GEO ESSENTIAL ERA-PLANET

Essential Variables workflows for resource efficiency and environmental management

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Creator	M. Gómez-Giménez (Senckenberg, Germany)
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Description	This deliverable provides insights into the potential of satellite remote sensing products and Dynamic Global Vegetation Models (DGVMs) for EBVs monitoring. We also provide a workflow example that generates fractional land cover and averaged fractional land cover values per region. This report was developed within the context of work package 4, which is focused on evaluating the streamlining of Essential Biodiversity Variables (EBVs) to foster their use in decision-making processes.
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Introduction

Since 1970s, satellite constellations have provided important global datasets for understanding large-scale processes. However, limitations still remain regarding biodiversity monitoring. In the last decades, NASA has been the main producer of remotely sensed ecologically significant products. Recently, the Copernicus Programme of the European Space Agency (ESA) has increased the availability of these global products at higher resolutions, which provides new opportunities for data assimilation. Multiple sources of information are needed to monitor ecosystem processes and models play a key role in linking them (Prentice et al. 2007). In particular, combining satellite remote sensing with vegetation models can potentially improve the understanding of large-scale spatial and temporal ecosystem patterns.

Vegetation models can be divided in static models (focus on yearly changes) and dynamic models (representing vegetation dynamics). Dynamic Global Vegetation Models (DGVMs) simulate changes in ecosystems accounting for biogeochemical processes and vegetation structure and composition dynamics (Myoung, Choi, and Park 2011). Some limitations regarding DGVMS are based on the representation of heterogeneity of natural ecosystems, natural and anthropogenic disturbances, and leaf phenology (Myoung, Choi, and Park 2011). Despite those limitations, DGVMs are able to represent a wide range of climate and land-use change issues (Prentice et al. 2007), which turns them into an indispensable tool to monitor EBVs and ecosystem processes.

In this report, we analyze the role of current and upcoming satellite missions for DGVMs development. Part of this report also appeared in 'Combining European Earth Observation products with Dynamic Global Vegetation Models for estimating Essential Biodiversity Variables' in International Journal of Digital Earth[1].

Furthermore, we include a workflow example (Figure A 1) that generates model inputs from ready-to-use remote sensing products. The workflow estimates i) fractional cover datasets and ii) averaged fractional cover values per region. Fractional land cover data is widely assimilated into models and averaged fractional cover values per region provide decision-makers with valuable information about temporal land cover changes. These products can potentially inform about the EBV ecosystem structure.

Monitoring Essential Biodiversity Variables (EBV)

The Group on Earth Observations Biodiversity Observation Network (GEO-BON) has contributed to rising consensus on the use of Essential Biodiversity Variables (EBVs) to monitor biodiversity around the world (Pereira et al. 2013). GEO-BON coordinates biodiversity monitoring efforts aiming at the United Nations Convention on Biological Diversity (UC-CBD) Strategic Plan for Biodiversity and the related Aichi targets for 2020. Six EBV classes and 21 candidates form the basis of biodiversity loss and change monitoring programmes. In particular, these variables focus on genetic composition, species

[1] https://doi.org/10.1080/17538947.2019.1597187

populations, species traits, community composition, ecosystem structure, and ecosystem function[2].

In recent years, the growth of open satellite image archives is leading to more sophisticated and biologically relevant remote sensing products, which we here refer to as Remote Sensing Bio-Geophysical Products (RS-BGPs). Some widely used examples are the Global Forest Cover Change (Hansen et al. 2013; Sexton et al. 2013b), Leaf Area Index, Ocean Salinity, Net Primary Production (NPP) and Evapotranspiration (Fensholt, Sandholt, and Rasmussen 2004). Due to their global coverage and high revisit times, satellite remote sensing platforms play a central role in monitoring EBVs (Kissling, Ahumada, et al. 2018; Kissling, Walls, et al. 2018; Pettorelli 2015). One current major remote sensing approach for monitoring EBVs is the Global Biodiversity Change Indicator (GBCI) initiative, developed by GEO BON (GEO BON 2015). The GBCIs, available to the community through several open access platforms (e.g. Map Of Life[3]), are based on global, open access RS-BGPs (Hill, Asner, and Held 2006) and empirical models. The indicators have a global coverage, a spatial resolution of 1 km, and cover species distribution, population abundance, taxonomic diversity, NPP and ecosystem extent and fragmentation EBVs. NASA- and NOAA-produced RS-BGPs are the main dataset sources for the GBCIs, in particular datasets from the MODIS sensor and the Global Forest Cover Change dataset (Hansen et al. 2013). However, new improved global, open access platforms are available which could significantly improve the monitoring of EBVs, such as those from the Sentinel-1 (Torres et al. 2012) and Sentinel-2 (Drusch et al. 2012) satellite missions which are part of the European Space Agency´s (ESA) Copernicus Programme[4].

In spite of recent progress in RS-BGP development, the missing link between biodiversity and remote sensing remains, due to the inherent difficulty of quantifying biodiversity from space (Pettorelli 2015). Consequently, it is unlikely that most EBVs will be only estimated using remote sensing, or in conjunction with simpler empirical models, which exhibit notorious limitations, such as the struggle to explain why high diversity (e.g. as measured by field studies) exists under limited resources (Weigelt et al. 2009). Recent efforts to understand global patterns of biodiversity have produced maps of several complex ecosystem properties, using remote sensing and statistical models such as Bayesian modelling of community-level plant traits (Butler et al. 2017), species distribution modelling (Kissling, Ahumada, et al. 2018), many of which are EBV candidates, and some included in the development of GBCI. Process-based modelling approaches aim at representing eco-physiological processes, such as photosynthesis, autotrophic (plant) and heterotrophic respiration, whereby the target variable, such as total ecosystem carbon storage, is an emergent model outcome, in contrast to empirical models that directly relate high-level target variables to environmental factors (Peterson, Papeş, and Soberón 2015). These promise a significant breakthrough in the production of global maps of ecosystem properties (Harfoot et al. 2014). Dynamic Global Vegetation Models (DGVMs) are a widely used type of process-based model, which simulate the distribution of biomes or vegetation types, vegetation dynamics and structure, and biogeochemical fluxes (e.g. carbon, water

[2] https://geobon.org/ebvs/
[3] https://mol.org/
[4] https://www.esa.int/Our_Activities/Observing_the_Earth/Copernicus

and nitrogen) between the soil, vegetation and the atmosphere (Prentice et al. 2004; Smith et al. 2014). DGVMs include processes from the leaf level (e.g. photosynthesis) to the biosphere (e.g. carbon cycle) and can, thus, be used to simulate several EBVs. Furthermore, as well as monitoring of current states of biodiversity, process-based models are also capable of predicting future dynamics, providing thus a powerful tool for adaptive planning (e.g. Gonzalez, Neilson, Lenihan, & Drapek, 2010; Sitch et al., 2008). For more regional applications, the global models are commonly adapted to the specifics of the target region (Scheiter and Higgins 2009; Hickler et al. 2012; Seiler et al. 2015), and some DGVMs also simulate crop yields (Jin et al. 2018; Schaphoff et al. 2018) and forest management (Jönsson, Lagergren, and Smith 2013; Yue et al. 2015). Some DGVMs also simulate dynamic changes in plant functional trait distribution, analogous to the species traits EBV candidates[5] but only at the Plant Functional Type (PFT) and ecosystem level (Scheiter, Langan, and Higgins 2013; Sakschewski et al. 2014), although DGVMs can, at least in species poor northern regions, be parameterized for major tree species (Hickler et al. 2012). Since DGVMs require spatially and temporally extensive data for model development, calibration and benchmarking as well as model forcing (Kelley et al. 2013), they have been frequently integrated with remote sensing data (e.g. (Smith et al. 2008; Forkel et al. 2017; Dietze, Lebauer, and Kooper 2013), see also section below). This model-remote sensing integration has therefore a great potential to produce new, high quality regional to global information on EBVs and additional variables related to biodiversity.

In this review we 1) describe the range of available and soon-to-be available RS-BGPs for estimating EBVs, with special focus on highlighting the newly available products from ESA's Copernicus program as well as additional ones from the United States agencies NASA and NOAA; 2.) Summarize the potential of DGVMs and their integration with remote sensing for estimating EBVs.

Current remote sensing products used for EBV monitoring and the potential of existing and upcoming missions

In Table 1 we list the current RS-BGP platforms variables and their platforms that provide products with potential for EBV estimation, in line with the requirements of the GBCI. MODIS and SPOT/PROBA-V from NASA and ESA platforms respectively offer similar products for most of the 19 selected variables. Despite redundancy, a variety of data sources can be useful to address uncertainties, although the demand is higher for improved versions of existing products. In the appendix, we have included a table (Table A1A) with studies comparing the RS-BGPs from NASA and ESA sources. For data produced after 2014, ESA offers increased spatial resolution (300m) for most vegetation-related products compared to NASA MODIS. This may be relevant for GBCIs that require finer spatial detail. With regards to temporal resolution, in most variables the MODIS products are superior in comparison with the SPOT/PROBA-V, offering daily, weekly or bi-weekly revisit times, while

[5] https://geobon.org/ebvs/what-are-ebvs/

ESA offers products in several cases only once every 10 days. Regarding the important Global Forest Cover Change (GFC) variable, which several current GBCIs are based on, NASA has currently the superior offer, based on LANDSAT land cover data (Hansen et al. 2013). The ESA CGLS could potentially offer even a superior product by exploring the Sentinel dataset, with higher spatial and temporal resolution than the Landsat platform. A demonstration tree cover Sentinel product has been produced, now currently only for the African continent[6]. Indeed, the fractional vegetation cover, on from which GFC is based, produced by SPOT/PROBA-V should already be explored in place of the MODIS VCF. Also in the related Land Cover (LC) variable the CGLS product shows similar temporal and spatial resolution in relation to MODIS, but wider coverage (1992 - present). Currently, no global products for Evapotranspiration (ET) are offered within the ESA platforms on the CGLS data portal. However, some initiatives exist to estimate this key physiology-related variable, such as the Sentinels for Evapotranspiration[7] which promises high-resolution (tens of meters) global evapotranspiration maps. In addition, prototype maps of evapotranspiration have been produced using PROBA-V data, which are expected to be produced on a daily temporal resolution[8]. Lastly, ice monitoring is crucial due to the vulnerability of the adapted species to climate change. In this category, both NASA and ESA products are offered, with the MODIS variant having higher spatial resolution (1 km) in comparison to the 12,5 km from SMOS. Improved ice products could also be produced by the Cryosat platform, which is based on active Synthetic Aperture Radar (SAR) technology, having also great potential for land application.

[6] http://2016africalandcover20m.esrin.esa.int/
[7] http://esa-sen4et.org
[8] https://proba-v-mep.esa.int/success-stories/evapotranspiration-estimation-based-proba-v

Table 1. Selected bio-geophysical products (BGP) from current global, freely available remote sensing platforms, relevant for the development of Essential Biodiversity Variable indicators, as well as examples of DGVM studies which used these products.

Product	Provider	Platform	Acquisition Period	Temporal Resolution	Spatial Resolution (km)	DGVMs with integration (Copernicus in bold)
Albedo (A)	NOAA	AVHRR	1981 - present	Daily	1	INCCA [1], JSBACH [32], LPJmL [8]
	NASA	MODIS	2000 - present	Daily	0.5	
	ESA	PROBA-V/SPOT	1998 - present	10 Days	1	
Leaf Area Index (LAI)	NOAA	AVHRR	1981 - present	Daily	1 km	LPJ [2][3], DALEC2 [4], CLM [5], ORCHIDEE [30], JeDi [31]
	NASA	MODIS	2000 - present	4 Days	0.5	
	ESA	PROBA-V/SPOT	1999 - present	10 Days	1 (0.3 after 2014)	
fAPAR	NOAA	AVHRR	1981 - present	Daily	1 km	LPJ [6][8][13][38], LPX [6], ORCHIDEE [7], CCDAS/BETHY [9][10][11], CCDAS/JSBACH [12]
	NASA	MODIS	2000 - present	4 Days	0.5	
	ESA	PROBA-V/SPOT	1999 - present	10 Days	1 (0.3 after 2014)	
Vegetation Indices (VI)	NOAA	AVHRR	1981 - present	Daily	1 km	ORCHIDEE [14], VEGAS [33], OCN [33], LPJ [33], JULES [33], CLM4.5 [33] SEIB-DGVM [34]
	NASA	MODIS	2000 - present	16 Days	0.25	
	ESA	PROBA-V/SPOT	1999 - present	10 Days	1 (0.3 after 2016)	
Temperature (T)	NASA	MODIS	2000 - present	5 minutes	1	ORCHIDEE [30]
	ESA	PROBA-V/SPOT	1998 - present	Hourly	5	
Vegetation Continuous Fields/Global Forest Cover Change (VCF/GFCC)	NASA	LANDSAT	2000 - present	Yearly	0.03	JSBACH [32]
	ESA	-	-	-	-	
Land Cover (LC)	NASA	MODIS	2001 - present	Yearly	0.5	CanESM2 [39][40], GFDL-ESM2G [39][40], HadGEM2-ES [39][40], Inmcm4 [39][40], IPSL-CM5A-MR [39][40],
	ESA	MERIS, PROBA-V, SPOT-VGT, AVHRR	1992 - 2015	Yearly	0.3	

Product	Provider	Platform	Acquisition Period	Temporal Resolution	Spatial Resolution (km)	DGVMs with integration (Copernicus in bold)
						MIROC-ESM [39][40], MPI-ESM-LR [39][40], LPJ [15], ORCHIDEE [30][37], JULES [36][37] JSBACH [37]
Burned Area (BA)	NASA	MODIS	2000 - present	Monthly	0.5	LPJ [6][15], LPX[6], LPJmL [8], JSBACH-SPITFIRE[18][35]], JULES [16][35], ORCHIDEE [17][30][35], CLM-DGVM [19][35][41], CTEM [20][35], LPJ-GUESS-SPITFIRE [21][35], LPJ-GUESS-SIMFIRE-BLAZE [22][35]
	ESA	PROBA-V	2014 - present	10 Days	0.3	
Evapotranspiration (ET)	NASA	MODIS	2001 - present	8 Days	0.5	ORCHIDEE [30]
	ESA	-	-	-	-	
Net Primary Production (NPP)	NASA	MODIS	2001 - present	Yearly	0.5	LPJ [6][33], LPX [6], HYBRID [23], JeDi [23][31], JULES [23][33], LPJmL [23][24], ORCHIDEE [23][30], SDGVM [23], VISIT [23], CLM [5][33], VEGAS [33], OCN [33]
	ESA	PROBA-V/SPOT	1999 - present	10 Days	1 (0.3 after 2014)	
Fractional Vegetation Cover (FVC)	NASA	MODIS (VCF)	2001 - 2017	Yearly	0.25	LPJ [6], LPX [6], LPJmL [8]
	ESA	PROBA-V/SPOT	1999 - present	10 Days	1 (0.3 after 2016)	
Chlorophyll Fluorescence (SIF)	NASA	-	-	-	-	TRIF-FID [25], LPJ [25], LPJ-GUESS [25], CLM4-CN [25],
	ESA	METOP-GOME2/GOSAT-FTS	2009 - present	3 Days	0.5	

Product	Provider	Platform	Acquisition Period	Temporal Resolution	Spatial Resolution (km)	DGVMs with integration (Copernicus in bold)
	ESA	SMOS	2010 - present	Daily	30-50	ORCHIDEE [25], OCN [25], SDGVM [25], VEGAS [25], BETHY/SCOPE [26], ORCHIDEE [27], JSBACH [28]
Ice Extent (IE)	NASA	MODIS	2001 - present	Daily	1	LPJ [29], ORCHIDEE [30]
	ESA	SMOS	2010 - present	Daily	12.5	
Carbon stock / Biomass (C)	ESA BIOMASAR-2	Envisat/ASAR (boreal and temperate, (Thurner et al. 2014)) + NASA ICESat GLAS LiDAR and MODIS and others (tropics)	early 2000s - 2010	-	0.5-1	CanESM2 [39][40], GFDL-ESM2G [39][40], HadGEM2-ES [39][40], Inmcm4 [39][40], IPSL-CM5A-MR [39][40], MIROC-ESM [39][40], MPI-ESM-LR [39][40], TRIF-FID [25], LPJ [25], LPJ-GUESS [25], CLM4-CN [25], ORCHIDEE [25], OCN [25], SDGVM [25], VEGAS [25], DALEC2 [4], ORCHIDEE [30]
	ESA GlobBiomass	Envisat/ASAR, ALOS PALSAR and Landsat	2010	-	0.15	
	NASA	NASA ICESat GLAS LiDAR and MODIS (only tropics) (Baccini et al. 2012)	2003-2014	Yearly	0.463	

Model References:
[1](Bala et al. 2007); [2] (Lucht et al. 2002) [3] (Schroder and Lucht 2003) [4](Bloom and Williams 2015) [5] (Randerson et al. 2009), [6] (Kelley et al. 2013), [7] (Ciais et al. 2005) [8] (Forkel et al. 2014) [9] (Kaminski et al. 2013) [10] (Kato et al. 2013) [11] (Knorr et al. 2010) [12] (Schürmann et al. 2016) [13] (Smith et al. 2008) [14] (Maignan et al. 2011) [15] (Poulter et al. 2015) [16] (Mangeon et al. 2016) [17] (Yue et al. 2015) [18] (Lasslop, Thonicke, and Kloster 2014) [19] (Li, Zeng, and Levis 2012) [20] (Melton and Arora 2016) [21] (Lehsten et al. 2016) [22] (Knorr et al. 2014), [23] (Thurner et al. 2017), [24] (Schaphoff et al. 2018), [25] (Parazoo et al. 2014), [26] (Norton et al. 2018), [27] (MacBean et al. 2018), [28] (Thum et al. 2017), [29] (Sitch et al. 2007) [30] (Guimberteau et al. 2018), [31] (Pavlick et al. 2013), [32] (Brovkin et al. 2013) [33] (Rafique et al. 2016) [34] (Sato, Itoh, and Kohyama 2007) [35] (Forkel et al. 2018) [36] (Harper et al. 2018), [37] (Hartley et al. 2017), [38] (Forkel et al. 2015), [39] (Carvalhais et al. 2014) [40] (Yang et al. 2018) [41] (Rabin et al. 2018)

The remote sensing data currently used by the GBCI is based on the MODIS and the Landsat platforms, often in combination with the PREDICTS meta-analysis (Newbold et al. 2015) to assign environmental scores to resulting land-use classes. The MODIS sensor (Moderate Resolution Imaging Spectrometer, on board the NASA Terra and Aqua satellites) has been producing widely used products or satellite-based estimates such as fAPAR (fraction of Absorbed Photosynthetically Active Radiation), NPP (Net Primary Production), GPP (Gross Primary Production), VCF (Vegetation Continuous Fields), ET (Evapotranspiration), LST (Land Surface Temperature) at spatial and temporal resolutions between 1- 0.250 km. Higher spatial resolution products (30 meters) have been produced using the Landsat satellite program, allowing the monitoring of EBVs with higher spatial detail. The Global Forest Cover Change dataset, developed by Hansen et al. (2013) based on Landsat archives and is used extensively in the GBCI (Table 2).

Table 2. Essential Biodiversity Variables (EBV), Global Biodiversity Change Indices (GBCI) and their related Remote Sensing Bio-Geophysical Products (RS-BGP).

EBV Class	EBV Candidate	GBCI	RS-BGP used in GBCI	Alternative Copernicus RS-BGP	Potential Copernicus RS-BGP
Genetic composition	Co-ancestry	-	-	-	-
	Allelic diversity	-	-	-	-
	Population genetic differentiation	-	-	-	-
	Breed and variety diversity	-	-	-	-
Species populations	Species distribution	SHI, BHI, SPI, LBII, SSII	VCF/GFCC (MODIS and Landsat)	FCV, LC (PROBA-V/SPOT)	FCV, LC (Sentinel)
	Population abundance	LBII	VCF/GFCC (MODIS and Landsat)	FCV, LC (PROBA-V/SPOT)	FCV, LC (Sentinel)
	Population structure by age/size class	-	-	-	-
Species traits	Phenology	-	-	FCV, VI (PROBA-V/SPOT)	VI (Sentinel), SIF (FLEX)
	Morphology	-	-	-	-
	Reproduction	-	-	-	-
	Physiology	-	-	fAPAR, SIF, VI, ET, LAI	VI (Sentinel), SIF (FLEX)
	Movement	-	-	-	-
Community composition	Taxonomic diversity	PARCI, LBII, SSII	VCF/GFCC (MODIS and Landsat)	FVC (PROBA-V/SPOT)	VI (Sentinel), SIF (FLEX)
	Species interactions	-	-	-	-
Ecosystem function	Net primary productivity	GERI	VCF/GFCC (MODIS and Landsat), NPP, LAI, T, A (MODIS)	NPP, LAI, T, A (PROBA-V/SPOT)	NPP, LAI, T, A (Sentinel), SIF (FLEX)
	Secondary productivity	-	-	-	-
	Nutrient retention	-	-	VI, SIF (GOME2)	VI (Sentinel), SIF (FLEX)

	Disturbance regime	-	-	GFCC, BA (PROBA-V/SPOT)	BA (Sentinel)
Ecosystem structure	Habitat structure	-	-	LAI, FVC, (PROBA-V/SPOT), IE (SMOS), C (BIOMASAR)	Tree Height (SAR, Lidar), FVC (SAR Sensors), C (BIOMASS)
	Ecosystem extent and fragmentation	SHI, BHI, PARCI, GERI	VCF/GFCC (MODIS and Landsat)	FVC, LC, IE	FCV, LC (Sentinel)
	Ecosystem composition by functional type	-	-	-	-

In order to expand the range of monitored EBVs (and to possibly improve the data quality of the current ones), current GBCI could be complemented with datasets from the European Space Agency´s Copernicus programme. The Copernicus Earth observation system[9], funded by the European Commission, provides global, freely available EO data from space, ground, sea and airborne platforms from low (~1 km) to high (<0.1 km) resolutions. The system currently provides 10 regular RS-BGPs of land properties, 3 datasets of energy, 3 on the Cryosphere and 4 on Water, which can be accessed in the Copernicus Global Land Service (CGLS[10]), part of the Copernicus Land Monitoring System (CLMS). Relevant platforms for the production of Copernicus RS-BGPs are PROBA-V/SPOT-Vegetation and ENVISAT/MERIS. However, the main backbone of Copernicus is the Sentinel constellation and especially the Sentinel 2A/B satellites for land monitoring, which are at the cutting edge of multispectral imaging technology providing information in 13 spectral bands at a spatial resolution up to 10 m every 10 days (at the equator). These features entail a significant improvement with regard to those provided by Landsat. In spite of this, almost no Sentinel data is currently used for the production of the RS-BGP offered in CGLS. In addition, upcoming Earth Explorer missions, especially tailored satellites for specific environmental variables, have large potential to generate significant RS-BGP.

Dynamic Global Vegetation Models and their integration with remote sensing

Although remote sensing datasets are able to provide large scale estimates of several biological properties such as vegetation productivity, the monitoring of most proposed EBVs from remote sensing (or field data due to spatial and temporal scale constraints) alone is understood to be unfeasible (Pereira et al. 2013; Pettorelli et al. 2016). The use of DGVMs (consisting of processes anchored in ecophysiological and ecological theory) can contribute in to this regard, by producing higher order biological information (e.g. Plant Functional Type (PFT) composition, plant functional trait distributions, and in some models, tree density and size structure, PFT-specific effects of disturbances such as fires) nutrient retention, taxonomic diversity) from limited extent (field) or simple (EO) data (Quillet, Peng, and Garneau 2009; Scheiter, Langan, and Higgins 2013).

In order to produce reliable projections, DGVMs ideally require ample amount of observational data for testing and calibration (Sellers et al. 1995; Dietze, Lebauer, and Kooper 2013), which should be ideally available for the targeted ecological variable at suitable spatial and temporal scales. Although field measurements are commonly used to validate DGVMs and to derive hypothesis for the mechanisms underlying an observed pattern or response (e.g. Medlyn et al., 2015; B. Smith et al., 2014), their acquisition cost and limited spatial extent constrain their effectiveness for most applications. Therefore other data sources such as remote sensing have been used to supply model data demands (Plummer 2000; Kelley et al. 2013).

[9] http://www.copernicus.eu
[10] https://land.copernicus.eu/global/

The use of remote sensing data to evaluate DGVMs is the most common form of RS-model integration, which seek as a rule to increase the confidence level of model results. Model evaluation, validation or benchmarking, of similar methodological nature and standard in most modelling approaches, involve the use of an independent dataset to test the model´s accuracy, using various error estimation methods (Plummer 2000; Zhu et al. 2015; Ito et al. 2017; Thurner et al. 2017) . Remote sensing is for this process an important data source. Variable datasets are commonly used in validation in a time series, in which past data is used to input the model and recent data as comparison dataset. In addition to measuring the performance of a single model, remote sensing data has also been used as a benchmark in order to compare different models, an increasingly popular approach (Dietze, Lebauer, and Kooper 2013; Dietze et al. 2014; Keenan et al. 2012; Kelley et al. 2013). Another model evaluation approach is to compare emergent relationships between vegetation, climate and socio-economic predictor variables and a DGVM output variable, here burned area, between satellite observations and DGVMs (Forkel et al. 2018).

Driving DGVMs with remote sensing data increases the accuracy at which the characteristics of the land surface are captured by the models (Plummer 2000). Examples include driving a model with satellite measurements of FPAR, the fraction of incoming photosynthetically active radiation absorbed by vegetation, or satellite-derived estimates of tree density to better capture carbon forest carbon balance (Smith et al. 2008), whereby FPAR and tree density are commonly simulated by DGVMs without such constraints; constraining the Gross Primary Productivity (GPP) simulated by DGVMs with measurements of solar-induced chlorophyll fluorescence from the Greenhouse Gases Observing SATellite (GOSAT) (Parazoo et al. 2014). In order to eliminate atmospheric effects, biases due to sensor characteristics and to increase temporal resolution, the use of multiple remote sensing sources is preferred, in a combined dataset (Marchetti, Soille, and Bruzzone 2016). The inclusion of Copernicus products in dataset production represents therefore a significant advantage.

With the increasing relevance of RS-Model integration came relevant studies in which data and simulations were “fused” (i.e. integrated), making model calibration, evaluation, testing and structural improvement using external data essential components of simulations (Williams et al. 2009). In model-data fusion (MDF), model parameters are changed within each model-data interaction according to the reference data, providing increased data-model output fits (Keenan et al. 2011). The MDF concept is also be considered by authors to be congruent in its whole or in parts with “data assimilation” or “data-model synthesis” (Scholze et al. 2017; Keenan et al. 2011). One prominent example is the model-integration approach described by (Forkel et al. 2014) in which land cover, tree cover and burnt area data from remote sensing was included as prescription data to constrain the model simulations, and FAPAR, albedo and GPP used as optimization or evaluation data for the LPJmL DGVM. A structure of this model-data integration approach can be seen in Figure 1 of M. Forkel et al. (2014). In addition, recent multi-model initiatives have increased the demand for unified driving and benchmarking remote sensing products, for example the FireMIP (Fire Modeling Intercomparison Project), which is one of the few recent approaches to use a Copernicus RS-BGP (Burned area RS-BGP from MERIS) (Forkel et al. 2018).

The potential of current RS-BGP and DGVMs for the development of EBV indicators

Considering the improvement of the current EBV monitoring capabilities, RS-BGPs, DGVMs and their MDF implementations can be used to enhance existing GBCIs. The EO-constrained or calibrated DGVMs can be used to estimate variables that cannot be directly or accurately measured with RS technology, such as soil carbon content, nutrient retention, timber production, crop yields and carbon fluxes. This can be achieved by:

The use of existing RS-BGPs to develop GBCIs

The current global, freely available RS product portfolio allows us potentially to observe the historical change of more than 35 years' worth of biodiversity data daily within a minimum 1 km resolution, and keep monitoring. However, although RS-BGPs from the ESA CGLS prove similar or in some cases superior to their NASA/NOAA counterparts, they have been poorly explored by both the DGVM and GBCI developers. To our knowledge, the few studies using data from Copernicus sources for evaluating DGVMs used MERIS products related to burnt area (Forkel et al. 2018), FAPAR (Smith et al. 2008; Forkel et al. 2015) and Land Cover (Guimberteau et al. 2018; Hartley et al. 2017; Harper et al. 2018; Carvalhais et al. 2014; Yang et al. 2018). In addition the GOME2/GOSAT solar induced fluorescence product from the ESA contributing mission portfolio was also used in a DGVMs (Parazoo et al. 2014), as well as models which used in the CMIP5 project (Carvalhais et al. 2014; Yang et al. 2018) biomass maps (BIOMASAR, (Thurner et al. 2014)) developed from the ESA ASAR sensor aboard the ENVISAR.

For the previously covered 5 EBVs by the GBCI, further datasets are also available from both NASA and Copernicus, offering great potential for improvement in the current indices. Considering that the most extensively used RS-BGP in GBCIs was the Global Forest Cover Change product, it is unfortunate that a similar one is not available from the ESA CGLS, especially considering the superior characteristics of Sentinel sensors in comparison with current or even planned Landsat missions.

Table 2 shows the relationship of the expert-agreed EBVs with the available GBCI and RS-BGP. It shows that existing RS-BGP could cover four more EBVs, besides the 5 already implemented by GBCI: Phenology, e.g. through the analysis of vegetation index (VI) time series (N. MacBean et al. 2015); Nutrient retention, also based on VI datasets (Chambers et al. 2007); Disturbance regime, more specifically burned area (Chuvieco et al. 2016, 2018); and Habitat structure, using leaf area index (LAI) or vegetation continuous fields (VCF) (Myneni 1997; Saatchi et al. 2008; Sexton et al. 2013a).

GBCIs from DGVM outputs

DGVMs directly simulate or can contribute to estimating almost all EBV candidates concerning ecosystem function and structure (Table 3, except secondary production, which can however be covered by a General Ecosystem Model (Harfoot et al. 2014)), in particular NPP; nutrient retention (but mostly regarding the nitrogen (Wärlind et al. 2014; Smith et al. 2014) and the phosphorus (Wang, Law, and Pak 2010) cycles); several outputs from the disturbance category, most notoriously fire; habitat structure (representing significant improvement in relation to remote sensing platforms due to the geometric representation of vegetation, which in some models is based on tree individuals (e.g. Smith et al., 2014)); ecosystem extent (considering biome limits and their shifts due to edaphic and climatic factors); and composition by functional type, which is a very common approach within DGVMs to group species, and thus is a standard output.

Considering species and trait EBV classes, at the functional level also some of the species traits EBV candidates are well represented, in particular phenology and general aspects of plant physiology. These change dynamically in some DGVMs that focus on representing trait variability (within PFTs, (Scheiter, Langan, and Higgins 2013; Sakschewski et al. 2014), whereby the most successful and dominant trait combinations are filtered via ecological sorting. DGVMs that are individual-based for trees (Medvigy et al. 2009; Smith et al. 2014) also capture species population EBV candidates (population abundances and population age/size structure) for trees (Fischer et al. 2016), in a DGVM parameterized for Europe also for main tree species (Hickler et al. 2012). Due to their integration with remote sensing, DGVM often produce similar global outputs as RS-BGP, also for benchmarking purposes, but could offer outputs with significant advantages in relation RS-BGP alone or with simpler empirical models. Estimates of NPP for instance, are based on empirical models for RS-BGPs, while more complex process- and ecological theory- based methods are inherent to DGVMs, which also account for soil hydrology and nutrient limitation (Smith et al. 2014). These could alternatively be included directly within a RS-BGP workflow in order to produce superior products. Recent DGVM developments also include higher trophic levels (EBV secondary productivity), such as wild ungulates in Africa (Pachzelt et al. 2015) and livestock (Chang et al. 2013). Another interesting approach in this regard is the Madingley general ecosystem model, which has been developed to capture primary and secondary productivity, including the population densities of heterotroph functional types, across the world oceans and terrestrial ecosystems (Harfoot et al. 2014).

Table 3. Essential Biodiversity Variables and DGVM outputs with potential to estimate indicators.

EBV Class	EBV Candidate	DGVM output	Model References
Ecosystem function	Net primary productivity	NPP	*See NPP in Table 1.*
	Secondary productivity		Madingley Model (GEM)
	Nutrient retention	N cycle, P cycle	LPJ-GUESS (Wärlind et al. 2014; Smith et al. 2014), CASACNP (Wang, Law, and Pak 2010)
	Disturbance regime	Fire-related outputs	*See Burned Area (BA) in Table 1.*
Ecosystem structure	Habitat structure	fractional vegetation cover, leaf area index	*See FVC,VCF/GFCC and LAI in Table 1.*
	Ecosystem extent and fragmentation	Area of Ecotype/Biome	*See LC in Table 1, LPJ* (Hickler et al. 2012)
	Ecosystem composition by functional type	species/functional diversity attributes	*Common approach within almost all DGVMs*

Future developments in remote sensing and DGVM for EBV indicator output

The current lack of means/tools/data to monitor EBVs indicators presented in this review (of available RS-Model methods) suggests that there is a great and urgent demand for producing regional to global RS-BGP for the monitoring of biodiversity, due to the current lack of indicators for most EBVs. Fortunately, a wealth of global, freely available remote sensing data, is available to fill this gap, and more importantly to provide data streams for models. The potential for the development of new RS-BGP from existing globally freely available datasets is large, in special due to the data offer from the Copernicus platform. For example, Sentinel-2 high resolution multispectral optical data could be used to produce improved versions of MODIS and PROBA-V BGPs, and water acidification measures from space could be extremely invaluable as a GBCI (Widdicombe and Spicer 2008). Also, Synthetic Aperture Radar (SAR) data from various platforms, as well as the recently launched NASA GEDI lidar, could be used to develop habitat structure BGP. Diversity measures from space are also within reach, at least on a functional level (Goodenough et al. 2002; Clark, Roberts, and Clark 2005; Asner et al. 2011), with the use of hyperspectral sensors such as EnMAP and Hyperion. One noteworthy program for EBV monitoring which is carried out by ESA is the Earth Explorers. The Earth Explorer missions are invaluable for the monitoring of biodiversity since they are tailored made for the generation of BGPs, such as Biomass and SIF.

The integration of EO data and DGVMs and other process-based models (see below), making more use of Copernicus products than so far, can improve EBV estimates substantially and enhance the EO data. The common reliance on the PFT approach limits the capabilities of DGVMs in covering species and genetic EBV candidates. However the DGVM developments concerning trait variability changes may prove invaluable for better representations of plant diversity and EBV monitoring. The adaptive DGVM (Scheiter, Langan, and Higgins 2013; Scheiter and Higgins 2009) intrinsically also captures evolution and genetic differences between woody individuals (at the PFT level) via their associated phenotypes. Apart from DGVMs, other process-based models may also provide support in monitoring EBVs. For instance, non-DGVM individual-based models represent and simulate the properties (size, age, growth rate) and interaction of individuals (competition for resources, mutualisms), allowing for a bottom-up understanding (e.g. local and regional scale biomass) of populations and communities of plants and animals (DeAngelis and Grimm 2014; Grimm et al. 2006).

Finally, one of the most significant values of understanding the current change in biodiversity is being able to estimate the future states (Sitch et al. 2008; Scheiter and Higgins 2009). For projections of ecosystem properties, DGVMs are particularly suitable, and have been applied extensively especially in relation to climate change scenarios, driven mainly by increases in CO2 concentrations and temperature. In this regard, model intercomparison projects (MIPs) have been carried out to evaluate, with extensive use of remote sensing, how different models project environmental change in relation to e.g. increases in CO2 (Ito et al. 2017). Likewise, MIPs could also be applied to EBV-related model outputs, with remote sensing support, to test how various models predict changes in biodiversity.

This study represents a call for action for the modelling community to produce outputs in accordance to the EBV requirements and in line with the GBCI approach. We also advocate a closer integration among RS and DGVM scientific communities. Such integration is also important to improve the reliability of future projections by DGVMs, e.g. as an important tool to assess climate adaptation and mitigation activities.

Abbreviations

EBV: Essential Biodiversity Variable

DGVM: Dynamic Global Vegetation Model

GBCI: Global Biodiversity Change Indicator

- SHI: Species Habitat Index
- BHI: Biodiversity Habitat Index
- SPI: Species Protection Index
- PARC: Protected Area Representativeness & Connectedness Index
- LBII: Local Biodiversity Intactness Index
- GERI: Global Ecosystem Restoration Index
- SSII: Species Status Information Index

RS-BGP: Remote Sensing Bio-Geophysical Product

- A: Albedo
- LAI: Leaf Area Index
- FPAR: Fraction of Absorbed Photosynthetically Active Radiation
- VI: Vegetation Indices
- T: Temperature
- GFC: Global Forest Change
- LC: Land Cover
- BA: Burned Area
- ET: Evapotranspiration
- NPP: Net Primary Production
- FVC: Fraction Vegetation Cover
- SIF: Solar Induced Fluorescence
- IE: Ice Extent

MDF: Model-Data Fusion

PFT: Plant Functional Type

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Appendix

Table A1. Studies comparing NASA/NOAA and ESA (Copernicus) Remote Sensing Bio-Geophysical Products (RS-BGP). Italic are NASA/NOAA and Bold are ESA products. Underlined are mixed (NASA/NOAA+ESA) products.

Product	Comparison	Results	Reference
Albedo	*MODIS* and **PROBA -V** albedo and direct validation using ground observations	• PROBA-V and MODIS C6 achieved a good agreement (RMSE ca. 0.03)	Roujean et al. (2018)
FAPAR	*MODIS*, **CYCLOPES (SPOT-VGT), JRC** *(SeaWifs)*, **and GLOBCARBON (SPOT-VGT)** over Northern eurasia for the year 2000.	• Products achieved similar results in deciduous broadleaf forests and croplands. • Low agreement found in needleleaf and mixed forests and grassland/shrublands. • MODIS and CYCLOPES reached high FAPAR values. • JRC and GLOBCARBON results were similarly low.	McCallum et al. (2010)
	MODIS, **MERIS**, *SeaWIFS*, *MODIS-TIP*, **SPOT-VEG**, *AVHRR* across Australia	• High agreement among products was found in savanna/ grassland, shrubland and managed land (agricultural land) biomes. • Low agreement was found in forest biomes.	Pickett-Heaps et al. (2014)
LAI/ FAPAR	*MODIS*, Formosat, **GEOLAND-2(SPOT-VGT)** and in situ measurements over crops in southwest France	• Results from all products were in good agreement with a significant positive correlation. • Uncertainty LAI: 0.35 • Uncertainty FAPAR: 0.07	Claverie et al. (2013)
FCOVER/ LAI/ FAPAR	The spatial and temporal consistencies of GEOV1 products (**FCOVER, LAI, FAPAR using SPOT-VGT**: GEOLAND2 project) were assessed by intercomparison with reference global products (*MODIS c5*, **CYCLOPES v3.1 (SPOT-VGT)**, GLOBCARBON v2 LAI **(SPOT-VGT, ENVISAT/AATSR)**, and JRC *SeaWIFS* FAPAR)	• GEOV1 products presented good performances. • GEOV1 products achieved higher quality in comparison with the reference products used in the study. • GEOV1 products had a lack of spatio-temporal continuity (e.g. over high latitudes and equatorial regions).	Camacho, Cernicharo, Lacaze, Baret, & Weiss, (2013)
FCOVER	**GEOV1 Fractional Vegetation Cover, FVC (SPOT-VGT)**	• FVC was overestimated in croplands (0.20).	Mu et al., (2015)
LAI	*ECOCLIMAP (NOAA/AVHRR)*, **GLOBCARBON (SPOT-VEG)**, **CYCLOPES (SPOT-VEG)**, and *MODIS*.	• Results were more similar over croplands and grasslands than forests. • ECOCLIMAP was the only product with no spatiotemporal gaps.	Garrigues et al. (2008)

Product	Comparison	Results	Reference
NDVI	*GIMMS (from AVHRR)* and *MODIS NDVI*	• The trends of GIMMS NDVI were in overall agreement with MODIS NDVI data except for artic areas in Northern Hemisphere and South America and Australia in Southern Hemisphere.	Fensholt & Proud, (2012)
LST	*EOS-MODIS MOD11_L2/MYD11_L2 LS*	• The M*D11_L2 product achieved lower uncertainty. • Underestimation of ca. −0.15 K was observed with uncertainty values ± 2K in a rice crop and a Mediterranean shrubland.	Niclòs, Valiente, Barberà, & Coll (2015)
Land Cover	**ESA CCI (ENVISAT MERIS, ASAR/ SPOT-VGT), GLC2000 (SPOT-VGT), GlobCover (ENVISAT MERIS),** GlobeLand30 (*Landsat* and HJ-A1/B: Chinese), *MCD12Q1*, GLC SHARE (global land cover products FAO, LCCS) IIASA IFPRI Cropland Maps (global land cover products and national statistics), GFSAD Crop Extent for Africa (Landsat 8 and Sentinel 2) in five Sahelian countries	• ESA CCI 2013, MODIS 2013 and GlobCover 2009 outperformed GLC2000. • GFSAD30 and GLOBELand30 obtained the best accuracy in croplands. (GFSAD30: 64.19% and GlobeLand30: 68.89%). • ESA CCI and MODIS achieved best accuracies in mixed crops. • All products reported accuracies lower than 75%. • All products overestimated cultivated areas (i.e. 170% on average).	Samasse et al. (2018)
	FAO-GLCshare (FAO Global Land Cover Network), Geowiki Hybrid-1 IIASA (MODIS, SPOT4, MERIS), **GLC2000-JRC (SPOT-4/VGT**), *GLCNMO v2-ISCGM (MODIS)*, GlobeLand30 (*Landsat TM/ETM7*, and HJ-A1/B: Chinese), **GlobCover 2009 (MERIS), LC-CCI 2010 (MERIS, SPOT-VGT), LC-CCI 2015-ESA(MERIS, PROBA-V, SPOT-VGT, AVHRR),** and *MODISLC 2010* (*MOD12Q1 v051*).	• Results were substantially different among products. • FAO-GLCshare and GlobeLand30 were the most suitable datasets to monitor croplands, • LC-CCI2010 overestimated cropland areas in Africa. • GLC2000 reported low accuracy.	Pérez-Hoyos, Rembold, Kerdiles, & Gallego, (2017)
	Corine Land Cover (CLC) and ESA CCI (LUCAS Land use dataset as ground truth) implications for fire modelling	• CCI-LC reached a higher agreement with LUCAS than CLC: 59% and 56%, respectively. • In terms of wildfire occurrence estimation: - Both datasets performed similarly at European scale. - CLC provided better results at local scale.	Vilar, Garrido, Echavarría, Martínez-Vega, & Martín, (2019)
BA	*FireCCI50* (MODIS) and **FireCCI41 (MERIS),** *GFED4* and *MCD64A1*	• Temporal and spatial trends were consistent among compared products. • FireCCI50 detected small fire patches better than previous versions.	Chuvieco et al. (2016)

Product	Comparison	Results	Reference
	<u>Hybrid product using MERIS and MODIS product (ESA_FIRE_CCI project)</u> compared with existing *MODIS Burned Area (BA) products*	• MERIS BA accuracy was in line with MODIS BA products (MCD45 and MCD64) (overall accuracy higher than 0.99). • MERIS, GEFD v4 and MCD45 achieved high agreement (r^2 > 0.99). • Seasonal trends between BA MERIS and existing products were similar (e.g. magnitude through temporal series).	Alonso-Canas & Chuvieco, (2015)

Workflow example

Figure A 1 shows the workflow developed within the WP4 task 4.5 to generate model inputs from the ESA Climate Change Initiative Land Cover product (ESA CCI LC). This workflow produces fractional land cover and averaged values of each fractional land cover class of interest per region. 24 rasters were used to obtain information about temporal land cover changes that inform about the EBV ecosystem structure.
Further information available at https://github.com/gomezgimenez/workflow151.git (private repository at the moment; contact details to get access to the code: marta.gomez-gimenez@senckenberg.de or mgomezimenez@gmail.com)

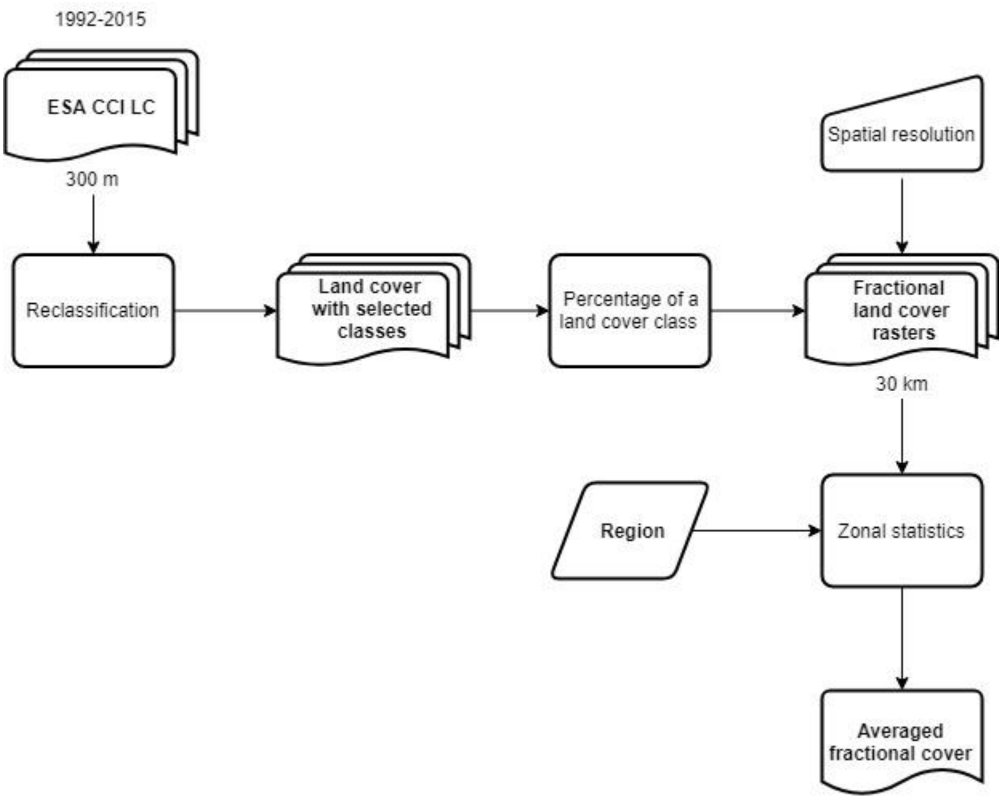

Figure A 1Flowchart of the process carried out to estimate fractional land cover and related statistics.