibel, F.; OFS. *L'utilisation du sol en Suisse–Résultats de la statistique de la superficie*; Office fédéral de la statistique (OFS): Neuchâtel, Switzerland, 2013.
23. IFN. L'inventaire forestier national suisse (IFN). 2018. Available online: https://www.lfi.ch/lfi/lfi-fr.php (accessed on 18 February 2018).
24. FAO of the UN. FRA 2000 on Definitions of Forest and Forest Change. 2018. Available online: http://www.fao.org/docrep/006/ad665e/ad665e00.htm#TopOfPage (accessed on 15 June 2018).
25. VanderPlas, J. *Python Data Science Handbook: Essential Tools for Working with Data*; O'Reilly Media, Inc.: Newton, MA, USA, 2016.

26. Office Fédéral de l'Environnement OFEV, "Division Forêts. 2018. Available online: https://www.bafu.admin.ch/bafu/fr/home/office/divisions-sections/division-forets.html (accessed on 18 April 2018).
27. Canton de Genève. Forêt | Nature. 2018. Available online: http://ge.ch/nature/foret (accessed on 18 April 2018).
28. République et Canton du Jura. Forêts jurassiennes—République et Canton du Jura. Available online: https://www.jura.ch/DEN/ENV/Forets/Forets-jurassiennes.html (accessed on 22 August 2018).
29. Congalton, R.G. Accuracy assessment and validation of remotely sensed and other spatial information. *Int. J. Wildland Fire* **2001**, *10*, 321–328. [CrossRef]
30. SITG. Cartes professionnelles | SITG. 2018. Available online: https://ge.ch/sitg/cartes/professionnelles (accessed on 18 April 2018).
31. Desai, D.; Schomerus, M. 'There Was A Third Man . . . ': Tales from a Global Policy Consultation on Indicators for the Sustainable Development Goals-Desai-2018-Development and Change. *Dev. Chang.* **2017**, *49*, 89–115. [CrossRef]
32. Kaika, M. 'Don't call me resilient again!': The New Urban Agenda as immunology . . . or . . . what happens when communities refuse to be vaccinated with 'smart cities' and indicators. *Environ. Urban.* **2017**, *29*, 89–102. [CrossRef]
33. Robinson, N.P.; Allred, B.W.; Jones, M.O.; Moreno, A.; Kimball, J.S.; Naugle, D.E.; Erickson, T.A.; Richardson, A.D. A Dynamic Landsat Derived Normalized Difference Vegetation Index (NDVI) Product for the Conterminous United States. *Remote Sens.* **2017**, *9*, 863. [CrossRef]
34. Redowan, M.; Kanan, A.H. Potentials and Limitations of NDVI and other Vegetation Indices (VIS) for Monitoring Vegetation Parameters from Remotely Sensed Data. *Bangladesh Res. Pub. J.* **2012**, *7*, 291–299.
35. Baniya, B.; Tang, Q.; Huang, Z.; Sun, S.; Techato, K.A. Spatial and Temporal Variation of NDVI in Response to Climate Change and the Implication for Carbon Dynamics in Nepal. *Forests* **2018**, *9*, 329. [CrossRef]
36. Schmidt, S.; Alewell, C.; Meusburger, K. Mapping spatio-temporal dynamics of the cover and management factor (C-factor) for grasslands in Switzerland. *Remote Sens. Environ.* **2018**, *211*, 89–104. [CrossRef]
37. Poursanidis, D.; Chrysoulakis, N.; Mitraka, Z. Landsat 8 vs. Landsat 5: A comparison based on urban and peri-urban land cover mapping. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *35*, 259–269. [CrossRef]
38. Forkel, M.; Carvalhais, N.; Verbesselt, J.; Mahecha, M.D.; Neigh, C.; Reichstein, M. Trend change detection in NDVI time series: Effects of inter-annual variability and methodology. *Remote Sens.* **2013**, *5*, 2113–2144. [CrossRef]
39. González-Alonso, F.; Merino-De-Miguel, S.; Roldán-Zamarrón, A.; García-Gigorro, S.; Cuevas, J.M. Forest biomass estimation through NDVI composites. The role of remotely sensed data to assess Spanish forests as carbon sinks. *Int. J. Remote Sens.* **2006**, *27*, 5409–5415. [CrossRef]
40. Jiang, Z.; Huete, A.R.; Chen, J.; Chen, Y.; Li, J.; Yan, G.; Zhang, X. Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. *Remote Sens. Environ.* **2006**, *101*, 366–378. [CrossRef]
41. Zhang, H.K.; Roy, D.P.; Yan, L.; Li, Z.; Huang, H.; Vermote, E.; Skakun, S.; Roger, J.C. Characterization of Sentinel-2A and Landsat-8 top of atmosphere, surface, and nadir BRDF adjusted reflectance and NDVI differences. *Remote Sens. Environ.* **2018**, *215*, 482–494. [CrossRef]
42. European Space Agency. *Satellite Earth Observations in Support of the Sustainable Development Goals—Special 2018 Edition*; European Space Agency: Paris, France, 2018.