EL-BIOS DATA CUBE: NATIONAL-SCALE BIODIVERSITY MONITORING IN GREECE THROUGH EO INDICATORS

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ABSTRACT

Conservation and management of biological diversity is central to human health and well-being. The EU-funded LIFE project “hELlenic BIOodiversity Information System: An innovative tool for biodiversity conservation - LIFE EL-BIOS” project aims to contribute in EU and national policies by designing, developing and implementing a central biodiversity information system, “EL-BIOS”, operated by the Greek Natural Environment and Climate Change Agency (NECCA). In this work, we present the development framework of the EL-BIOS EO Data Cube, a service that provides access to biodiversity indicators and variables in analysis ready form, based on Open Data Cube framework for big data management and web service applications. Using freely available Copernicus Sentinel-2 imagery, six national-scale and four local-scale biodiversity indicators are generated in a spatial and temporal systematic framework for assessing and monitoring biodiversity state and condition.

***Index Terms*—** biodiversity conservation, Open Data Cube, Satellite Image Time Series, national scale, Analysis Ready Data, EO workflows

1. INTRODUCTION

Conservation and management of biological diversity is central to human health and well-being. As human activities contribute to the ongoing loss of species, there arises an escalating imperative to systematically document, comprehend, and assess the intricacies of biological diversity [1]. Research by the International Union for the Conservation of Nature found that the socio-economic systems of food production, infrastructure, and energy accounts for around 80% of the impact on threatened species, as identified by the IUCN Red List [2]. Therefore, EU Biodiversity Strategy for 2030 aims to ensure that Europe's biodiversity will be on the path to recovery by 2030, that will require action by citizens, businesses and research community to protect and restore nature [3].

Greece is situated within the Mediterranean basin biodiversity hot-spot and hosts an incredible variety of ecosystems and species. The uniqueness of Greek nature is characterized by high species density, endowed with a variety of different ecosystems and landscapes. Notably, Greece has a particularly rich and interesting flora, with 5,700 recorded species, of which approximately 13.2% are endemic due to its complex landscape and morphology [4]. Like the flora, the Greek fauna is also notable for its high rate of endemism, with a total of 23,130 recorded species of terrestrial and freshwater animals as well as 3,500 marine species [4]. According to the World Wildlife Fund (WWF), Greece accommodates 8% and 40% of Europe’s animal and plant species [5].

Biodiversity monitoring demands accurate measurement of each multi-taxon community, traditionally obtained through challenging field surveys [6]. Within this context, remote sensing is increasingly employed in biodiversity modelling and reporting, bridging the gap between biodiversity indicators, paving the way for a more systematic sustainable management [7]. Remote sensing provides cost-efficient observations across broad scales in a consistent manner and multitemporal archives, enabling long-term dynamics monitoring and change detection [8]. Additionally, earth observation (EO) data are distributed under free, full and open data policy [9], contributing in the harmonization of databases under standard protocols [10]. Between the most widely used satellite constellations, Landsat and Sentinel-2, numerous biodiversity-oriented studies have been conducted, namely, in the analysis of functional diversity and the estimation of structural [11] and spectral [12] diversity, tree species diversity [13] and bird richness [14].

Numerous biodiversity studies have utilized Landsat's extensive imagery archive, albeit its medium spatiotemporal resolution. Concurrently, Sentinel-2 is gaining prominence in the monitoring domain as its historic archive grows. Moreover, Sentinel-2 provides more bands than Landsat and finer spatiotemporal resolution, which could enable a more comprehensive biodiversity monitoring [15]. Therefore, to manage big data in terms of volume, variety, velocity, and veracity [16], with homogenization of both open and commercial data, the need of powerful software, data structures and standard protocols emerges.

The necessity to meet the demands of big EO data in terms of storage, process and analysis, both in cloud and distributed systems, providing access to data in analysis ready form [17], has driven the development of such integrated systems. A promising solution is represented by EO Data Cubes [18] and their variations, such as Google Earth Engine (GEE) [19], Euro Data Cube[1], OpenEO [20], and Open Data Cube (ODC) [21]. In EO Data Cubes ecosystems, open data are consumed by cloud providers (e.g. GEE, AWS, Microsoft Computer) or regional and national initiatives [22]. In particular, ODC functions as an intermediary to facilitate the seamless interaction between data and applications, featuring a suite of open source-tools and a Python based API for high performance data access and querying [23]. Currently ODC supports continental, national and regional operational initiatives, with some of most important being the Digital Earth Australia [24], Digital Earth Africa [25], Digital Earth Pacific[2], Swiss Data Cube [26], Brazil Data Cube [27], Colombian Data Cube [28], and regional cubes in Catalonia [29] and Virginia[3].

The aim of this study is to present the conceptualization and development framework of the EL-BIOS Data Cube. This infrastructure will represent the first national-scale data cube, aiming to mainstream EO usage for biodiversity management and conservation in Greece.

Thus, EL-BIOS information system, backed by the EL-BIOS Data Cube, will contribute to improved policymaking, spanning a range of topics, from sustainable management to environmental-economic accounting [30]. In an attempt to align with the Digital Earth vision [31], the Data Cube is providing analysis ready biodiversity indicators, as proxies of net primary productivity, vegetation structure and diversity, phenology and seasonality of carbon fluxes. These indexed products are also being served through OWS (open web services) and a web GIS graphical user interface that provides visualization and download capabilities. In the remaining sections of this manuscript, we present the structure of the EL-BIOS Data Cube, the selection of the biodiversity indicators, and the development of EO workflows for the satellite image time series (SITS) analysis.

2. EL-BIOS DATA CUBE

The EL-BIOS Data Cube is a four-fold structure and is supported by ODC to index, process, store and serve its data. The data index catalogue is hosted in a PostgreSQL database, which is initialized under the AGDC schema. After defining the products that will be hosted, Sentinel-2 Level-2A Cloud-Optimized GeoTIFF imagery is indexed in the data cube from the Registry of Open Data on Amazon Web Services (AWS) S3 Bucket. The Sentinel-2 L2A data cover the wider region of Greece (mainland and islands) with 60 MGRS tiles from January 2017 to December 2023, with an indexing process being executed on a monthly basis to include new acquisitions.

The stages of processing and storing are orchestrated by a single API that was built using the FastAPI framework and Docker containers, for scalability in both on-premises and cloud infrastructures. The Docker image accommodates both Python and R functionalities. To analyze big data we deployed a distributed processing architecture, using the Dask framework and Docker virtualization technology, for parallel processing and scheduling.

The processing of the archive is conducted per MGRS tile. The processing is initialized by a query that filters the matching datasets using the ODC Python API and loads the data into *xarrays*, which is a powerful multidimensional structure, appropriate for spatiotemporal data. Following the EO workflows developed for each biodiversity indicator, the computations are distributed to the workers for efficient computation and memory management. The final computed dataset and its metadata are then stored in the EL-BIOS storage archive and indexed back to the EL-BIOS Data Cube.

The EL-BIOS Data Cube provides data in both visual and downloadable formats. Visualization is available through datacube-OWS web services (OGC WMS, WMTS and WCS). The archive currently hosts 6TB of analysis ready biodiversity indicators and variables, which will increase by almost 1TB per year with new Sentinel-2 acquisitions.

3. BIODIVERSITY INDICATORS

The identification of biodiversity indicators to be hosted in the ELBIOS Data CUBE included meticulous literature research and recording of the needs and requirements of Greece's scientific and management communities involved in biodiversity conservation and management.

Due to the rich flora and fauna found in Greece in an underlying complex topography, the selection of the biodiversity indicators aimed to thoroughly monitor the species richness, diversity in plant phenology and structure, and primary production.

Following the testing of HRL Copernicus products, as well as indicators reported in biodiversity studies and data

[1] https://eurodatacube.com/

[2] https://www.spc.int/DigitalEarthPacific

[3] https://www.data4va.org/

cube instances, we concluded in six EO-derived biodiversity indicators for national-scale coverage, along with three EO-based variables. Furthermore, two pilot areas have been selected for the EL-BIOS project: Northern Pindos National Park and Kotychi – Strofylia Wetlands National Park. In the context of the project, four additional biodiversity indicators have been identified for these pilot areas. These areas will be studied as independent local cubes, a methodology frequently recommended for data cube analyses [22].

3.1. Selected Biodiversity Indicators and Variables

The EL-BIOS Data Cube will provide six biodiversity indicators and three variables on a national scale. Regarding the biodiversity indicators, Fractional Vegetation Cover (FVC) is an NDVI derived indicator serving as proxy to vegetation structure and primary productivity [32]. Moreover, the NDVI-based indicators of the Integrated NDVI ($NDVI_{Integral}$), Intra-Annual Relative Range ($NDVI_{IARR}$) and Date of annual Mode ($NDVI_{DoM}$), were selected as proxies to net primary production [33], seasonality of carbon fluxes [34], and vegetation phenology and diversity [35], respectively [36]. Additionally, Plant Phenology Index (PPI) is a DVI based indicator, using Red and NIR bands, and is was selected to model phenological diversity [37]. Finally, Leaf Area Index (LAI), is used as a proxy to monitor aboveground productivity and plant diversity [38].

For the pilot areas, additional indicators has been selected including among proxies for α-diversity based on Shannon index [39], [40], and proxies for cumulative productivity, minimum productivity, intra-annual variation of productivity obtained by Dynamic Habitat Index [41].

On a national scale, three variables, NDVI, Enhanced Vegetation Index (EVI) [42], and Surface Albedo [43] are being served, with NDVI being used in four biodiversity indicators, while EVI was used as an input in the LAI indicator.

3.2. Satellite Image Time Series preprocessing

Satellite data can be affected by various factors that can lead to complexity and errors. These factors include sensor resolution and calibration, digital quantization errors, terrestrial and atmospheric conditions, as well as orbital and sensor degradation. In order to ensure the accuracy of the dataset a standard cloud cover range from 0 to 40% was used. Utilizing L2A data, SCL image was used to mask high and medium cloud probabilities, cloud shadows and thin cirrus, with a dilation of 30m. The gaps created in the raw time series are then interpolated. The linear method proved to be the most suitable between spline and cubic, to provide a more generic national-scale solution. However, to ensure optimal data quality, it is recommended that time-series be smoothed before use, as some noise may remain in the datasets. This noise is primarily due to remnant cloud cover, water, snow, or shadow. To address fluctuations in the time series, a three-observation rolling median was used, followed by a Savitzky-Golay signal smoothing filter with a (m, d) combination of (4,2) was applied. The resulting time series comprises of 60 observations per year. It is worth noting that PPI was not included in this preprocessing workflow due to its model's handling of cloud contamination.

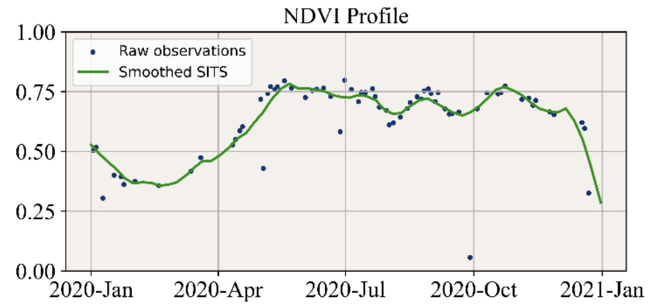

Figure 1. Processed NDVI time series and its raw values.

3.3. Modelling of Biodiversity Indicators

Regarding the functional indicators derived from the annual positive NDVI curve [44], the $NDVI_{Integral}$ was calculated as the sum of NDVI [33], the $NDVI_{IARR}$ was calculated as maximum NDVI minus minimum NDVI, divided by $NDVI_{Integral}$ [34], and the $NDVI_{DoM}$ was equal to the date of annual maximum NDVI.

The FVC for each pixel is estimated from the annual NDVI time series for each quarter using a linear mixing model [45] as: $FVC = (NDVI_{Q,mean} - NDVI_S) / (NDVI_V - NDVI_S)$, where $NDVI_{Q,mean}$ represents the mean value for each quarter, $NDVI_S$ denotes the bare soil, and $NDVI_V$ stands for the dense green vegetation. The method used to determine the $NDVI_S$ endmember involved selecting the 5th percentile of annual maximum NDVI values for barren land, as defined by the CORINE Land Cover 2018 classes. To calculate $NDVI_V$, it was assumed that 25% of pixels were fully vegetated, and the 75th percentile of annual maximum NDVI values for all land cover classes was used [45].

The Leaf Area Index was calculated as the ratio of the one-sided (illuminated) foliage area to the soil surface it can cover. The formula used was the linear relationship with EVI [38], [42], $LAI = 3.618 \times EVI - 0.118$, using the annual EVI pre-processed time series to obtain monthly LAI metrics.

The retrieval algorithm of Plant Phenology Index is derived from radiative transfer equations and is calculated from red and near-infrared (NIR) reflectance. It is designed on modified Beer's law to have nearly linear relationship to LAI given a fixed soil effect [37], [46], defined as $PPI = -K \times ln[(MDVI - DVI)/(MDVI - DVI_S)]$. The formula uses the difference vegetation index DVI, the quarterly maximum DVI $MDVI$, and DVI_S is the quarterly minimum DVI of the soil. The gain factor K is formed as a function of sun zenith angle θ, a geometric function of leaf angular distribution and instantaneous diffuse fraction of solar radiation [46]. $MDVI$ and DVI_S were obtained spatiotemporally for each 1098×1098 sub-area of the included S2 images and upscaled using bicubic interpolation to the whole image [47]. Effects of reflectance outliers were avoided by setting the upper limit of *MDVI* to 0.8.

In the pilot areas selected for the study, α-diversity was assessed using *biodivMapR* [40]. PCA analysis was conducted using mean band values from the July and August datasets. Spectral species mapping was performed by applying k-means clustering to the first four principal components derived from PCA. Shannon α-diversity was calculated by using a distribution of 50 clusters with 100m window sizes across the entire image. For the DHI metrics, monthly LAI observations over 5-year periods are averaged to a 1-year period, from which cumulative sum, variance and minimum metrics are obtained.

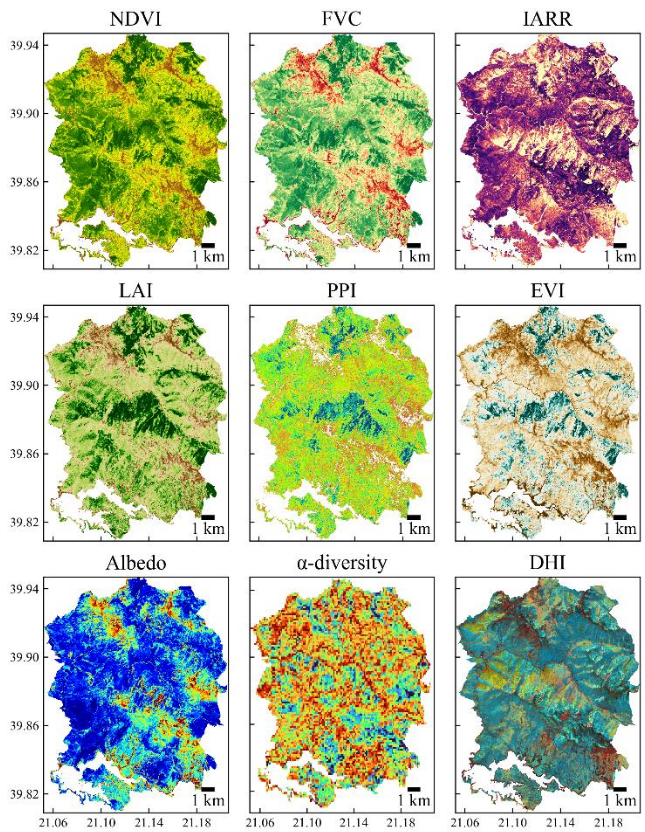

Figure 2. The EL-BIOS Data Cube indicators in Valia Kalda region within the National Park of Northern Pindos.

3.4. Service of products

The generic EO workflow is composed of the data cube querying, the time series loading as xarrays, SITS processing, the calculation of biodiversity indicator or variable metrics, and finally the COGs export and indexing of the outputs. On a national scale, FVC, $NDVI_{Integral}$, $NDVI_{IARR}$, $NDVI_{DoM}$, PPI, NDVI, EVI and Albedo products are served as three-month composites. LAI product is served as a monthly composite. All indicators and variables have a pixel size of 10m, with the exception of α-diversity which is 100m. For PPI, LAI, NDVI, EVI, and Albedo products, the metrics include mean (Fig. 2), median, maximum, minimum, and standard deviation as sub-products.

4. CONCLUSIONS

Greece has important biodiversity and EL-BIOS project has the properties to effectively monitor and report it. Today, an operational national-scale biodiversity monitoring data cube in Greece does not exists. EL-BIOS Data Cube will be the foundation for a standardized biodiversity-oriented SITS analysis, when fully operational, populated with a variety of analysis ready biodiversity indicators and variables. Additionally, the selected pilot areas will serve as local data cubes for a more focused modelling on areas of significant biodiversity. The usage of EODC technology promotes the replicability and reproducibility of the analyses, significantly enhancing the operational applicability of EL-BIOS Data Cube [48], while Open Standards such as the OGC Web Map Service enables time-series analysis directly within a web-based application [29].

The selected analysis ready biodiversity indicators will be useful for biodiversity-related researchers that perform analyses to correlate field data with EO-derived observations, without the need of expertise in remote sensing data processing. This way, the necessary interdisciplinarity in biodiversity reporting will be supported by standard products enhancing more direct research of sustainable management and biodiversity conservation. Moreover, the SITS filtering, interpolation and smoothing enhances the accuracy and robustness of the time series data, providing a foundation for the assessment of biodiversity dynamics and associated proxies. Finally, the in-service SITS pre-processing analysis receives continuous modifications to minimize computational costs of memory and time management.

The EL-BIOS project will contribute to policy changes, that until today remain a challenging task, as biodiversity state dissemination is not conducted under a single agency. The potential for modern sensors to identify areas of significance to biodiversity, predict species distributions and model community responses to environmental and anthropogenic changes, would offer new insights to support better policy making issues.

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