Satellite Observation Requirements

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I. Table of CONTENT

II. List of Figures

III. List of Tables

Acronyms and Abbreviations

ABT	Aichi Biodiversity Targets
AVHRR	Advanced Very High-Resolution Radiometer
BIP	Biodiversity Indicator Partnership
CBD	Convention on Biological Diversity
CEOS	Committee on Earth Observation Satellites
CI	Conservation International
COP	Conference Of the Parties
DOY	Day Of Year
EBV	Essential Biodiversity Variable
ECV	Essential Climate Variable
EEF	Ecosystem Extent and Fragmentation
EM	Electromagnetic
EMS	Electromagnetic Spectrum
EnMAP	Environmental Mapping and Analysis Program
EO	Earth Observation
EOS	End Of Season
ESA	European Space Agency
EV	Essential Variables
FPAR	The Fraction of Photosynthetically Active Radiation
GBO	Global Biodiversity Outlook
GCOS	Global Climate Observing System
GEO-BON	Group on Earth Observation – Biodiversity Observation Network
GEOSS	Global Earth Observation System of Systems
GPP	Gross Primary productivity
FHD	Foliage-Height Diversity
HISUI	Hyper-spectral Imager SUIte
HR	High Resolution
HyspIRI	Hyperspectral Infrared Imager
ICESat	Ice, Cloud, and land Elevation Satellite
IPBES	Intergovernmental Platform on Biodiversity and Ecosystem Services
IRM	Implementation Road Map
IUCN	International Union for the Conservation of Nature
LAI	Leaf Area Index
LARCH	Landscape Ecological Analysis and Rules for the Configuration of Habitat (model)
LPI	Living Planet Index
LPV	Land Product Validation
LSP	Land Surface Phenology
MCD12Q2	MODIS Land Cover Dynamics Product
MERIS	Medium Resolution Imaging Spectrometer
MODIS	MODerate-resolution Imaging Spectroradiometer
MTCI	MERIS Terrestrial Chlorophyll Index
MW	Microwave
N	Nitrogen
NPP	Net Primary Productivity
NBSAP	National Biodiversity Strategy and Action Plan
NIR	Near-Infrared Region
NPP	Net Primary Productivity
PROBA-V	Project for On-Board Autonom-Vegetation
PSR	Productivity and Species richness Relationship
RD	Reference Documents

RED	Red Edge Position
RS	Remote Sensing
RS-enabled EBV	Remote Sensing enabled Essential Biodiversity Variable
SBG	Surface Biology and Geology
SBI	Subsidiary Body on Implementation
SBSTTA	Subsidiary Body on Scientific, Technical and Technological Advice
SDG	Sustainable Development Goals
SOR	Satellite Observation Requirement
SOS	Start of Season
SRL	Science Readiness Level
SWIR	Shortwave Infrared Region
TIR	Thermal Infrared
TM	Thematic Mapper
TOPC	Terrestrial Observation Panel for Climate
UNE	United Nations Environment
VIS	Visible
VH	Vegetation Height
VS	Vegetation Structure
WGCV	Working Group on Calibration and Validation
WRI	World Resources Institute
WWF	World Wide Fund for Nature

Terminology

Contextual definition of biological, ecological, remote sensing and other terms as used in the document.

Term	Definition
Accuracy	In this document, accuracy is described as the closeness of variable values estimated from remote sensing to *in situ* measurement.
Biodiversity	The variability among living organisms from all sources (including terrestrial, marine and aquatic ecosystems) and the ecological complexes of which they are part, including diversity within and between species and of ecosystems.
Biome	A biome is a specific geographic area where an assemblage of organisms is determined by large-scale climatic and vegetation characteristics. A biome can be made up of many ecosystems.
Biophysical Attributes	A biophysical attribute is a biotic and abiotic component of an ecosystem (e.g., leaf area index, ice-cover, land cover, urban footprint or vegetation height) covering the Earth that incorporates and support biodiversity and has an influence on organisms survival, development, and evolution.
Canopy chlorophyll content (CCC)	The total amount of chlorophyll *a* and *b* pigments in a contiguous group of plants per unit ground area (Gitelson et al., 2005).
Ecosystem	A functional unit or system of the earth's surface that is the whole system including the organisms, the physical factors and their interaction that form the environment (Basu and Xavier, 2016)

Ecosystem fragmentation (EF)	Ecosystem fragmentation is the process by which the division of large, continuous habitats into smaller, more isolated remnants, might result in biodiversity loss
Ecosystem function	Processes related to productivity/respiration (biomass build-up function), decomposition (biomass breakdown function), energy transfer/loss and nutrient cycling in an ecosystem (Myster, 2001).
Ecosystem structure	The minimal pattern of organization necessary for an ecosystem function to operate (Myster, 2001).
Essential Biodiversity variable	A variable that is measurable at particular points in time and space and is essential to document biodiversity change.
Essential Climate Variables (ECVs)	ECVs are "physical, chemical, or biological variables or a group of linked variables that critically contributes to the characterization of Earth's climate (Bojinski et al., 2014).
High spectral resolution	An Earth observation system is assumed having a high spectral resolution if it records spectral information in more than 15 spectral bands.
High spatial resolution	In this document, an Earth observation system is assumed having a high spatial resolution if it has ground (spatial) resolution of ≤ 30 m.
Land surface phenology (LSP)	In this document, satellite-based LSP refers to products which characterize the seasonal shifts in vegetation greenness and photosynthetic activity at the ecosystem scale. It includes metrics such as date of vegetation green-up (start of season), peak of growing season date, date of senescence (end of season) and growing season length (length of season). Phenology metrics are derived from curve-fitting methods applied to vegetation index time-series and therefore my differ between products.. LSP dynamics reflect the response of vegetated surfaces of the earth to seasonal and annual changes in the climate and hydrologic cycle
Physiology	The term 'physiology' is used to refer to photosynthesis activity related products such as NPP and GPP, as well as to the foliar content of chlorophyll, nitrogen and phosphorus.
Satellite observation requirement	The types and detail level of a set of attributes of RS-enabled EBVs that are required by the user community for biodiversity assessment and monitoring.
Prioritization and selection	Prioritization and selection refer to the activities and processes performed to identify and arrange RS-enabled EBVs in order of importance to assess and monitor terrestrial ecosystem structure and function.
Remote Sensing enabled EBVs	EBVs that are directly measurable or derived from Earth observation satellite data.
RS-enabled EBV product(s)	A product or multiple of products obtained through processing remote sensing data that potentially informs about the RS-enabled EBV.
Resolution	The ability of a remote sensing device to detect subtle variation regarding energy (radiometric resolution), space (spatial resolution) and time (temporal resolution).
Satellite RS	Remote sensing (RS) data acquired through earth orbiting satellites.

Scale	The term scale in this document refers to the scope or spatial extent of the RS-enabled EBVs observation but not to the relationship between distance on a map and a corresponding distance on the ground.
Spatial configuration	Two dimensional geographic distribution of land cover patterns
State variables	A set of variables that can be used to describe the "state" of a dynamic system. In the context of a terrestrial ecosystem, state variables are those sets of variables that describe sufficiently the ecosystem to determine its future behavior in the absence of any external forces affecting the ecosystem.
Terrestrial ecosystem	Communities of organisms and their environments that occur on the land masses of continents and islands (Chapin et al., 2002).
Thematic accuracy	The degree to which the non-positional characteristic of a spatial data entity (attributes) derived from radiometric information agree with *in situ* observations.
Vegetation Height	The observable height of vegetation, relative to the ground.
Vegetation structure	A class of EBVs related to the horizontal and vertical abundance of canopy material.

The SOR document overview

A. Purpose

The Group on Earth Observations–Biodiversity Observation Network (GEO-BON), which represents the biodiversity component of the Global Earth Observation System of Systems (GEOSS), is making a coordinated effort together with decision-makers and the scientific community to address the need for a global biodiversity observation network that contributes to effective management of the world's biodiversity and ecosystem services. Such a network will help to compute indicators for assessing the progress towards the 2020 Aichi Biodiversity Targets (ABT) and contribute to initiatives such as the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) regional assessments (GEO-BON, 2017). To improve the detection of significant changes in global biodiversity, GEO-BON is currently adopting the concept of essential variables.

Essential Biodiversity Variables (EBVs) are key variables that help to coordinate worldwide biodiversity monitoring by enabling consistent tracking of changes in the state of biodiversity, and reporting progress towards the Aichi targets. In the last few years, several studies dedicated to the prioritization and specification of EBVs have been undertaken (e.g., Pereira et al., 2013, Skidmore et al., 2015, Pettorelli et al., 2016b). Pereira et al. (2013) introduced 22 EBVs under six classes that include genetic composition, species populations, species traits, community composition, ecosystem structure and ecosystem function.

Skidmore et al. (2015) proposed a number of EBVs that can be directly measured and monitored using remote sensing. Remote sensing (RS) is anticipated to play a significant role, particularly for the effective monitoring of rapidly changing ecosystems that cover extensive areas. In conjunction with *in situ* data, RS imagery, which can be derived from airborne and space-borne sensors, provides vital input for biodiversity assessments and monitoring at a fine spatial resolution and high temporal frequency. However, the potential of remote sensing data in the context of EBVs has not been thoroughly investigated yet.

Against this background, the purpose of the Satellite Observation Requirement (SOR) document is to support the efforts of both space agencies (e.g., ESA) and biodiversity communities (e.g., GEO-BON) in determining and prioritizing the observation requirements of RS-enabled EBVs. It provides a prioritized list of RS-enabled EBVs and their satellite observation requirements for global level biodiversity assessments. It does this by enhancing the utility of freely available high temporal and spatial resolution remote sensing data such as the Copernicus Sentinel-2 and Landsat Earth observation satellites. In particular, it details, through a literature survey and theoretical analysis, the complete portfolio of RS-enabled EBVs required to characterize the structure and function of terrestrial ecosystems. Engineering activities for the definition, specification, benchmarking, prototyping, validation, up-scaling and utility demonstration of RS-enabled EBVs, are expected to benefit from the information reported in this document.

Thus, it is proposed that the document serves as a baseline for the development and engineering of RS-enabled EBVs (ESA, 2016).

Importantly, this document is primarily aimed at supporting the efforts of the Convention on Biological Diversity (CBD) (Secretariat of CBD, 1992), IPBES (Cardinale et al., 2012) and GEO-BON (Scholes et al., 2008), and partners, in generating global knowledge-base characterizing the status and changes in terrestrial ecosystem structure, and function through the use of satellite remote sensing data. Additionally, it aims to benefit space agencies for the future progression of Earth Observation (EO) by identifying the required set of satellite measurements to address key science questions relevant to the assessment and monitoring of the state of biodiversity and change in terrestrial ecosystems. The document further intends to support ecologists, biodiversity conservation and remote sensing scientists' efforts to answer pressing questions concerning the structural, and functional aspects of terrestrial ecosystems, in order to develop adaptation responses to deal with the inevitable impacts of global change. Finally, it intends to make a significant contribution towards the efforts of policy-makers, natural resource managers and decision-makers, to develop and implement biodiversity monitoring policies, strategies and action plans.

B. Scope and objectives

The SOR document contains the overall requirements gathered from a literature review and theoretical analysis and is used as the primary input for all project engineering tasks. One of the major inputs to the SOR is the prioritization and selection of EBVs that can be retrieved globally from remote sensing data. The prioritization and selection process of RS-enabled EBVs within this document is based on the outcomes of a series three biodiversity and remote sensing expert workshops, led by the University of Twente's Faculty of Geo-Information Science and Earth Observation (ITC) Professor Andrew Skidmore, between 2015-2017, and which were concerned with the prioritization exercise and which resulted in a number of publications (e.g., Pereira et al., 2013, Skidmore et al., 2015, Pettorelli et al., 2016b).

The latest RS-enabled EBVs workshop was conducted on 7th and 8th of September 2017 to discuss the criteria need to prioritize existing RS-enabled EBVs proposed in the literature. Following the RS-enabled EBVs prioritization process, the satellite observation requirements of selected RS-enabled EBVs, were documented. The satellite observation requirements of RS-enabled EBVs are the basis for the integration of satellite observations in the development of EBVs.

The scope of the SOR, therefore, encompasses the evaluation of remote sensing-based EBV portfolio requirements and the prioritization and selection of potential remotely-sensed EBVs. The specific objectives, as reflected in the structure of this document, include:

- Review of scientific and policy background relating to terrestrial ecosystem structure, and function;
- Describe the role of EBVs, their relationship to a set of target indicators (CBD Aichi Targets), and how they can be used to monitor the progress of sustainable development goals (SDG) (COP-CBD, 2012);
- Propose a list of priority EBVs to be retrieved from remote sensing that can be used by the biodiversity and remote sensing communities to characterize the structure, and function of terrestrial ecosystems;
- Evaluate the satellite observation requirements by defining all appropriate spatial, spectral and temporal scales needed for biodiversity monitoring;
- Demonstrate the usability of the selected EBVs in terrestrial biodiversity monitoring and assessment;
- Provide adequate input to decision and policymakers as well as the scientific community, for their endorsement of the process of prioritizing and evaluating RS-enabled EBVs.

The portfolio requirement analysis detailed in this document is limited to terrestrial EBVs retrieved by space-borne remote sensing sensors. The prioritization and observation requirement definition process was performed in a hierarchical manner. Firstly, the candidate EBVs proposed for characterizing and monitoring the structure, and function of terrestrial ecosystems, as well as their observation requirements, were defined through a comprehensive literature review and theoretical analysis. Secondly, the prioritized-enabled EBVs and their associated satellite observation requirements were consolidated through a broad consultation of the biodiversity and remote-sensing communities, in a series of expert workshops and open reviews.

C. Reference documents

References used are provided as an Annex.

Part I:

General Background

1.1. Terrestrial ecosystems and biodiversity

Biodiversity is fundamentally a multidimensional concept that can be measured at genetic, species and ecosystem levels. Each of these levels has **compositional**, **structural** and **functional** attributes, which can be considered as the three dimensions or attributes of biodiversity (Hassan et al., 2005). The three attributes are interdependent, interconnected and bounded by the Earth system (Noss, 1990). Hence, the assessment and monitoring of biodiversity involve evaluating, observing, checking the progress of, or quality of, key biodiversity attributes at the genetic, species or ecosystem level. In effect, the search is on for methods to facilitate the rapid and objective assessment and monitoring of biodiversity. Recently, the concept of Essential Variables (EV) (GCOS, 2003) has been adopted by the biodiversity community to unify and standardize biodiversity monitoring using a limited set of variables. These variables are vital to studying, reporting, and monitoring biodiversity change across its three dimensions. Many of the proposed EVs are measurable from satellite remotely sensed data. The following chapter introduces the concept of terrestrial ecosystems and the existing remote sensing approaches, with a particular focus on EVs to measure terrestrial biodiversity.

Ecosystems can be conceptualized as the integration of biotic and non-biotic components in nature. Earth supports an enormous array of natural ecosystems, inhabited by an overwhelming diversity of living organisms on land and in the oceans. Ecosystems can be as extensive as the entire Arctic tundra, or as small as a particle of soil (BAWG, 2009). The cross-scale nature of ecosystems includes ecological processes that operate from centimeters and days to hundreds of kilometers and millennia and collectively affect biodiversity (Vold and Buffett, 2008). They are characterized by their composition, function and structure which in turn depends on the local environment,

Terrestrial ecosystems are communities of organisms and their environments that occur on the landmasses of continents and islands. Terrestrial ecosystems are unique because vegetation acquires resources from three media - air, soil and sun (Chapin et al., 2002). The differences in physical properties between water and air result in fundamental differences in structure and function between aquatic and terrestrial ecosystems (Ditsche and Summers, 2014).

Ecosystems are sometimes referred to as biomes; however, a biome is a specific geographic area where assemblages of organisms are determined by large-scale climatic, geological and vegetation characteristics. Thus, a biome can be made up of many ecosystems. The primary terrestrial biomes are tundra, taiga, temperate deciduous forest, tropical rain forest, grassland, savanna, and desert; it should be emphasized that these biomes often merge in wide transition areas termed ecotones. Temperature ranges, moisture availability, light, topography and nutrient availability determine what types of life are most likely to flourish in a specific terrestrial ecosystem (biome) (Annenberg Foundation, 2017). The major types of terrestrial ecosystems may occur at similar latitudes and altitudes on different continents, as a function of distance from the equator and height above sea level, and parallel variation in temperature, thereby demonstrating the central role that temperature plays in determining the distribution and characteristics of vegetation (Figure 1). Thus, geographical location has a profound impact on ecosystems because global circulation patterns and climate zones set the underlying physical conditions for the organisms that inhabit a given area (Annenberg Foundation, 2017). Terrestrial biodiversity is highest near the equator, where the warm climate that has persisted throughout much of Earth's history has led to high primary productivity and exceptional biodiversity hotspots (Gaston, 2000).

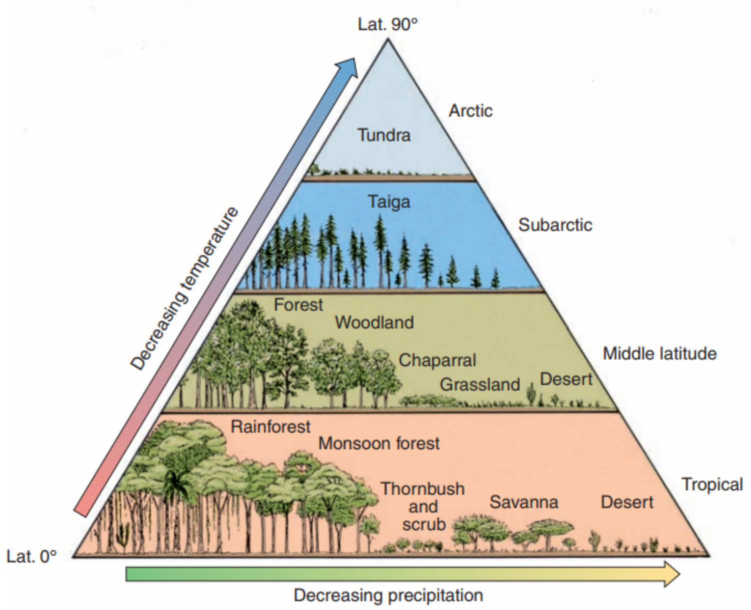

Figure 1: Biome type in relation to temperature and rainfall (Source: http://www.cengage.com)

1.2. Social, economic and environmental benefits of terrestrial ecosystems

Terrestrial ecosystems are intimately linked with human well-being. Ecosystems have economic, recreational, ethical, social, medicinal, aesthetic and spiritual values for human beings. Humans derive a variety of direct economic benefits from harvesting terrestrial ecosystem products. Natural ecosystems provide the settings for a wide range of recreational opportunities including camping, boating, sports fishing, hunting, and hiking. Many people derive enjoyment and comfort from experiencing nature or from merely knowing that minimally disturbed natural ecosystems exist and will be available for future generations to enjoy.

Through their normal functioning, terrestrial ecosystems provide many life-supporting ecosystem services for the planet and help maintain local environmental quality. Terrestrial ecosystems preserve the integrity of the Earth system through regulating carbon monoxide balance and biochemical cycles and promoting absorption and breakdown of pollutants and waste materials through decomposition. They also regulate climate and surface energy balance as well as provide protective services, e.g., by acting as windbreaks or as indicators of environmental changes (GBO-4, 2014, Hassan et al., 2005).

Terrestrial ecosystem preserves ecological processes, such as the fixing and cycling of nutrients, air and water, and soil formation. The act as global regulatory mechanisms maintaining the water balance within ecosystems, watershed protection, keeping streams and rivers flowing throughout the year, as well as controlling erosion and flooding. Food, clothing, housing, energy, medicines, and control of pests and pathogens, are all resources that are directly or indirectly linked to the biological diversity present in the biosphere, which encompasses both terrestrial and marine ecosystems. Ecosystems collectively determine the biogeochemical processes that regulate the Earth's system. For example, the absorption and sequestration of carbon dioxide and the production of oxygen by plants are critical to the global carbon cycle and therefore critical to climate regulation (Hassan et al., 2005). In effect, forests with more than 30% canopy cover are the global epicenter for carbon dioxide conversion into carbon and oxygen (Bharucha, 2005). A review made in 2000 indicated that terrestrial ecosystems absorb approximately 2.3 Gt of carbon per year, or over one-quarter of the human emissions (Malcolm and Pitelka, 2000).

1.3. Causes and consequences of terrestrial biodiversity decline

Despite the fundamental role of biodiversity in the Earth system, human activities are leading to both biodiversity loss and substantial alterations of biodiversity distribution, composition, and abundance (Pereira et al., 2012). Humans have been modifying ecosystems throughout history to improve food availability and decrease the success of their ecological competitors (Gaston, 2000). Most ecologists agree that human society is in the midst of an ecological crisis; the most direct and substantial human alteration of ecosystems is through the transformation of land for production of food, fiber, and other goods. These change processes altered the functioning, structure, and composition of ecosystems as well as the climate, compromising their ability to provide global ecosystem services (Chapin et al., 2002).

An ever-increasing human population has affected and altered natural ecosystems in many ways; for instance, through air and water pollution and other by-products of development, as well as species loss, habitat change, and the introduction of invasive exotic species. Human impacts on the environment, from local to global scales, cause not only a general decline in biodiversity but also predictable ecosystem functional shifts, as sets of species with particular traits are replaced by other species with different traits. Some human activities directly affect ecosystems through resource harvest and land-use change, while the effects of other activities are indirect, and include changes in atmospheric chemistry, hydrology and climate (Vitousek et al., 1997).

Added to these existing pressures on ecosystems comes to a new threat — the potential for rapid warming of the planet under the influence of increasing concentrations of greenhouse gases in the atmosphere, primarily from fossil fuel combustion and deforestation. Climate is a major factor controlling the distribution of species and the functioning of ecosystems (i.e., the characteristic way in which ecosystems modulate flows of energy and materials). As a result, there is widespread concern among scientists and decision-makers over the potential impacts of significant and rapid human-caused climate change on ecosystem functioning and biodiversity.

1.4. Worldwide policies, strategies, and institutes for biodiversity conservation

In order to address the challenges of the biodiversity loss, distribution, composition, and abundance, adequate local, national and international policies need to be adopted and implemented. To achieve this, decision-makers need scientifically rigorous and independent information that takes into account the complex relationships between biodiversity, ecosystem services and humankind. The role of the scientific community is to develop effective methods to collect and interpret data and simultaneously provide decision-makers with the relevant information for decisions to be made.

Therefore, to support the sustainable use and protection of the Earth's ecosystems and biodiversity, and the fair and equitable sharing its services and goods, an intergovernmental agreement among 193 countries was reached with the formation of the Convention on Biological Diversity (CBD) in 1992 at the Rio Earth Summit. The establishment of CBD brought biodiversity center-stage in environmental policy; following the convention, the Subsidiary Body on Scientific, Technical and Technological Advice (SBSTTA) was established in 1994 to provide timely scientific advice on the status of biological diversity as per the requirements of the Convention. Since then, a plethora of regional and international environmental agreements, treaties and protocols aimed at halting the declining biodiversity and ecosystem services and promoting the sustainable use of natural resources and ecosystems have been adopted. Indeed, an estimation for the period between 1857 and 2012 suggest that more than 700 multilateral environmental agreements were adopted (Kim, 2013).

Nations have set clear policy directions on environmental conservation. They developed policies and regulations to protect and conserve the natural environment based on citizen participatory approaches (Chandler et al., 2016). Institutes and Ministries were established to ensure that biodiversity is valued, effectively conserved as well as sustainably used for the economic, environmental and social well-being of present and future generations (Secretariat of CBD, 2017).

Over recent decades, numerous bodies, such as the United Nations Environment (UNE), Conservation International (CI), the International Union for the Conservation of Nature (IUCN), and the World Wide Fund for Nature (WWF), have called for increased protection of biodiversity. Biodiversity conservation is also one of the United Nation's 17 Sustainable Development Goals (SDGs), which aims to "*protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss*" (http://www.un.org/sustainabledevelopment/biodiversity).

In 2002, the parties to the CBD committed to a significant reduction in the rate of biodiversity loss by 2010. Despite this agreement, evidence gathered in 2010 indicated that biodiversity loss at the global scale was continuing, often at increasing rates (GBO-3, 2010).

This observation stimulated renewed commitments in the strategic plan for biodiversity 2011–2020; it called for compelling and urgent action to be supported by 20 Aichi Biodiversity Targets (ABT) to be met by 2020 at the latest (COP-CBD, 2010). Many of the measures required to achieve the ABT will also support the goals of greater food security, healthier populations, and improved access to clean water and sustainable energy for all. The strategic plan for biodiversity 2011–2020 is thus part of the agenda for sustainable development (GBO-4, 2014), and parties committed to using the ABTs as a framework for setting national targets and reporting on progress using indicators. An indicator framework, which contains a list of 98 indicators providing a flexible basis for parties to assess progress towards the ABTs, was also adopted (COP-CBD, 2012).

A principal instrument for the implementation of these Aichi targets is the National Biodiversity Strategy and Action Plans (NBSAPs) of the parties to the CBD. NBSAPs are a national-level framework for guiding effective management and utilization of biodiversity; essentially, they translate the CBD into governmental actions. As of mid-2017, 196 countries were party to the CBD, of which 189 have developed NBSAPs (Secretariat of CBD, 2017). Recognizing the varying circumstances faced by different countries, the ABTs can be modified and made more appropriate for unique national conditions, while still contributing to the global targets. Every NBSAP envisions conservation, management, and utilization of biodiversity sustainably for sound and resilient ecosystems and national posterity.

In 2012, governments established a new assessment body, the Intergovernmental science-policy Platform on Biodiversity and Ecosystem Services (IPBES). IPBES was created to address critical gaps requiring the attention of both the science and policy if the Aichi targets are to be met, and if ecosystems are to continue providing the services needed to support more people sustainably (Cardinale et al., 2012). The IPBES is operationalized by the UNEP based on resolution 65/162 of the United Nations general assembly, and currently, 127 countries are members. The main objectives of IPBES are “assessing the human impact on biodiversity and ecosystem services; assembling existing data on biodiversity and ecosystem services to generate new insights relevant for policy; promoting a continuous dialogue between science, knowledge holders and policy, and detecting and filling gaps in the global knowledge base on biodiversity and ecosystem services” (Bridgewater, 2017, Schmeller et al., 2017b). IPBES was designed to develop assessments matched to policy needs proactively, and to support capacity building across scales and topics (Díaz et al., 2015).

Despite all these efforts, there are multiple indications of a continuing decline in biodiversity in all three of its main components —genes, species and ecosystems (Tittensor et al., 2014, Butchart et al., 2010, Brummitt et al., 2015). GBO-3 (2010) indicated that the targets agreed by the world’s governments in 2002, namely, “*to achieve by 2010 a significant reduction of the current rate of biodiversity loss at the global, regional and national level as a contribution to poverty alleviation and to the benefit of all life on*

Earth”, has not been met. As a result, ecosystem services such as the provision of food, fiber, medicines and freshwater, pollination of crops, filtration of pollutants, and protection from natural disasters, are threatened by declines and changes in biodiversity (Chapin et al., 2002). Social services such as spiritual and religious values, opportunities for knowledge and education, as well as recreational and aesthetic values, are also declining (GBO-3, 2010). Projections made based on a range of indicators in accordance with current trends suggested that pressures on biodiversity will continue to increase and that the status of biodiversity will continue to decline (Pereira et al., 2010, GBO-4, 2014).

A wide range of studies and reports have demonstrated why mitigation strategies are failing to halt biodiversity loss. For example, as indicated in the global biodiversity outlook 4 (GBO-4, 2014), even with society's commitments to curb the problem, biodiversity loss is increasing dramatically partly due to time lags between positive actions taken and discernible outcomes. Besides, responses and actions are insufficient relative to pressures, such that they may not overcome the growing impacts of the drivers of biodiversity loss. Other proposed reasons highlight the complexity of biodiversity, ecological interactions, and the numerous pressures interacting synergistically to impact multiple aspects of biodiversity; together, these factors make tracking trends in the state of biodiversity, against tractable and easily achievable conservation goals, highly challenging.

1.5. Biodiversity monitoring and assessment approaches

Progress towards international environmental targets has to be objectively evaluated in order to assess their impact and efficacy. In strategic biodiversity plans, biodiversity targets, which cover “pressures” on, “states” of, “benefits” from biodiversity and “responses” to the biodiversity crisis, are set. However, there are limitations to quantitatively evaluating those targets; for instance, the renewed strategic plan for biodiversity 2011–2020 is supported by 20 Aichi biodiversity targets to be met by 2020, to take effective and urgent action to halt the loss of biodiversity and to ensure the persistence of resilient ecosystems. Yet, as the end of this 10-year period approaches, progress toward the Aichi targets has not been quantitatively evaluated (GBO-4, 2014, McOwen et al., 2016). It remains unclear how specific variables, or aggregated indicators of biodiversity and ecosystem change, can be developed and applied globally to evaluate the progress toward the Aichi targets by 2020 (Scholes et al., 2012, Geijzendorffer et al., 2016). The latest plenary meeting of the intergovernmental platform on biodiversity and ecosystem services in Bonn, March 2017, highlighted the slow progress toward this global assessment (Schmeller et al., 2017b). In order to progress towards the attainment of the ABTs, the strategic plan for biodiversity 2011-2020 needs to be assessed on a continuous basis; comprehensive and robust monitoring systems, from which indicators of progress can be readily extracted and easily interpreted, would significantly enhance our ability to do this (Secades, 2014). However, quantifying biodiversity remains problematic since there is no universal method that adequately assesses and monitors the different dimensions of biodiversity (COP-CBD, 2010). Much of the research carried out on biodiversity assessment and monitoring places emphasis on the uniqueness of individual species, and their singular contributions to ecosystem services, although other forms of diversity (i.e., genetic and ecosystem-level diversities), are equally important and informative. For instance, Shannon's and Simpson's diversity indices are the two well-known and widely used proxies in such species-level diversity assessment. These indices are centered on "*Organism-based metrics that count the number of distinct species in a defined area (species richness)*" (GEO-BON, 2014a). Yet, most ecosystem processes are driven by combined biological activities, and it is often not possible to determine the relative contributions of individual species to ecosystem processes. Importantly, this issue highlights the need for more experimental research that manipulates biodiversity across scales to demonstrate to what extent ecosystem biogeochemical processes and functions are impaired by the loss of biodiversity (Naeem et al., 1999).

The United Nations CBD of 1992 promoted an ecosystem approach to conserving biodiversity, in contrast to the species-based methods that predominated previously. Since ecosystems are an essential link between species and populations on the one hand, and habitats and ecosystems on the other, they should play a central role in biodiversity surveillance and monitoring. What may be measured in ecosystems potentially touches on all the major dimensions of biodiversity. Therefore, strategic choices have to be made about what should be measured, and how and where to measure it, since ecosystems can be as extensive as the entire Arctic tundra, or as small as a particle of soil (BAWG, 2009). Ecosystems are thus understood to exist at multiple scales. This means choices have to be made on the scale at which monitoring should be carried out. Measuring changes in the extent of ecosystems is difficult, because there is no globally agreed classification of ecosystems, and boundaries are often variable and elusive (Carreon-Lagoc, 1994). Consequently, most approaches rely heavily on expert judgment, which makes the methods difficult to ensure reliability across the world, and limits their use in the scientific analysis (BAWG, 2009).

This demands that the complexity of biodiversity in general, and the terrestrial ecosystem in particular, be distilled into a manageable list of priority measurements. A more coordinated approach for observing biodiversity on a global scale has to be developed to prioritize conservation actions and assess the return on investment through monitoring changes (Brummitt et al., 2015). However, these aims pose several significant challenges to the scientific community, in particular, they include; i) the identification of a single variable for a critical aspect of biodiversity, ii) the translation of information between different biological and geographical realms (e.g., terrestrial and marine), iii) the heterogeneity of methods and data for measuring and recording different components of biodiversity, and iv) distilling the complexity of biodiversity into measurable variables to compare between regions, between different taxonomic groups, and between various aspects of biodiversity, (Brummitt et al., 2015). These issues arise partly because such approaches need to record data systematically over larger spatial and temporal scales (Paganini et al., 2016). It also demands that biodiversity data be inter-operable, in order to infer broader trends, so that appropriate measurements of biological diversity remains valid (Kissling et al., 2015).

Generally, science and policy has dealt poorly with the scattered distribution of necessary detailed information to inform biodiversity conservation, and urgently needs to find a solution to assemble, harmonize and standardize biodiversity data; this gap has led to the development and adoption of the essential biodiversity variables (EBVs) concept (Schmeller et al., 2017c).

1.6. The discovery of Essential Variables (EVs) as a system assessment approach

The prospect of monitoring a minimum set of variables, which collectively captures biodiversity change at multiple spatial scales, and within given time intervals, has been suggested in response to biodiversity monitoring and assessment challenges (Pereira et al., 2013). This led to the concept of essential variables (EVs); EVs are the minimum set of variables required to characterize the change in a system. The idea was first proposed as a response to the need for a more coordinated approach to global climate observations, and to prioritize and coordinate the monitoring of climate by the Global Climate Observing System (GCOS) in the 1990s. These Essential Climate Variables (ECVs) were defined as "*physical, chemical, or biological variables or a group of linked variables that critically contributes to the characterization of Earth's climate*" (Bojinski et al., 2014). Criteria to identify ECVs included: relevance in characterizing the climate system and its changes, the feasibility of observing and deriving the variables, and cost-effectiveness. The ECVs have been widely endorsed in both science and policy circles. The ECV prioritization process, guided by regular reviews and updates, continues to evolve in response to changing needs, new knowledge and innovation (Bojinski et al., 2014). Ocean scientists adopted a similar approach under the framework for ocean observing, leading in 2010 to community-defined Essential Ocean Variables (EOVs) (Constable et al., 2016). Likewise, the implementation of EV concept to focus on sustainable development goals monitoring has been proposed by Reyers et al. (2017).

1.7. Essential biodiversity variables development and their role in terrestrial ecosystem (biodiversity) assessment and monitoring

1.7.1. The EBV Development framework

The ECV development process has been followed within the biodiversity observation community to develop EBVs (Brummitt et al., 2015, Skidmore et al., 2015, Pereira et al., 2013). GEO-BON, which represents the biodiversity component of GEOSS adopted the concept of EBVs in 2013 to harmonize biodiversity data into meaningful metrics (Pereira et al., 2013). Consequently, 22 potential EBVs in a framework of six classes (genetic composition, species populations, species traits, community composition, ecosystem structure, ecosystem function) were proposed (Pereira et al., 2013) (Table 1). The EBV concept aimed to provide an internationally recognized way to monitor essential aspects of biodiversity, such that data from many kinds of sampling programs can be integrated. Thus, it would allow comparison of trends in biodiversity across local to national and global scales.

Proença et al. (2016) highlighted that operationalizing the EBV concept requires a hierarchy of importance (essentialness) of candidate variables, that incorporates their capacity to detect change reliably, and indicated that the EV concept proposes a conceptual interface between raw observations and indicators. Following this principle, Turak et al. (2016b) identified 22 priority activities for three of the EBV classes (species populations, community composition, and ecosystem structure) which include "*a globally systematic approach to collecting and assessing species data, collating existing and new data within global platforms, coordinated effort towards mapping wetland extent at high spatial resolution, linking in-situ data to modeling across regions, and mobilizing citizen science for the collection and verification of data*." Thus, EBVs can be seen as a unifying conceptual framework for organizing complex biodiversity data from diverse ecosystems and species in different parts of the world, into a limited set of biological indicators for documenting biodiversity change (Brummitt et al., 2015). EBVs may provide a critical step towards revising strategic goals for the coordination of large-scale, integrative biodiversity monitoring by helping to formalize a harmonized data framework across different ecological fields (Schmeller et al., 2015, Proença et al., 2016).

Table 1: The 22 EBVs under six classes proposed by Pereira et al. (2013).

EBV class	Essential Biodiversity Variable
Genetic Composition	Allelic diversity, Co-ancestry, Population genetic differentiation, and Breed and variety diversity
Species Population	Species distribution, Population abundance, and Population structure by age/size class
Species Trait	Phenology, Body mass, Natal dispersal distance Migratory behavior, Demographic traits, and Physiological traits
Community Composition	Taxonomic diversity, and Species interactions
Ecosystem Structure	Vegetation Height, Ecosystem extent and fragmentation, and Ecosystem composition by functional type
Ecosystem Function	Net primary productivity, Secondary productivity, Nutrient retention, and Disturbance regime

In order to draw up the EBV framework, a multitude of discussions, reviews, and research activities have been conducted, starting from refining the definition of EBVs. Schmeller et al. (2017a) argue that "*EBV is a biological state variable that is measurable at particular points in time and space to document biodiversity change*." Hence, Schmeller et al. (2017a) refined the definition of EBVs as the harmonized and standardized totality of all biological data across time and space and along a third axis representing the level of biological organization (i.e., gene, individual, species, community, ecosystem, aka biological component), together framing an EBV data cube. They claimed that an EBV cube encapsulates a multidimensional view of a specific biodiversity variable, and consists of measurements or estimates of essential aspects of biodiversity that support a comparison of the state of biodiversity across space and through time. For advancing EBV development, EBVs need to be clearly distinguished from variables describing pressures and responses of biodiversity, such as ecosystem services or disturbance regimes. For instance, the impacts of pressures such as habitat loss or exploitation can be linked to changes in biological variables, such as population abundance, species distribution or habitat structure; however, the pressures themselves are not biological and thus outside of the EBV definition proposed by Schmeller et al. (2017a).

For the EBV class ecosystem function, the EBV "disturbance regime" would not fall into Schmeller et al. (2017a) definition of an EBV, as it is not a biological variable, in contrast to the definition proposed by Pereira et al. (2013). The disturbance regime is instead a natural or anthropogenic driver of change in ecological processes and encompasses succession and regeneration of biodiversity states. Further, Schmeller et al. (2017a) argue that for the EBV class ecosystem structure, EBVs should only cover the biological components, but should not include abiotic variables (i.e., chemical composition, slopes, and climatic conditions), despite their importance in understanding why an EBV may change in space and over time. This clarification focuses efforts directed towards delivering EBVs, and in delimiting the data that should be considered suitable for calculating an EBV. It would also allow partitioning the amount of biodiversity data into sub-components that can be realistically and practically addressed in the real world, within the frame of existing constraints defined by, e.g., administrative borders, legislative periods, international assessment reporting periods, etc. These real-world constraints may delimit the extent and grain sizes to which EBVs should be matched (Schmeller et al., 2017a).

In general terms, the process to generate an EBV, starts with standardizing, harmonizing, and integrating raw biological observations (i.e., primary data) from different sources over space and time and ends when its spatiotemporal changes are fully documented (Schmeller et al., 2017a). EBVs are state variables that stand between primary observations (i.e., raw data) and high-level indicators (e.g., the living planet index (LPI), which is first developed by WWF in 1998), and may represent essential aspects of biodiversity (from genetic composition to ecosystem functioning). They may be integrated with other EBVs or with different types of data, such as data on drivers and pressures, to deliver high-level indicators (GEO-BON, 2014b, Pereira et al., 2013). Hence, the development of indicators and the understanding of the causes of the documented change do not fall within the EBV framework but are a logical next step in using the EBV data. Taken in combination, EBVs would be a representative set of key components of biodiversity, and thus would help to prioritize data collection methods, management, and publication. The final EBV suite would need to be evaluated based on the added benefit (essentialness) of each EBV to all others, using a set of objective criteria such as complementarity, policy relevance, predictive ability, significance of change, sensitivity to change, and applicability across biological realms; thus, the essentialness of an EBV then could be used to prioritize on which EBV to focus efforts. It is also important to recognize that different stakeholders and groups of scientists are likely to hold differing views on the suite of candidate EBVs that should be operationalized. Policymakers, as such, might favor a narrow set of EBVs that produces

unambiguous signals of change based on streamlined infrastructure (data flow pipelines, etc.).
Therefore, identifying a minimum set of fundamental variables needed to support multi-purpose, long-term biodiversity monitoring required at various scales that can be used to inform scientists, managers, and the public on global biodiversity change should be a key goal of EBV framework (Pereira et al., 2013). The EBV framework (Figure 2) should allow answering essential questions about biodiversity change, its consequences for human well-being, the effectiveness of responses and future harmful biodiversity changes.

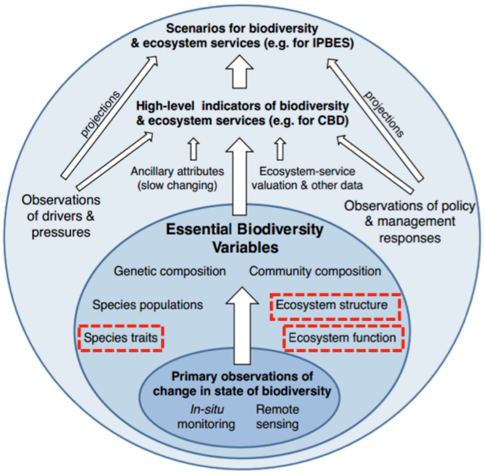

Figure 2: Biodiversity Global Observing System framework developed by GEO-BON. The red-dashed boxes highlight eBVs that can be supported by the EO system. Image adapted by Coca-Castro (2016) from Pereira et al. (2012).

The EBV concept is theory-driven rather than data-driven (Geijzendorffer et al., 2016), can be applied to multiple spatial scales (Pereira et al., 2013), and is independent of measurement methods and environmental problems (Pettorelli et al., 2016b). Its adoption helps to improve the comprehensiveness, efficiency, and usefulness of biodiversity monitoring data at local, regional and global levels, by clarifying gaps and prioritizing efforts towards measures capable of detecting change. The EBV framework has been conceptually defined to streamline the monitoring of the state of biodiversity, as well as the condition of, and trends in, ecosystem services provided to society, through a small number of ecologically relevant, technically feasible and economically viable variables (Paganini et al., 2016). EBVs are expected to possess a set of characteristics, which include (i) being sensitive to change over time; (ii) being focused on the 'state' of biodiversity, as per the 'pressure–state–response' framework from the CBD; and (iii) being defined at a level of specificity intermediate between that of low-level (primary) observations and high-level indicators of biodiversity change. Importantly, EBVs are expected to be scalable, technically feasible to measure and economically viable for global implementation (Pereira et al., 2013).

1.7.2. Role of EBVs in biodiversity assessment and monitoring

The launching of the concept of EBVs has stimulated progress to unify biodiversity monitoring globally (Pettorelli et al., 2016b, CBD SBI, 2016), and to find measurable parameters for all relevant dimensions of biodiversity, to attain consensus on what to monitor, and, subsequently, to decide where to focus the limited monitoring resources (Pereira et al., 2013). The development of the EBV framework distills the complexity of biodiversity into a manageable list of priority measurements (Brummitt et al., 2015) and facilitates globally consistent reporting of changes in the state of biodiversity. Comparison between regions, different taxonomic groups and various aspects of biodiversity becomes more straightforward when the complexity of biodiversity is broken down into EBVs. EBVs allow comparison and harmonization of biodiversity measurements, thereby facilitating the evaluation of progress towards global biodiversity targets. Measures of EBVs may also be used to prioritize conservation actions and to assess the return on investment through monitoring changes in those EBVs (Brummitt et al., 2015). This minimizes the massive challenge in documenting and quantifying global biodiversity change due to sparse or biased data, and a general lack of agreed international data standards. The EBVs enable the consistent aggregation variables across time, space and taxa. Therefore, the monitoring of a limited number of essential variables on the structural, functional and compositional aspects of biodiversity is seen as the most cost-effective and efficient framework to develop a global and consistent knowledge-base of the changing status of biodiversity (Paganini et al., 2016).

Nevertheless, the global implementation of EBVs has significant scientific and technical challenges. As indicated by Kissling et al. (2015) there are a multitude of scientific challenges related to the EBV concept including such questions as how are specific EBVs precisely to be defined; which biodiversity data are needed and available and for where; how can relevant data be accessed and how can EBVs be determined; what are relevant spatial and temporal scales; and how sensitive are EBVs to variations in underlying data? Finally, a key technical challenge of implementing EBVs encompasses their requirement for the global cooperation of biodiversity research infrastructures to serve comparable data sets and analytical capabilities, ensure their interoperability.

1.7.3. Remote sensing enabled EBVs

The goal of global biodiversity monitoring is to measure biodiversity responses to environmental change. This requires biodiversity datasets that cover extensive areas with a high temporal frequency, which implies the use of time series, in particular, long-term data capable of capturing on-going changes through time (Scholes et al., 2012, Han et al., 2014). Data must also be scalable so that biodiversity change can be assessed across scales and sites, as well as be taxonomically representative, thereby yielding a complete understanding of biodiversity change (Paganini et al., 2016, Pettorelli et al., 2016b, Schmeller et al., 2017a).

Traditional approaches of monitoring terrestrial ecosystems through measurements, although offering detailed and highly accurate information, are often inadequate at regional-to-global scales due to time constraints, high costs, and sometimes non-replicability of measurements as a result of inconsistencies in the measuring protocol (Clark et al., 2001). Thus *in situ* datasets are scarce for many parts of the globe. Earth observation data from space-borne, airborne and ground-based sensors, with their synoptic view and repetitive data collection capabilities, are expected to play a significant role in improving monitoring systems by complementing conventional *in situ* data collection and by providing other types of information at regional-to-global scales (Gong et al., 2013, Dash and Ogutu, 2015). Furthermore, widely available Earth observation data might encourage increased *in situ* data collection efforts, for instance, for validation purposes. Satellite remote sensing allows global-scale, synoptic, repeatable, standardized and cost-effective measurements, thereby making satellite remote sensing a valuable instrument for the development of the EBVs (Pettorelli et al., 2016b). The importance of satellite observations for biodiversity monitoring was underscored in a recent review of the adequacy of Earth Observation approaches in monitoring progress towards the 2020 ABTs of the CBD (Secades, 2014).

Since their conceptual definition in 2013, EBVs have been based upon both remotely sensed observations that can be measured continuously and globally by satellites, and field observations (*in situ* observations) from local sampling schemes integrated into large-scale generalizations. Remote sensing imagery provides a viable solution to EBV monitoring and minimizes the efforts by ecologists to collect EBV data to track biodiversity changes through field surveys that are often laborious, cover relatively small extents and short temporal periods, (Palmer et al. 2002, Collen et al. 2013). Remote sensing provides an opportunity to derive a comprehensive set of variables for assessing and monitoring biodiversity globally (Skidmore et al., 2015). Thus, remote sensing enabled EBVs (RS-enabled EBVs) can help fill the spatial and temporal gaps left by *in situ* observations, being periodic observations that are spatially contiguous. Further, the number of data providers is fewer (primarily national space agencies), which makes coordination more manageable, and many of the observations already exist or are in an advanced stage of planning (CBD SBI, 2016).

Remote sensing captures most biodiversity-relevant variables by proxy rather than directly. Recently, ten RS-enabled EBVs (Table 2) that capture biodiversity change on the ground and can be monitored from space were identified by Skidmore et al. (2015) and later reaffirmed by CBD SBI (2016). These remotely sensed EBVs were identified as critical to developing indicators for monitoring progress towards Aichi targets. O'Connor et al. (2015) explored the potential role of EO as a tool to support biodiversity monitoring against the ABTs and EBV frameworks. They have shown that EO-based measurements are adequate for assessing progress towards 11 out of 20 ABTs. Also, 14 of the 22 candidate EBVs have a fully or partly remotely sensed component and can potentially be considered as RS-enabled EBVs.

The application of remote sensing data in global biodiversity assessment and monitoring is presently not yet well developed. Both biodiversity and remote sensing communities need to work together to determine the EBVs that can be monitored systematically and globally from space (Skidmore et al. 2015). This partly since the development of high-quality and reliable RS-enabled EBVs require a precise definition of their observation requirements (e.g., temporal frequency, spatial resolution, thematic accuracy), that can then be translated by the space agencies into measurement specifications for the satellite instruments, and subsequently into algorithm specifications on how the satellite measurements are to be processed (Paganini et al., 2016). However, the biodiversity community has not yet precisely articulated their needs to the space agencies to exploit the full potential of satellite observations (Skidmore et al. 2015). RS-enabled EBVs will become a reality only if the biodiversity community and space agencies unite in defining and developing the satellite observations and processing algorithms needed for continuous monitoring and production of useful biodiversity information (Paganini et al., 2016).

Table 2: Candidate EBVs that can be derived from earth observation systems as proposed by (Skidmore et al., 2015). EBV classes are based on Pereira et al. (2013). Each EBV has a potential contribution to assess many of the Aichi biodiversity targets (CBD SBI, 2016) and Sustainable development goals (SDG).

EBV class	Candidate RS-enabled EBV	Potential support for	
		Aichi biodiversity targets	SDG targets
Species Population	Species distribution	4,5,7,9,10,11,12,14,15	15.1, 15.5
	Species abundance	4,5,7,9,10,11,12,14,15	15.1, 15.5
Species Traits	Phenology	5,7,9,12,14,15	15.4
	Plant traits (e.g., specific leaf area, leaf nitrogen	7,9,12,14	15.4
Community Composition	Taxonomic diversity	8, 10, 12, 14	15.1, 15.5
	Functional diversity	5,7,10,12,14,15	15.1, 15.2, 15.4
Ecosystem Function	Productivity (e.g., NPP, LAI, fAPAR)	5,7,10,12,14,15	15.2
	Disturbance regime (e.g., fire and inundation)	7,9,10,12,14,15	15.2, 15.3
Ecosystem Structure	Habitat structure (e.g., height, crown cover and density)	5,7,9,14,15	15.2, 15.3, 15.5
	Ecosystem extent and fragmentation	5,11,12,14,15	15.1, 15.2, 15.3
	Ecosystem composition by functional type	5,7,10,12,14,15	15.1, 15.2, 15.4

1.7.4. The interrelationship between EBVs in terrestrial ecosystems

The interdependence among EBVs characterizing terrestrial ecosystem structure and function parameters have been widely documented, and a review of the literature confirms the presence of a strong correlation within EBVs. For instance, the ecosystem function EBVs Net Primary Productivity (NPP) (i.e., the rate of conversion of resources to biomass per unit area per unit time), which is one of, has a significant correlation with several EBVs, including species richness, disturbance regime, phenology, functional diversity, Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation (FPAR).

More specifically, the relationship between NPP) and species richness has been the subject of long-running debate (McBride et al., 2014). Šímová et al. (2013) reported a unimodal scale-dependent Productivity and Species Richness Relationship (PSR). Most studies agree that productivity and species richness interaction is high at large scales (Waide et al., 1999). Nevertheless, at all scales, PSR is positive, but the strength of the PSR increases positively with the ecoregion scale. In small ecoregions, factors correlating with productivity play only a minor role in species richness patterns, while in large-scale ecoregions, NPP modeled from remotely sensed data could explain most of the variation in species richness (McBride et al., 2014). In an ecological experiment, Flombaum and Sala (2008) also found an increase in aboveground NPP with the number of plant species, which supports the existence of a positive relationship between plant species diversity and primary production. Similarly, a strong correlation between aboveground NPP and species diversity in alpine meadow community have been reported by Li et al. (2015).

Although the consideration of disturbance regimes as EBV is still debatable, the productivity-diversity relationship varies as a function of the natural disturbance regime of an ecosystem. For example, an increase in NPP was measured with an increase in fire occurrence under present climatic conditions, and frequency of fire return intervals over a range of 50–200 years (Peng and Apps, 1999). Moreover, a study by Cardinale et al. (2005) showed that the relationship between the species richness of primary producers and net rates of biomass production depends on disturbances; this finding supports the hypothesis that the strength of the diversity-productivity relationship depends explicitly on the disturbance regime of an ecosystem. Finally, Grime (2006) predicted that increased productivity leads to the convergence of functional traits, while disturbance may increase functional diversity.

Another species trait EBV which is strongly correlated with the productivity of an ecosystem is phenology. Variation in the vegetation growth onset (start of season) time might have collateral effects on the length of the summer growing season and annual NPP (Chung-Te et al., 2013). A strong correlation ($R^2 = 0.83$) between litter-fall and overall NPP was noticed in tropical forests (Malhi et al., 2011). Earlier findings also confirmed that terrestrial Gross Primary Productivity (GPP) is jointly controlled by ecosystem-level plant phenology and photosynthetic capacity (Xia et al., 2015).

The FPAR absorbed by a plant canopy has been related to NPP as a function of a light use efficiency coefficient, defining the carbon fixed per unit radiation intercepted. Experiments undertaken in crops indicate a close correlation between LAI and biomass and between biomass and NPP or yield. Positive correlations between LAI and biomass of winter wheat in different developmental phases were reported (from $r = 0.66$ to $r = 0.84$) and, the biomass was correlated with yield ($r = 0.65$) (Petcu et al., 2003). Many studies showed that vegetation's biomass is related to LAI and the FPAR absorbed by vegetation; for example, (Zhou et al., 2002) observed that FPAR absorbed by vegetation is approximately linearly related to the amount of biomass, while LAI and FPAR are linearly related.

FPAR increased with LAI and stabilized together with LAI, resulting in correlation coefficients of up to 0.994. A significant correlation between LAI and Specific Leaf Area (SLA) and between LAI and leaf Nitrogen (N) content were also documented in the literature. Pierce et al. (1994) reported that the LAI across the Oregon transect is closely related to canopy average SLA ($R^2 = 0.82$) and leaf N content on a mass basis ($R^2 = 0.80$). Their study suggested that it is possible to predict the spatial distribution of canopy-average SLA and leaf N content across biomes from satellite estimates of LAI.

Nitrogen content has a very close link with other leaf chemical traits, including chlorophyll. A lack of N in the mineral nutrient supply of plants results in reduced chlorophyll formation (Tam and Magistad, 1935). Hence, leaf chemical traits provide insight into the functional strategies of plants. For example, a combination of six chemical traits (lignin, hemicellulose, zinc, boron, magnesium, and manganese) predicted the species of savanna woody plants with 91% accuracy (Colgan et al., 2015).

Significant positive linear relationships between taxonomic diversity, functional dominance, functional diversity, and community aboveground biomass were reported by Zhang et al. (2017): "Aboveground biomass depends on the community-weighted mean plant height, which explained 57.1% of the variation in the community aboveground biomass. Functional dominance rather than taxonomic diversity and functional diversity mainly determines community productivity and that the selection effect of species plays a dominant role in maintaining the relationship between biodiversity and community productivity in the Inner Mongolia grassland" (Zhang et al., 2017).

Habitat structure, which is defined as the amount, composition, and three-dimensional arrangement of physical matter (both abiotic and biotic) at a location, has a substantial direct and/or indirect relationship with many ecological patterns and processes (Byrne, 2007). Differences in habitat structure across space create landscape patterns, which in turn affect communities and ecosystem processes (Byrne, 2007). The majority of studies have found positive correlations between habitat heterogeneity/diversity and animal species diversity (Tews et al., 2004, Casas et al., 2016, Verdonschot et al., 2012, Godbold et al., 2011, Telleria et al., 1992, Howell et al., 1978). This confirms the 'habitat heterogeneity hypothesis,' which assumes that structurally complex habitats may provide more niches and diverse ways of exploiting the environmental resources and thus increased species diversity (Bazzaz, 1975). A study in the Iberian forests by Telleria et al. (1992) has shown the role of forest structure as a predictor of bird diversity along the studied gradient. Another study in successional Atlantic rainforests revealed that habitat structure influences the diversity, richness and composition of bird assemblages (Casas et al., 2016).

Williams et al. (2002) demonstrated that the composition of the mammal assemblages in a tropical rain forest was strongly related to vegetation structure across and within habitats, at the spatial scales examined. They found species richness was highest in the open forest and decreased across the gradient into the rainforest. Their spatial scale, species diversity, and habitat structure analysis revealed that >80% of the variation in species richness at the local level could be explained by vegetation structure. Likewise, the local-scale species richness of ground-dwelling mammals was mostly a product of the spatial variability in assemblage structure (β diversity), which was associated with the spatial variability in vegetation structure. Local-scale habitat heterogeneity thus promoted local-scale species richness via the close ecological interaction between mammals and habitat structure (Williams et al., 2002). In addition, small-scale variations in habitat structure were found to influence species contributions to ecosystem properties at larger scales (Godbold et al., 2011).

Overall, EBVs may have either direct or indirect relationships and dependency with each other. The interrelationship analysis elicited that some EBVs such as net and gross primary productivities are entirely dependent on other EBVs, and their global assessment can be easily derived from other EBVs such as LAI, AGB, and FPAR.

1.7.5. The relationship between EBVs and biodiversity indicators, biodiversity targets and SDGs

Indicators are the primary mechanism developed for monitoring progress towards the Aichi Biodiversity Targets (ABT) and Sustainable Development Goals (SDGs). Indicators help to identify whether actions for protecting biodiversity are working and should continue, or if different approaches need to be examined. They are statistical measures that help scientists, managers and politicians quantify and understand the condition of biodiversity and progress toward the SDGs, as well as the factors that affect them. Furthermore, indicators are standardized measures that make it easier to monitor, compare and communicate changes.

Consequently, the development of national, continental and global indicators has received increasing interest. After the launching of the ABTs in 2010, the Biodiversity Indicator Partnership (BIP) developed a universal set of indicators that focus on monitoring progress towards the 2020 ATBs in particular (https://www.bipindicators.net/). Several other indicators of global biodiversity currently in use include the IUCNs Red List of Threatened Speciesindex, which measures changes in the overall risk of a group of species becoming extinct, the IUCNs Red List of Ecosystems, which aims to represents the risk of and ecosystem collapsing, the LPI which measures the state of the world's biological diversity the Ocean Health Index (OHI) to evaluate the benefits the oceans provide and track changes over time, and finally, the Global Wild Bird Index (GWBI) which measures trends in relative abundance of a group of bird species

A first attempt at developing indicators for the 2020 CBD targets identified close to 100 operational indicators (AHTEG, 2011). Similarly, 230 indicators have been proposed for the 2030 agenda for sustainable development (IAEG-SDGs, 2016). Therefore, it is difficult to select a shortlist of variables that are useful and feasible to monitor biodiversity and the SDGs everywhere. To overcome this challenge, clear priorities need to be established to guide the development of observation systems worldwide. Here, EBVs can play a crucial role as they focus effort on a finite set of measurements, essential for the characterization of global biodiversity change; moreover, they are intended to facilitate the harmonization of existing monitoring schemes to guide the implementation of new monitoring schemes.

EBVs can be independently used to derive indicators or can be combined with other information for the calculation of indicators. For instance, an observation system that collects data on species abundance for several taxa at multiple locations on our planet can support the derivation of the LPI, GWBI, measures of species range shifts, and many other high-level indicators (COP-CBD, 2012). Some biodiversity indicators require the integration of two or more EBVs, together with other datasets. For instance, the species extinction risk estimates that are the basis of the red list index include information on trends in species abundance and occurrence (an EBV); trends in ecosystem extent and distribution (another EBV); complemented with ancillary information about the species, such as generation time or migratory behavior.

EBVs are viewed as enduring entities insulated from changing technologies at the observation level, and from changing approaches and information needs at the indicator level (Pereira et al., 2013). In other words, EBVs are mostly not indicators themselves but can be used for the calculation of indicators, for instance, to assess progress towards the CBD 2020 targets. EBVs can also be used to develop scenarios for the future of biodiversity under different policy and management responses. They are intended to help to guide the development of biodiversity observation systems. EBVs are intrinsically linked to primary observations; they do not necessarily directly provide information that can be communicated merely to policy-makers, but by combining EBV observations with other information, such as on the attributes of biodiversity, or drivers and pressures of biodiversity change, indicators can be developed which are directly useful for policy support. Therefore, EBVs have multiple uses; they comprise an intermediate abstraction layer between primary observations and indicators (Figure 3). In addition, they could be used as a tool to identify existing biases in policy reporting and indicator use, through which the comprehensiveness of biodiversity reporting can be enhanced. Additionally, the use of EBVs could help to prioritize data mobilization and modeling efforts, facilitate data integration over large spatial scales and across a broad taxonomic spectrum, and importantly, improve the availability of information on past and current biodiversity changes at all biological levels (genes, populations, species and ecosystems) (Geijzendorffer et al., 2016).

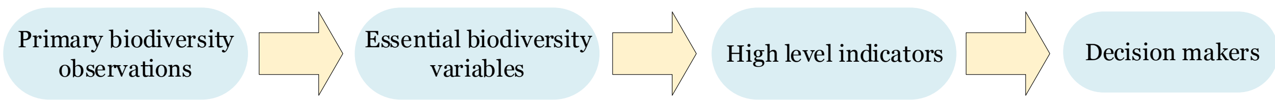

Figure 3: EBV relationship to high-level indicators (GEO-BON, 2017)

The implementation of EBVs can transform the shape of monitoring systems from an ever-broadening pyramid to a more streamlined form, by enabling monitoring systems to make more efficient observations (Reyers et al., 2017). Besides, since EBVs have the capacity to capture key ecosystem dimensions, one EBV can potentially contribute to multiple indicators, and the same observation can link to more than one EBV, thus potentially enabling a reduction in the numbers of observations needed to deliver those indicators (Figure 4). See Table 2 in section 1.7.3 for the potential contribution of RS-enabled EBVs in assessing progress toward the ABTs and SDG.

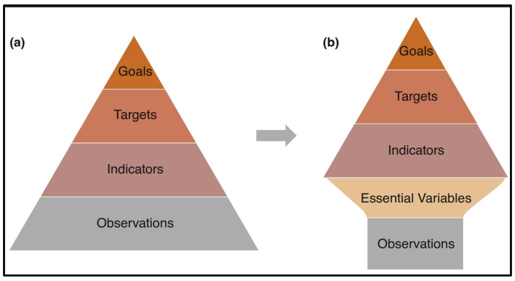

Figure 4: As defined in Reyers et al., (2017) "The introduction of Essential Variables (EV) as a layer between primary observations and indicators can transform the shape of monitoring systems from (a) an ever-broadening pyramid to (b) a more streamlined form. In (b) a limited number of EVs, directing a targeted set of repeatable and universal observations, underpin a changing superstructure of policy-relevant indicators, targets, and goals." (Reyers et al., 2017).

1.7.6. How EBVs can serve the practical operational needs of National Biodiversity Strategies and Action Plans

As stated in Article 6 of the CBD, the National Biodiversity Strategies and Action Plans (NBSAPs) are the principal instruments for implementing the convention at the national level. In other words, the NBSAP is intended to define the current status of biodiversity, the threats leading to its degradation, and the strategies and priority actions needed to ensure its conservation and sustainable use, within the framework of the socio-economic development of the country. NBSAPs lay down how a given state intends to fulfill the objectives of the convention in light of its specific national circumstances. The convention requires countries to prepare a national biodiversity strategy and action plan (or equivalent instrument) and to ensure that this strategy is mainstreamed into the planning and activities of all those sectors whose activities can have an impact on biodiversity. That is why close to 96% of nations of the parties of CBD have developed NBSAPs (Secretariat of CBD, 2017). NBSAPs have been designed to formalize plans for actively pursuing nations commitment to the conservation, sustainable use of, and the equitable sharing of benefits from their biological diversity by taking into account the ABTs and the five strategic goals of the Strategic Plan for Biodiversity 2011-2020 (COP-CBD, 2012).

Developing, updating and implementing NBSAPs follows an iterative process suggested in the national biodiversity planning guidelines, prepared by the World Resources Institute (WRI), IUCN and UNEP, and was recommended to parties by the Conference of the Parties (COP) in 1995. The seven-steps required when developing an NBSAP are: i) getting started, ii) assessment/ country study, iii) developing a strategy, iv) developing a plan of action, v) implementation, vi) monitoring and evaluation, and vii) reporting (Secretariat of CBD, 2011).

EBVs can play a crucial role in many of these NBSAP development processes (Table 3). For instance, the second step of the NBSAP planning process requires an assessment of the status and trends of the nation's biodiversity and biological resources, which can be efficiently and timely addressed using EBVs. Since EBVs provide a small but comprehensive set of monitoring variables to coordinate biodiversity monitoring worldwide, NBSAP managers benefit from using EBVs to give a more balanced picture of the development of biodiversity, and the attainment of national biodiversity targets (Vihervaara et al., 2017). EBVs also help to improve the comprehensiveness, efficiency and usefulness of biodiversity monitoring data, by clarifying gaps and prioritizing efforts towards measures capable of detecting change. Vihervaara et al. (2017) consider EBVs as a conceptual tool that may help in making national scale biodiversity monitoring more robust, by pointing out where to focus further development resources. Thus, EBVs fill the gaps that exist in the current indicator-based NBSAP monitoring and evaluation scheme. As indicated in the seventh step of the NBSAP planning process, the parties to the CBD are required to present to Conference of Parties (COP) periodic reports on measures they have taken to implement the convention and the effectiveness of these measures (Secretariat of CBD, 2011). Parties may also prepare other reports on biodiversity policy. Implementation of the EBV framework at the national level will help nations to present standardized and consistent reporting changes in the state of biodiversity (Turak et al., 2016a, Proença et al., 2016). This, in turn, helps to evaluate the effectiveness of measures taken across nations in meeting international obligations. However, the adoption and implementation of the EBV framework at the national level need CBD guidance. Nations must be convinced of the tangible benefits of EBVs other than merely fulfilling the requirement of CBD (Turak et al., 2016a).

Table 3: Overview of the possible roles of EBVs in developing, updating and implementing national biodiversity strategy and action plans (NBSAPs), as adopted from the national biodiversity planning guideline (Secretariat of CBD, 2011).

Step for Biodiversity planning	Description of main activities	Possible roles of EBVs
Step 1. Getting started	• Defining a schedule for the NBSAP preparation or revision • Establishing criteria and modalities for the gathering of information and streamlining communication between participants • Designing guidelines for the biodiversity assessment/diagnostic phase • Developing a public awareness package about the NBSAP being developed or revised and how the public can participate • Identifying a lead organization, Committee, or Working Group to coordinate the preparation of the NBSAP • Establishing a clear coordination structure, lines of communication, and institutional responsibilities	EBVs help to establish clear initial criteria for gathering information and support to frame possible biodiversity assessment guidelines
Step 2. Assessment/ country study	• The status and trends of the nation's biodiversity; and an evaluation of the possibility of reducing the loss of each biodiversity component in question • The drivers of biodiversity loss • The relationship between biodiversity and human well-being in the country • The country's framework of biodiversity relevant laws, policies, programs, and expenditures; and an estimation of how different policy instruments might work to reduce the loss of biodiversity • The relevant national organizations, and human and technical capacity	EBVs ensure proper assessment of the status of national biodiversity in the past and present to figure out the trend and plan accordingly for its effective future conservation

Step for Biodiversity planning	Description of main activities	Possible roles of EBVs
	• The state of awareness, knowledge, and concern about biodiversity issues in the different sectors of society • The status and potential sources of biodiversity financing in the country • Lessons learned from the planning and implementation of the previous NBSAP (if any) • Gaps and unmet needs	
Step 3. Developing a strategy	• The vision sets out where the country wants to be with regards to biodiversity and its relation to human well-being • The statement of principles consists of the values and beliefs underlying the NBSAP in light of its particular circumstances, biodiversity and issues identified. • The priorities will be that set of most pressing issues that can feasibly be addressed in the NBSAP period. The targets of the NBSAP will be the national targets established to correspond with the Strategic Plan for Biodiversity 2011-2020 and the global Aichi Targets established at COP 10	In developing a strategy, EBVs could be used as a benchmark to identify and focus on crucial aspects of biodiversity in which efforts and resources can be invested to make significant progress
Step 4. Developing a plan of action	• Identifying the actions required to meet the NBSAP goals, objectives, and targets established in the strategy • Prioritizing which action to undertake • Identifying and securing the human, technical and financial resources necessary to carry out this action • Specifying the national coordination structures for ensuring implementation and follow-up to the NBSAP • Strengthening the national clearinghouse for biodiversity to promote the sharing of knowledge and expertise needed for implementation of the NBSAP • Establishing a monitoring approach including the identification of indicators by which progress towards national targets will be measured and reported	EBVs can play an indispensable role in framing the NBSAP monitoring approach. The implementation of the EBV concept makes the development and measurement of indicators very straightforward
Step 5. Implementation	NBSAP implementation involves carrying out the agreed plan of action in the way envisaged, within the allocated time frame	Standard definitions of EBVs encourages a standard implementation and hence global monitoring using the data from the parties to the CBD Efficient as each party does not need to 're-invent the wheel' Global products can be produced from remote sensing that can be implemented in NBSAP
Step 6. Monitoring and evaluation	Measure the effectiveness of activities carried out under the plan of action and to systematize and validate the assessment of outcomes so that they will have a reliable basis on which to conduct the process for reviewing and updating the NBSAP	EBVs give a balanced picture of the development of biodiversity and the reaching of national biodiversity targets

Step for Biodiversity planning	Description of main activities	Possible roles of EBVs
Step 7. Reporting	Parties to the CBD are required to present to COP periodic reports on measures they have taken to implement the Convention and the effectiveness of these measures	EBVs help nations to offer a standardized and consistent report which enables evaluating the effectiveness of actions taken across countries universally

1.7.7. Role of GEO-BON and other bodies in EBVs development and implementation

The past decade has seen the rise of global networks aiming to develop earth observation systems, most notably the Group on Earth Observations (GEO), whose vision is "a future wherein decisions and actions for the benefit of humankind are informed by coordinated, comprehensive and sustained Earth observations and information." GEO-BON was formed in 2008 to support the collection, management, analysis and reporting of data relating to the status of the world's biodiversity (Scholes et al., 2008). GEO-BON represents the biodiversity component of the Global Earth Observation System of Systems (GEOSS) , and is making a coordinated effort with other actors to address the need for an observation system for biodiversity monitoring. GEO-BON has been facilitating the development of biodiversity observation networks (BONs) to improve the coordination and harmonization of observation systems. BONs are organized around three categories: thematic BONs focus on a specific biological theme, such as the freshwater and marine realms; national BONs are endorsed by national governments; and regional BONs. Species and ecosystems, and the pressures that affect them, are not constrained by political borders. Therefore, the regional and thematic BONs connect monitoring efforts across different dimensions and scales of biodiversity. National BONs are directly oriented to serve the needs of national and sub-national policy-makers and correspond to the operational scale of many monitoring initiatives. In particular, they address policy needs for reporting on multilateral environmental agreements (e.g., CBD, Ramsar Convention), and support processes such as ecosystem accounting, Environmental Impact Assessments, or land- and ocean-use planning. In practice, BONs produce, test and apply tools to deliver EBV-relevant data that can be up-scaled and downscaled to support sustainable development and conservation decisions. In being part of a global framework and a system of observation systems, BONs also reinforce the scientific basis of both biodiversity monitoring and indicator development. Finally, to improve the design of biodiversity observation systems further, GEO-BON is developing capacity building and knowledge transfer platforms and facilitating the establishment of new national, regional and thematic BONs. Navarro et al. (2017) reported that GEO-BON envisions a broad and robust network of national and regional BONs, with multiple EBV products openly available that cover the different dimensions of biodiversity and components of ecosystem services. Together, all these components will contribute to informing local to global assessments of the status and trends of biodiversity, and its contribution to society in the coming ten years.

Additional organizations active in the provision of remote sensing and *in situ* data useful for the development of EBVs, for the harmonized monitoring of biodiversity, including the

Global Biodiversity Information Facility (GBIF), Ocean Biogeographic Information System (OBIS), EU-BON and e-infrastructures (Despot-Belmonte et al., 2017). These organizations are working towards identifying knowledge gaps and have made significant advances in making data discoverable (i.e., adequately documented), accessible (i.e., uploaded in public repositories) and interoperable (Wetzel et al., 2015).

In summary, the concept of EVs was adopted by GEO-BON to improve the detection of significant changes in global biodiversity. Currently, GEO-BON is guiding the development of EBVs by publishing methods, protocols collaborating with various remote sensing and biodiversity organizations, and providing EBV datasets in a dynamic virtual environment. In addition, the GEO-BON management committee has developed a strategy document that contains the criteria for defining EBVs which is regularly updated on the GEO-BON website (see GEO-BON, 2017 for the latest EBV development strategy document).

Part II:

Prioritization and Selection of Remote Sensing Enabled Essential Biodiversity variables of Terrestrial Ecosystem Function and Structure

1 Introduction

The adoption of a prioritized list of EBVs endorsed by key user groups (CBD, IPBES, industry) may stimulate a standard set of global EBV products for biodiversity monitoring (Skidmore et al., 2015). Such a list of EBVs derived from remote sensing is highly relevant for space agencies and funding agencies, to encourage continuity of biodiversity products at relevant spatiotemporal scales. In short, a prioritized and endorsed list of EBVs will assist in developing global standards for operational EBV products. EBV prioritization allows users responsible for reporting and incorporating biodiversity information, as well as businesses interested in the sustainability of their operations, to evolve a set of biodiversity variables suitable for monitoring from remote sensing.

Remote sensing provides the opportunity to monitor EBVs over sufficiently long periods and a large (global) spatial extent. EBVs products that may be retrieved from remote sensing can vary from individual organisms to ecosystems, through the monitoring of change in ecosystem structure, function, community composition, and species traits. Therefore, to ensure cost-effective and timely monitoring of biodiversity, it is essential to focus on systematic observation of a limited set of critical variables like the ECVs described by the Terrestrial Observation Panel for Climate (TOPC) (Bojinski et al., 2014).

Here we aim at prioritizing the EBVs that inform about the state and change in biodiversity and can be retrieved from existing and proposed RS technologies with particular attention to RS-enabled EBVs of terrestrial ecosystems function and structure. We adapted ECV criteria to prioritize the selection of EBVs based on policy requirements, feasibility as well as maturity in terms of implementation and operational status.

2 Method

2.1 Selection and prioritization criteria

The selected biodiversity variables should capture significant changes in biodiversity and have a high biodiversity policy relevance (Pereira et al., 2013), as well as be measurable at a global scale with reasonably high precision and accuracy by using simple, robust and reliable retrieval techniques (Pettorelli et al., 2016a). Likewise, global monitoring (in space and in time) should be affordable and cost-effective (O'Connor et al., 2015). Also, the selection should allow the assessment of the state of biological diversity, the conditions of ecosystems, the benefits provided by the ecosystem services and should give opportunities to understand the drivers of changes (ESA, 2016). They should also provide key information needed to develop biodiversity indicators and serve multiple policy frameworks. The selected sets of RS-enabled EBVs should benefit international, regional and national institutes to monitor progress towards the 2020 ABT as well as the 2030 SDG.

Adopting the parsimony principle for the selection and prioritization process, the prioritization and selection criteria, as developed by GCOS for Essential Climate Variables (Bojinski et al., 2014) were adapted for EBVs by the expert working groups. The four broad criteria were modified into biodiversity assessment and monitoring requirements as listed in Table 4. Subsequent to the expert meetings, the Group on Earth Observations Biodiversity Observation Network built on the ideas of the expert meetings, creating an exhaustive list of criteria required to define an EBV, as provided in the GEO BON Strategy for development of Essential Biodiversity Variables document (GEO-BON, 2017).

Table 4: EBV products were scored based on prioritization criteria, and observation requirement attributes including definitions of relevance, scientific feasibility, remote sensing product accuracy, as well as remote sensing product maturity.

Prioritization criteria	***Description***	***Ranking factor 1***	***Ranking factor 3***
Relevance	You know who wants the EBV product, what they will do with it and how it will be used. The relevance of RS-enabled EBVs to management questions to inform the convention on biological diversity (CBD) Aichi targets, sustainable development goals SDG(s) as well as social impact.	Use and user fully identified	EBV product less directly linked to science and societal questions
Feasibility	The science community knows how to measure the EBV product at appropriate scales that such measurements can realistically be made and/or that observations already exist. Includes the availability of remote sensing (RS) data and ease of access; completeness of RS in space and time; ease and cost of data integration and analysis.	Indicates the maturity of science/ technology/experience needed to make the EBV product	Indicates that significant research & development effort remains or that EBV products on the scale needed are technically, logistically or financially difficult to make
RS status: Accuracy	A measure of current activity for the accurate observation of a given RS-enabled EBVs product. The effectiveness of RS data and techniques to achieve an accurate and precise value of the RS-enabled EBV.	Fully operational network or service is in place generating EBV products accurate for the purpose	Indicates that no or very limited action has been taken to generate accurate EBV products
RS status: Maturity	Institutions/organizations to generate RS-enabled EBVs products can be identified and/or proposed to a funding body	Operationally implemented. It is known who needs to act, and what action needs to be taken so that the RS-enabled EBVs can be produced now	Indicates a complete lack of relevant infrastructure as well as relevant implementation organisations – the RS-EBV cannot be produced within 5 years

2.2 The selection and prioritization processes

The prioritization and selection of RS-enabled EBVs have been performed in two steps. Firstly, all biodiversity variables that can be retrieved from remote sensing were identified based on information obtained from the workshops attended by over 100 participants (Annex 2) on 27-29 January 2015 at IDV, Leipzig, Germany; on 27-28 May 2015 at ESRIN, Frascati, Italy; and on 07-08 September 2017 at ITC, Enschede, The Netherlands as well as from GEO-BON documentation and from reviewing the literature.

Secondly, during the 07-08 September 2017 workshop, the participants of the workshop in a number of breakout sessions:

- Further nominated candidate biodiversity variables that can be retrieved from remote sensing
- Have recognized a number of variables under the EBV classes developed by Pereira et al. (2013).
- Have merged further the variables into the EBVs derivable from remote sensing.
- Listed for each EBV, products derivable from remote sensing.
- Following the GCOS ECV prioritization process developed by the participants, values ranging from 1 (high priority) to 3 (low priority) were assigned to each EBV product according to the prioritization criteria in Table 4.
- The potential contribution of the EBV and its constituent properties to assess the 20 Aichi biodiversity targets and the SDG targets were also examined and recorded.

The workshop participants found that the original EBV classes are recognizable and understandable to both ecology as well as remote sensing specialists. However, when the proposed EBVs were examined, the workshop participants observed the following issues with the EBVs and their products (i.e., below the level of EBV class):

- Not all remote-sensing-enabled-EBVs (RS-enabled EBVs) fit the scope of the originally defined EBVs.
- RS-enabled EBVs occur across multiple EBV classes
- RS-enabled EBVs are essentially biological, though it is recognized that some RS-EBVs are defined by key physical aspects (e.g., fire disturbance cannot occur in the absence of (suitably structured) biomass).
- A related but separate issue is that some RS-enabled EBVs are not biological but have a clear and unambiguous biological cause and effect
- Some RS-enabled EBVs are very similar

In order to address these issues, the possible proposed solutions were:

1. Define RS-enable EBV variables names using commonly used and referenced names in both the biological and the remote sensing literature.
2. Recognize that an RS-enabled EBV may occur in multiple EBV classes, at various scales, and be a product of fusing multiple remote sensing sources.
3. Merge similar original EBVs into a new single RS-enabled EBV. For example, the original EBVs 'habitat structure' and 'ecosystem composition by functional type' are both remotely sensed measures of vegetation cover. Consequently, the 'Biophysical Attributes' EBV incorporates products such as land cover (and its derivative such as urban footprint or ice cover) as well as 3D biophysical structures like vegetation height, leaf area index, deadwood and ocean fronts, and 'ecosystem extent' and 'fragmentation' are merged into 'spatial configuration'.

4. RS-enabled EBVs are essentially biological but can include physical measures and disturbances that are intimately linked to the diversity of life. 'Fire occurrence' and 'Inundation' are relevant RS-enabled EBVs that can be effectively monitored by remote sensing from space, but only when comprising non-periodic events with a clear and significant biological cause and effect. Physical measurements of the rate that biodiversity produces energy or recycle nutrients, such as net primary production (NPP), also fit this interpretation of RS-EBVs.

Following those recommendations, the RS-EBVs that can be retrieved from remote sensing were merged, culled and sorted into a list of remote sensing enabled EBV and RS-EBV products retrievable by remote sensing (Annex 1). These RS-enabled EBVs are defined such that they can be recognized by both the remote sensing and the biological communities.

A summary of satellite observation requirements for each RS-EBV was prepared through literature review and personal communications with experts in remote sensing and ecology/biodiversity so that the workshop participants could have a common understanding before assigning priority scores. The SOR of selected RS-enabled EBVs will be dealt with in detail in part III of this document.

3 RS-enabled EBVs prioritization and selection Results

Currently, there is no prioritized set of EBVs that are known to be measurable using remote sensing data. The workshop participants assigned a ranking factor that ranges from 1 to 3, as detailed in Table 4. The prioritization of the candidate RS-enabled EBVs was determined by summing the ranked scores detailed in Annex 1. The RS-EBVs falling within the top 20 priority lists were reported. The 20 RS-enabled EBVs of terrestrial ecosystem function and structure with the highest rankings are summarized in Table 5.

These priority RS-enabled EBVs would be most suitable for long-term terrestrial ecosystem function and structure monitoring. According to the experts' ranking, inundation and fire occurrence have the highest priority both in ecosystem function and structure EBV classes. See Annex 1 for each EBV products score and the ranking of EBV products within class and across all terrestrial ecosystem structure and function candidate RS-enabled EBV products. It is noteworthy that many of the prioritized RS-enabled EBVs such as leaf area index and inundation occur in both ecosystem structure and function EBV classes.

In general, because of the diverse nature of terrestrial ecosystem functional and structural variables, it is worth noting that the selection and prioritization process should not be a one-time activity. Periodical revision of variables (i.e., adding or removing) should be performed depending on satellite observation availability and their utility for biodiversity monitoring. The ongoing selection and prioritization are highly constrained to the efficiency and effectivity of the prevailing remote sensing data and techniques, though they are desperately relevant to biodiversity monitoring.

Table 5: The 20 EBVs with the highest rankings

No.	*Remote sensing-biodiversity product(s)*	Remote sensing enabled EBV(s)	EBV class	Rank
1.	Biological effects fire disturbance (direction, duration, abruptness, magnitude, extent, frequency)	Ecosystem disturbance	Ecosystem function Ecosystem structure	1
2.	Biological effects of Irregular inundation	Ecosystem disturbance	Ecosystem function Ecosystem structure	1
3.	Leaf area index	Ecosystem physiology Habitat structure	Ecosystem function Ecosystem structure	3
4.	Land cover (Vegetation type)	Habitat structure	Ecosystem structure	3
5.	Ice cover habitat	Habitat structure	Ecosystem structure	5
6.	Above-ground biomass	Habitat structure	Ecosystem structure	6
7.	Foliar N/P/K content	Ecosystem physiology	Ecosystem function	6
8.	Fraction of vegetation cover (FVC)	Habitat structure	Ecosystem structure	8
9.	Urban habitat	Habitat structure	Ecosystem structure	8
10.	Habitat structure	Habitat structure	Ecosystem structure	8
11.	Vegetation height	Habitat structure	Ecosystem structure	8
12.	Plant area index profile (canopy cover)	Habitat structure	Ecosystem structure	8
13.	Ecosystem fragmentation	Spatial configuration	Ecosystem structure	8
14.	Ecosystem structural variance	Spatial configuration	Ecosystem function	8
15.	Net primary productivity	Ecosystem physiology	Ecosystem function	8
16.	Gross primary productivity	Ecosystem physiology	Ecosystem function	8
17.	Fraction of absorbed photosynthetically active radiation (fAPAR)	Ecosystem physiology	Ecosystem function	8
18.	Chlorophyll content and flux	Ecosystem physiology	Ecosystem function	18
19.	Carbon cycle (above-ground biomass)	Ecosystem physiology	Ecosystem structure	18
20.	Peak season, green-up, & senescence	Ecosystem phenology	Ecosystem function	18

Part III:

Satellite Observation Requirement Definition and Analysis for Selected Terrestrial Ecosystem Remote Sensing Enabled EBVs

1. Introduction

1.1. Purpose

This part of the document outlines the requirements for satellite observations of RS-enabled EBVs on the structure and function of terrestrial ecosystems. Terrestrial ecosystems are marked by high variability in bio-geophysical and optical properties, and there is no unified theory describing those properties and their changes over time. Satellite observations have a valuable contribution in providing a synoptic picture for studying and monitoring biodiversity change. Terrestrial ecosystem function and structure as characterized by habitat structure, extent, fragmentation, a composition by functional type, net primary productivity, canopy biochemical traits, FPAR, disturbance regime, etc., are recognized as RS-enabled EBVs by GEO-BON. The workhorse for monitoring of these terrestrial ecosystems structural and functional EBVs is Earth Observation data obtained from optical, thermal, Radar and LiDAR sensors, as well as *in situ* measurements. The potential contribution of satellite-based datasets and derived products have to be exploited, evaluated and benchmarked so that space agencies could provide observations for terrestrial ecosystem structural and functional RS-enabled EBVs on an increasingly routine basis. Therefore, this part of the document (part 3) focuses on identifying the required set of satellite observation requirements to assess and monitor the state/change of terrestrial ecosystem structure and function at national, regional and global scales with consistency in space and time. The following sections provide details on the datasets and products for biodiversity assessment and monitoring that are required to monitor terrestrial ecosystem structure and function.

1.2. Scope

The scope of this chapter is to assemble the satellite observation requirements for RS-enabled EBVs on the structure and function of terrestrial ecosystems. The aim is to identify the observation requirements to support scientific investigations aimed at improving our ability to assess and monitor biodiversity, particularly, terrestrial ecosystem structure and function. Overall, this document provides the observational requirements needed to monitor the structural and functional properties of terrestrial ecosystems that are of most significant interest concerning biodiversity change.

1.3. Target audience

The Satellite Observation Requirements document analyzes the current status and requirements of remote sensing-based EBVs. It thereby supports the efforts of the Convention on Biological Diversity (CBD), Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) and Group on Earth Observation – Biodiversity Observation Network (GEO-BON), to generate a global monitoring and knowledge base, with which to report on the status and changes in terrestrial biodiversity, ecosystem structure and ecosystem function. Additionally, this document is aimed at benefiting space agencies by identifying the key satellite observation requirement for terrestrial biodiversity monitoring and change detection within the context of EBVs. The Satellite Observation Requirements document is likewise addressed to local, national and international government and not-for-profit organizations tasked with biodiversity monitoring, assessment and target reporting. Here, it specifically demonstrates, through four use-case studies, how RS-enabled EBVs and the indicators derived thereof, can be used to inform biodiversity monitoring and change detection, and simultaneously contribute towards addressing issues pertaining to minimizing the costs of *in situ* data collection, analysis and reporting.

1.4. Method

The document is assembled based on a review of the literature on terrestrial ecosystem research activities supported by experts' opinion. First, a generic template for the observation requirement was developed, reviewed and filled through a literature review. Second, the list of observation requirements considered and its content was reviewed in an expert workshop. The satellite observation requirements of each RS-enabled EBV were then synthesized after the expect workshop and revised including the experts' opinion. Finally, the observation requirement document was further improved through open review by expert groups of remote sensing and biodiversity community.

1.5. Clearing up the ambiguity

Scale: The word scale has multiple meanings in various disciplines, which leads to an ambiguous usage of the term-scale and thus an appropriate qualifier has to be used for a more productive approach (Schneider, 2001). In remote sensing, the scale might be resolution and can be thought of as the smallest objects being distinguished by sensors. For ecology, the scale is likely to be grain, which is the measured size of patches. In environmental studies, the scale could be, the area or time interval in which the parameter of interest is homogeneous. While in cartography, the scale is defined just as the ratio between the distance on the map and the ground (Wu and Li, 2009).

Wu et al. (2006) proposed a three-tiered conceptualization of scale, which organizes scale definitions into a conceptual hierarchy that consists of the dimensions, kinds, and components of scale (Figure 5). Dimensions of scale are most general, components of scale are most specific, and kinds of scale are in between the two. This three-tiered structure seems to provide a clear picture of how various scale concepts differ from or relate to each other (Wu et al., 2006). Within the hierarchical scale definitions, the scales used in this document fall under observation scale (scale of measurement or sampling) kind and presented as spatial, spectral, and temporal resolution.

i. **Spatial resolution**: refers to the size of the area covered by a pixel in a satellite image. In optical and thermal remote sensing, each pixel in an image corresponds to a patch on the Earth's surface. It is also known as 'ground resolution' and is usually expressed in meters.

ii. **Spectral resolution**: refers to the wavelength intervals. It describes the ability of a sensor to define narrow wavelength intervals. The finer the spectral resolution, the narrower the wavelength range for a particular channel or band.

The following categories are used in setting the requirement for spectral resolution in accordance with the characteristics of the RS-enabled EBV:

- Panchromatic – 1 band (black and white)
- Multispectral – 4 to ±15 bands
- Hyperspectral – hundreds of bands

iii. **Temporal frequency (resolution)**: is the required interval between two successive instances of an RS-enabled EBV measurement in the same area and often expressed on an hourly, daily, weekly, monthly, yearly basis depending on the nature of the RS-enabled EBV.

1.6. Chapter outline

The observation requirements are structured into ten sections and defined for each RS-enabled EBV separately. The structure and content of the parts are as follows:

1.6.1. Definition of the RS-enabled EBV

In this section, the most widely accepted and scientific description of the RS-enabled EBV is described and introduced in clear terms. For some RS-enabled EBVs, several sub-definitions might exist among the different communities, and this chapter shall include separation where needed, and relation with other similar EBVs are highlighted.

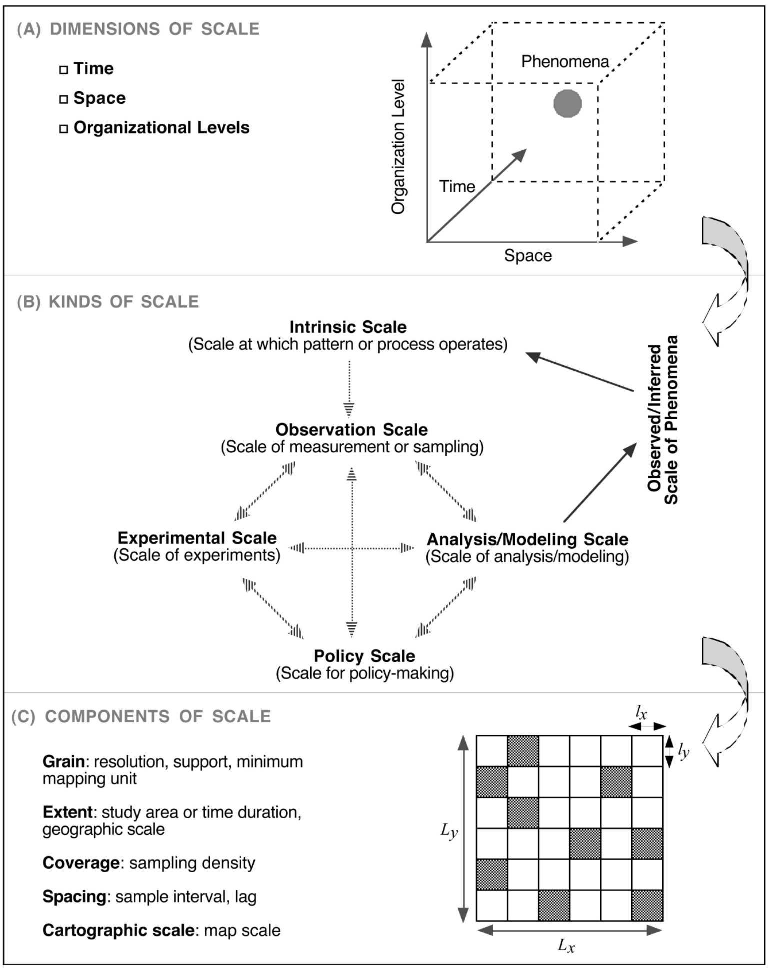

Figure 5: A hierarchy of scale concepts: (A) dimensions of scale, (B) kinds of scale, and (C) components of scale (from Wu et al., 2006).

1.6.2. The role of the RS-enabled EBV in biodiversity assessing and monitoring

Section 2 introduces the need and use of the RS-enabled EBV for biodiversity monitoring and assessment. It includes current (and future) areas of application, including the use of the data set. The contribution of the RS-enabled EBVs in assessing biodiversity targets (COP-CBD, 2010) and the sustainable development goals indicators (IAEG-SDGs, 2016) are discussed. The relationship between the RS-enabled EBV with other biological, environmental and climate variables is also reported in this section.

1.6.3. Spatiotemporal coverage

In section 3, the target geographic regions where the RS-enabled EBV is contributing to biodiversity assessment and the temporal observation coverage (inter and intra-annual observation requirements including seasonality) needed for effective monitoring is defined. Many RS-enabled EBVs cannot contribute equally to all biomes (see page 5 in part I of the SOR for biome definition) and therefore, this section shall highlight where the RS-enabled EBV's contribution to the biodiversity assessment is highest. The optimum length of observation period required is identified based on the RS-enabled EBV characteristics in order to provide reliable long-term trends and capture seasonal variability. Detailed spatial and temporal observation requirements are contained in section 1.5.5.

1.6.4. Remotely sensed EBV Products

This chapter defines the bio-geophysical and optical properties that shall be computed from remote sensing data and made available as data products to assess a specific RS-enabled EBV. One or several properties might be needed to represent the RS-enabled EBV and can include current available or future products. A matrix of properties with a short definition including units shall be listed.

***RS-enabled EBV* property**	**Definition [unit]**
…	…

1.6.5. Spatial extent and temporal frequency requirements

This section discusses the general framework regarding the spatial and temporal resolution required for assessing and monitoring biodiversity with the RS-enabled EBV, on different geographical scales (from global to local biodiversity assessments). The application and use of products' and their dependence on the spatial resolution are discussed at different geographic scales such as global, regional, landscape, catchment, local habitat or individual (species) levels (if applicable). Temporal resolution shall be addressed in terms of how often the different products (and their related satellite observations) need to be calculated (e.g., once a year, monthly weekly, daily), what should be the frequency of observations per product and what is the temporal accuracy needed to detect changes (e.g., detect changes within a week). Please note that the temporal frequency requirements for satellite observations might be different from the temporal resolutions of the product (RS-enabled EBV property).

The section shall also indicate if these spatial and temporal observation requirements are changing between biomes or regions. Also, a critical assessment of the benefit or loss of information when changing the required temporal or spatial resolution is addressed. For instance when the temporal or spatial resolution change by a given factor (for example from daily to weekly observations or from 10 to 30m spatial resolution), the effect on the information content of the EBV products are described in this section.

1.6.6. Transferability of retrieval approaches

a) Transferability among biomes

This section highlights the possibility of the transferability of the retrieval approaches depending on biomes with the scope to produce products with global coverage (with the restrictions mentioned in Section 3). Possible hurdles occurring when one retrieval approach is transferred to another biome or ecoregion are explained.

b) Transferability across scale

Differences and adaptation needed when changing spatial resolution are discussed in this subsection.

1.6.7. Calibration and Validation

Section 7 addresses the importance of independent observations that are required for the calibration and validation of satellite data derived RS-enabled EBV. Datasets for validation or calibration might be for instance in-situ data, observation networks or airborne/ground-based remote sensing data, citizen science datasets, etc., that are suitable for the validation and calibration of global data products. Issues regarding the estimation of accuracy and precision of the RS-enabled EBV data product are addressed, and challenges when combining the different data types are discussed.

1.6.8. Existing data sets and performance

Existing datasets of the RS-enabled EBV with a focus on global products are explained in this section, including the approach for generating these RS-enabled EBV products. The part includes a brief explanation of the used input data (e.g., satellite sensors, type of satellite observations, quality level), spatial/temporal resolutions of the datasets, and use and application. The independent data that has been used for calibration/validation (e.g., *in-situ* data) is also described as well as the overall product accuracies/uncertainties. The chapter also includes an outlook of potential future (new) approaches and/or used sensors that might be developed.

1.6.9. Feasibility, scientific and technology readiness levels

A critical discussion regarding the feasibility and current limitation(s) of remote sensing to develop the RS-enabled EBV is made. The inherent limitations of using remote sensing and the combination of complementary data sets, to overcome these limitations, are assessed. The current status and the scientific and technology readiness level are estimated through analysis of the science readiness level (SRL) matrix.

1.6.10. Summary and outlook

The overall observation requirements of the RS-enabled EBV are briefly summarized. Opportunities and challenges in the future, which would extend or hinder the capacities to meet the satellite observation requirements identified and presented here. Recommendations on when and how the observation requirement should be updated are specified.

2. Observation requirements of terrestrial ecosystem structural and functional RS-enabled EBVs

The following RS-enabled EBVs, which are suggested by GEO-BON and are streamlined into the priority RS-enabled EBVs candidate list by Skidmore et al. (2015) in the terrestrial ecosystem structure and function domain are being investigated for their satellite observation requirement and recommended for priority action by space agencies (*Table 6*). The feasibility and capabilities of current Earth observation systems to ensure quality and consistency data for all these products are investigated, and recommendations made about availability and subsequent reprocessing of data for each RS-enabled EBVs. Also, any other supplemental data that may be needed to assist interpretation and analysis of the RS-enabled EBV are identified whenever necessary.

Table 6: Overview of candidate RS-enabled EBVs (sub-variables) of the terrestrial ecosystem for which satellite observation requirement investigated and determined.

EBV Class	Candidate RS-enabled EBV	EBV Products from Satellite Observation	Data records from satellite missions
Ecosystem structure	1. Vegetation height (VH)	Global vegetation canopy height and 3-D structure	LiDAR, SAR and optical structure metrics
	2. Ecosystem extent and fragmentation (FRAG)	Land cover maps, maps of ecosystems, patch size, and patch density	Multispectral VIS/NIR imager radiances
Ecosystem function	1. Land Surface Phenology (LSP)	Global annual time series of terrestrial vegetation phenology metrics including start, end, and length of the growing season	Multispectral VIS/NIR infrared imager reflectances
	2. Canopy chlorophyll content (CCC)	Global map of CCC	High spatial resolution (≤30m) multispectral VIS/NIR imager radiances

2.1. RS-enabled EBV Land Surface Phenology

2.1.1. Definition of Land Surface Phenology

The RS-enabled EBV Land Surface Phenology (LSP) characterizes recurrent events in the annual profile of vegetated land surfaces at the ecosystem scale as observed from RS. LSP is a widely used indicator of terrestrial ecosystem response to environmental change, and useful for biodiversity monitoring for many reasons (Richardson et al., 2013), including its strong link to the climate system and its potential to describe functional biodiversity groups. LSP relates to a plant or community-level phenology but should not be interpreted as a species trait.

2.1.2. The role of Land Surface Phenology in biodiversity assessing and monitoring

LSP is an aggregated signal consisting of the phenological signatures of species within the observational unit and is, therefore, a functional indicator of the ecosystem or the plant community. The temporal and spatial variation in LSP is partly driven by species traits and ecosystem composition and may be used to define functional groups of vegetation and their dynamics. Spatial distribution of LSP, in particular at high spatial resolution, may provide a measure of the spread of different species and the influence of locally variable environmental conditions, such as soil and topography in natural ecosystems (Schneider et al., 2017).

On a community level, LSP properties have successfully been used to predict plant alpha diversity on a regional scale (Revermann et al., 2016). LSP is commonly represented in scientific studies by different so-called LSP properties such as length of the growing season (GSL) as for instance used in Oehri et al. (2017), who found LSP properties to be positively impacted by species richness biodiversity metrics. LSP-based properties are also relevant for biodiversity studies, for instance by informing empirical and mechanistic species distribution models (SDM) (Chuine, 2010, Gritti et al., 2013). Together with integrals of vegetation activity, GSL could be used as proxies for ecosystem productivity (e.g., Wang and Fensholt, 2017). In addition, the general ecosystem's sensitivity to climatic and environmental variation can be observed and monitored with LSP.

Long-term and short-term responses of an ecosystem to changing climate and other environmental conditions are important factors for the stability of the ecosystem and its plant communities. Changing LSP can, for example, show indications of spatial migration of species (e.g., through invasive species), of species, shift phenological events (e.g., advance their green-up) in response to a changing climate, or of a loss in biodiversity (Wolf et al., 2017). Nevertheless, climate and biodiversity need first to be considered in a consistent way to adequately capture such shifts (Brown et al., 2010). Potentially, one might detect changes in environmental conditions and their impact on the species distribution faster and for larger extents with RS than with *in situ* observations and trends might be visible earlier as well.

Additional applications of LSP may include health monitoring of particular species or input for the prediction of animal phenology. The former uses the amplitude of the phenological signature as an indicator for the health status of pure stands (e.g., Wu et al., 2018), while the latter makes use of the timing of phenological events to predict animal phenology (e.g., Poyry et al., 2018).

Finally, several studies demonstrated the important role of LSP for i) SDM (e.g., Jarnevich et al., 2014, Bradley and Fleishman, 2008), ii) in global-circulation and Earth-system models describing biosphere-atmosphere interactions (e.g., Garonna et al., 2018), iii) as a parameter for productivity estimations in a wide range of fields (agriculture, land degradation, carbon cycling), and iv) as a covariate for mapping ecosystem or habitat extent, among other application domains (e.g., Schwartz, 2013).

2.1.3. Spatiotemporal coverage

LSP is relevant globally and for almost all biomes and geographical regions. However, most use cases are found in areas with distinct vegetation seasonality. LSP is rarely suitable for biodiversity assessments in biomes without a clear seasonal profile – such as (tropical) rain forests or (arctic) deserts. The focus for generating LSP products should, therefore, be on biomes with a seasonal pattern such as temperate, Mediterranean and subtropical and tropical dry forests, boreal taiga and arctic tundra, wetlands, shrublands, tropical and subtropical savannah. Next to monitoring of natural and protected areas, LSP as input for observation and monitoring of agricultural areas are of high interest to policymakers, for example, it enables them to directly regulate and implement agriculture practices by law to foster biodiversity.

LSP properties are inherently based on annual profiles, for which the region of interest needs to be observed all year long and with a sufficiently dense sampling interval during the complete growing cycle. Ideally, the observation period is between the start of dormancy of the preceding cycle until the start of vegetation activity of the subsequent vegetation cycle, in order to allow for enough data points during a period (satellite observations often dominated by cloud coverage). Nevertheless, only with a sufficiently long time series (i.e., spanning several subsequent vegetation cycles, e.g., more than a decade) can trend in LSP be adequately detected and related to climate change, changes in biodiversity, or protection efforts.

2.1.4. Remotely sensed EBV Products

The core component of LSP observations is the yearly evolution of the vegetation activity of a vegetated area of interest with its onset and green-up in spring or wet season and transition from senescence to dormancy in autumn (or dry season) as well as the intensity of vegetation activity. This seasonal profile, often represented by the changes of a vegetation index (VI) depending on date, can be mathematically described by a curve or function for an area of interest (i.e., a geolocated pixel) and the derived properties thereof. In general, the ecological meaning of the extracted dates on a species level is highly debated, and direct relation between remotely sensed LSP properties and *in situ*/visual observations are usually not straight-forward (Keenan et al., 2014a).

The most commonly retrieved properties - extracted and used from the annual VI-profile - are the Start of Season (SOS) and End of Season (EOS) that indicated the start and end of the vegetation season. These properties are highly correlated to green-up (spring) and leaf senescence and dormancy (autumn) of the vegetation. These dates can be expressed as day of the year (DoY) and are highly dependent on the used procedures and model (e.g., Xu et al., 2014).

For instance, extracted LSP properties can be strongly dependent on the chosen VI as they represent vegetation activity differently. In general, two main groups of VIs can be distinguished depending on whether they are based on the spectral reflectance of vegetation (e.g., Normal Difference Vegetation Index NDVI and Enhanced Vegetation Index EVI) or based on (additional) non-spectral model assumptions (e.g., Leaf Area Index (LAI) and fraction of absorbed photosynthetically active radiation (fAPAR)). By defining a curve describing the seasonal vegetation profile for the area of interest (e.g., one pixel), several additional properties can be extracted to characterize the LSP profile. These properties include maturity onset (day), the peak of season (day) and senescence onset (day), rates of green-up / senescence (VI/day), the magnitude of variation (amplitude VI), base VI during dormancy and various VI integrals (e.g., Wu et al., 2018). In conclusion, LPS properties of different studies might be difficult to compare when different VIs, curve models or retrieving methods have been used.

Depending on biome and land cover type, also the number of growing seasons per year needs to be considered as a parameter or for the extraction of the other properties. This is, for instance, the case in agricultural areas and areas with summer drought (Garonna et al., 2016).

Additional properties such as length of season (LOS, also GSL) derived as mathematical difference between EOS and SOS or the amplitude as the difference between peak VI and winter VI are simple, derived metrics that may be of high interest to the users. Table 7 summarizes possible LSP properties that are used and useful for LSP studies.

Table 7: List of LSP properties and their definition

LSP Property	Definition
SOS	Start of the season, start of green-up [DoY]
EOS	End of season, the start of dormancy [DoY]
LOS / GSL	Length of the season / Growing Season Length (EOS minus SOS) [DoY]
Maturity-onset	The onset of summer [DoY], e.g., end of green-up phase
Peak of season	Time of peak of the season [DoY], e.g., time of peak of vegetation activity
Winter VI	The minimum level of VI index Low/no vegetation activity [VI unit]
Peak VI	Maximum level of VI index, amplitude [VI unit]
Amplitude	The magnitude of variation (Peak VI – Winter VI) [VI unit]
Rates of green-up	The incline of vegetation activity from SOS [VI unit/day]
Rates of senescence	The decline of vegetation activity until EOS [VI unit/day]
Integral	Different integrals can be extracted from the profile as a measure for the vegetation activity over a certain period of time [VI/time]
# growing seasons	Number of growing seasons per yearly profile [-]

2.1.5. Spatial extent and temporal frequency requirements

A dense time series with sufficient temporal sampling is required to generate an accurate LSP profile, in particular during green-up and senescence phases due to the fast increase or decrease of vegetation activity during this period; it defines, therefore, the reliability and accuracy of the extracted properties. These transition phases in vegetation activity, i.e., between start and peak of the vegetation season and between the onset of senescence and dormancy, are most sensitive for changes in the ecosystems and therefore also most important for biodiversity studies. Ideally, the sampling frequency during these transition phases is at least double to the total transition time. Depending on the biome, in particular, the green-up rate can be high, for instance after snowmelt. Therefore, a higher sampling frequency may be required in certain biomes and certain times of the year.

In general, characterization of the phenological transition events requires sub-weekly temporal resolution. During growing seasons, temporal sampling can be lower (e.g., weekly) and during dormancy even lower (e.g., bi-weekly). Additional attention and ideally denser temporal sampling are required in regions where multiple vegetation seasons occur and – if of interest – for heavily managed land types. Observations are needed year-round and for multiple years in order to capture long-term changes and to study the interaction with biodiversity changes.

If the sampling frequency is too low for a reliable model fit and representation of the profile, the time series needs to be flagged as invalid. A sufficient sampling frequency strongly depends on the green-up/senescence rate and on the precision of the individual measurements (scattering) and/or outlier detection.

The required spatial resolution for LSP products depends strongly on the application and the level of detail that should be characterized. Coarse spatial resolution products (ecosystem level) can be used for assessing vegetation-climate interactions and for the detection of hotspots of change. In turn, moderate spatial-resolution products can be used for the documentation of large-scale ecosystem dynamics. High spatial-resolution images (30 m and less) can be used to observe links to community phenology (consisting of several species) and ecosystem composition. Specifically, when spatial resolution increases, the information content increases non-linearly and the gap between LSP and individual plant phenology narrows.

2.1.6. Transferability of retrieval approaches

a) Transferability among biomes

When transferring the retrieval approach (i.e. processing chain and mathematical model) among biomes, most difficulties regarding the vegetation activity profile arise from i) the different speeds of change between low and high vegetation activity and vice-versa, and ii) the different amplitude between low and high vegetation activity. Some biomes are characterized by low vegetation amplitude (e.g., semi-arid grass, scrublands), where the same vegetation amplitude would indicate a mixed pixel (e.g., with street) or invasive species and disease for other biomes' vegetation. A retrieval approach needs, therefore, to consider possible differences in (biological) meaning of extracted VI properties (see Chapter **Error! Reference source not found.**) in different biomes depending on the biomes' specific activity profile.

In addition, extreme weather like drought and flooding can alter a vegetation profile in an unknown way and might also induce additional vegetation seasons. Detection and definition of multiple vegetation seasons are challenging as the transition between lower summer amplitude of vegetation activity, for instance, due to summer drought and a double vegetation season (e.g., for crop fields), is smooth.

b) Transferability across scale

Two types of upscaling-effects should be distinguished: First, phenological processes are inherently scale-dependent, and different processes may, therefore, be observed at various spatial data resolutions. While resolution increases, the information content increases non-linearly and thereby narrows the gap between LSP and individual plant phenology. An example is the mixture of phenological profiles of species within an observational unit when changing the size of that unit (e.g., pixel size). Scaling between these different resolutions requires a sound understanding of the processes and their impact on the LPS signal (e.g., Vrieling et al., 2017, Fisher and Mustard, 2007).

The other, more straightforward, type of upscaling is enlarging the spatial extent in terms of the number of observational units. Commonly, LSP retrieval uses a per-pixel approach, which makes this type of upscaling highly dependent on the computational power when the spatial resolution or spatial extent increases.

2.1.7. Calibration & Validation

The most common current approach for validation of LSP is the use of ground-based phenocams. They are installed either on the ground or a tower above the canopy, at a known location and angle of view and repeatedly observe the vegetation. Several PhenoCam networks exist, each is composed of webcams that regularly take digital photographs in the visual bands and in some cases in near-infrared. The most common approach is using the visible channels for calculating the Green Chromatic Coordinate (GCC) for comparison with satellite-derived GCC or other VI values. The NIR-channel for extracting the vegetation activity is still seldom used, as the few cameras with NIR-channel available are in addition mostly uncalibrated for using RGB and NIR channels together. Calibration would be needed if a VI based on NIR and RED, such as NDVI, is used. LSP validation with phenocams has been successfully applied for MODIS time series on ecosystem-scale (Browning et al., 2017). However, an even higher correlation between phenocam observations and satellite-derived LSP properties can be expected when using higher spatial resolution satellite data, such as Sentinel-2 with up to 10m pixel-resolution (Lange et al., 2017). By using ground-based images, the influence of the atmosphere on satellite images can be investigated. Nevertheless, the highest uncertainties are the transformation of the phenocam field of view to the pixel raster of a satellite image.

Also, validation data for LSP can be acquired by Unmanned Aerial Vehicles (UAV). UAVs are now often used in agriculture and crop monitoring (Torres-Sanchez et al., 2014, Bendig et al., 2014, Michez et al., 2016). However, only a few studies exist about LSP validation of satellite data because of the high costs and effort for repeatedly acquiring UAV observations (Klosterman et al., 2018).

A similar approach to the validation with UAV observations follows the idea of the comparison of multiple-resolution results observed from different satellites. The approach can be used to enhance the reliability of phenological products and for detecting outliers (e.g., Liu et al., 2017). Differences due to varying spatial resolution, spectral resolution and geographic reference systems and ground projections need to be taken into account.

Plant phenology is observed by *in situ* measurements at various sites and for selected species. The connection between LSP properties and plant phenology, i.e., from a single tree to the pixel level, is challenging due to the different processes that both approaches observe (e.g., Keenan et al., 2014a). Nevertheless, approaches with local phenological observations (e.g., Revermann et al., 2016, Verger et al., 2016), existing phenological databases (Lange et al., 2017), or citizen science (Kosmala et al., 2016) have been used for validation already. In addition, on-ground carbon flux measurements have been used to validate LSP observations of coarse-resolution (e.g., Melaas et al., 2013, Gonsamo and Chen, 2016).

In general, most of the above-mentioned *in situ* based validation approaches were applied to local or regional areas. A validation approach at a global scale is currently challenging due to sparse coverage with ground observations (Keenan et al., 2014b). Standards and data access for *in situ* phenology observations can be different among the local and regional networks, which further complicates validation at a large spatial coverage.

The Committee on Earth Observation Satellites' (CEOS) working group on calibration and validation with its Land Product Validation Subgroup is also developing a "validation good practice" for phenological data. The group identified the large variation in existing definitions and retrieval algorithms for the start and end of the season as major concern and source of uncertainty. In addition, a standardized database including species-level field observations and standardized processing of phenocams shall be developed. They list on their webpage the currently best available reference data sets for LSP validation (https://lpvs.gsfc.nasa.gov/Pheno/Pheno_home.html).

2.1.8. Existing data sets and performance

Many studies demonstrated the extraction of LSP properties from coarse and moderate resolution data (500-1000m). Various methodological approaches are well established and have been compared (White et al., 2009). Global products exist at coarse spatial resolution (Garonna et al., 2016) and moderate resolution, for instance, the MODIS product (MCD12Q2[1]) that is currently being updated (Friedl et al., 2018). At high spatial resolution, extraction algorithms have to rely on irregular time series and although first steps have been taken (Vrieling et al., 2017), large-area products are not yet available.

Currently available datasets include 34+ year time series at coarse resolution (based on AVHRR), 17+ years at moderate resolution (based e.g., on MODIS, SPOT VEG) and decades of high resolution (based on Landsat 4-8, Sentinel-2) although only sufficiently dense since the launch of Landsat 8 (2013, 30m resolution) and Sentinel-2 (2015, 10m resolution) and with substantial data gaps in the 1990s due to the Landsat commercialization strategy at the time. Regarding achievable performance, this can be considered "very good/mature" for coarse and moderate spatial resolutions LSP, where the main product uncertainties are caused by cloud cover and over-generalization of the retrieval algorithms. For high spatial resolution time series with irregular sampling, the achievable performance is substantially weaker, although developments in this field are fast.

[1] https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12q2

Other systems than multi-spectral sensors, such as synthetic aperture radar (SAR) or hyperspectral data, were also used for LSP assessment. With the SAR technology and the Sentinel-1 satellite, cloud cover could be overcome and the high repetition time would be very well suited. Rice crop monitoring is already operationally tested using Sentinel-1 (e.g., Nelson et al. 2014) and first phenological studies for crop classification (e.g., Veloso et al. 2017) and forest classification (Rüetschi, Schaepman, and Small 2018) exist using polarized SAR data. The technique, nevertheless, is still very data-intensive and systematic processing of larger areas is challenging. In contrast, hyperspectral observations are easier to process than SAR data sets, however, not available for satellite remote sensing.

2.1.9. Feasibility, scientific and technology readiness levels

LSP retrieval by remote sensing is non-taxon specific and therefore suitable for observing community and stand-level variation, rather than a species-specific variation. So far, LSP derived from RS is mostly based on spectral vegetation indices and a chosen mathematical model to represent the annual variation in vegetation activities. Mathematical models (e.g., double-logistic, harmonic or spline curves) are selected and adapted depending on local vegetation and conditions (e.g., biomes) and therefore do not directly represent a specific eco-physiological process. The vegetation indices are often based on spectral information that is derived from the integrated absorption of electromagnetic radiation at different wavelengths by the top layers of the canopy and may be interpreted as 'vegetation activity'. The correlation to biophysical events is made in a second step and interpretation of this signal can be use case-specific and requires expert knowledge.

LSP as commonly understood assumes certain yearly amplitude in vegetation activity and cannot cover other types of cyclicality, for instance, induced by climatic oscillations. Biomes with minimal or no seasonality (e.g., desert or rainforest) are commonly excluded, or retrievals may be accompanied by significant levels of uncertainty.

In general, LSP retrieval algorithms are mature and have been successfully applied on a wide range of vegetation-index time series from regional to global scales. The algorithms have mostly been developed on coarse- to moderate-spatial resolution RS data for global applications. High-resolution products at local scales were, however, often developed biome-specific only. These LSP retrieval algorithms need still some adaptation for high-resolution products with global coverage derived from modern multispectral satellites with high repetition rates such as Landsat 8 and Sentinel-2. Rapid developments in computational power (e.g., cloud computing) make the global processing of LSP retrieval algorithms feasible.

2.1.10. Summary and outlook

From the biodiversity monitoring point of view, the high potential of LSP lies in narrowing the gap between plant-level and ecosystem-level traits. It is currently recommended to interpret LSP at the ecosystem level because of its demonstrated links to ecosystem functioning. However, application at high spatial resolution opens doors to a multitude of new ecological applications and to a better description and understanding of functional biodiversity. A most important development is to design an algorithmic approach to assess a global dataset among all biomes and regions that can be validated by ground measurements and provide quality measures.

2.2. RS-enabled EBV canopy chlorophyll content (CCC)

2.2.1. Definition

Chlorophyll is the green pigment in plants that is used by plants to absorb solar radiation to make food from carbon dioxide and water. There are two primary forms of chlorophyll found in nature: chlorophyll-*a* and chlorophyll-*b* with a small difference in absorbing light from the sun at slightly different wavelengths. In natural plants containing chlorophyll, there is a ratio of 3:1 chlorophyll-*a* (a bluish-black solid) to chlorophyll-*b* (a dark green solid), which both work together to reflect the dark green pigment that is visible to the human eye (Chappelle et al., 1992).

Canopy chlorophyll Content (CCC) is the total amount of chlorophyll-*a* and -*b* pigments in a contiguous group of plants per unit ground area often expressed in g/m^2 (Gitelson et al., 2005). It is a product of leaf chlorophyll content (i.e., chlorophyll content of a fresh green leaf divided by its one side area (g/m^2) and leaf area index (LAI). CCC is a terrestrial ecosystem functional EBV that describes chlorophyll pigments distribution within the 3D canopy surface. Thus, it determines the total photosynthetically active radiation absorbed by the canopy (Gitelson et al., 2015, and 2005).

2.2.2. The role of canopy chlorophyll content in assessing and monitoring biodiversity

Chlorophyll is a plant pigment that provides valuable information about plant physiology and ecosystem processes (functions) at different scales so that ecologists, farmers, and decision-makers able to assess the influence of climate change, and human factors (e.g., exploitation and manipulation of ecosystems) and natural factors (e.g., disease breakout, inundation and fire) on plant functions. Monitoring the dynamics of CCC helps to understand the adaptation of forests, crops, and other plant canopies to such factors (Féret et al., 2017). Photosynthesis, which is an important physiological parameter in plants ultimately depends on chlorophyll content. Chlorophyll controls the amount of photosynthetically active radiation absorbed for photosynthesis (Ustin et al., 2009). Therefore, information on the amount and spatial distribution of chlorophyll is key to measure and understand plant growth, primary ecosystem productivity and the general relationship between photosynthesis and relative growth rate. Besides its role in controlling photosynthetic rate, chlorophyll is of co-evolved traits that vary across species depending on environmental conditions (Reich et al., 2003). Studies across species from different biomes around the world have shown the presence of "strong positive correlations between photosynthetic rates, leaf nitrogen content, and specific leaf area. And a strong negative correlation between photosynthetic rate and leaf lifespan indicating consistent trade-offs among these trait relationships. Such relationships highlight the utility of photosynthetic capacity (chlorophyll content) in predicting other plant functional traits as well as whole plant strategies for resource use" (Cavender-Bares and Bazzaz, 2004).

In addition to its role in photosynthesis, chlorophyll is an essential indicator of nutritional stress and growth status of plants and can be used to evaluate: the ability of plants to photosynthesize, stress levels caused by diseases, and effect of heavy metal pollution (Cui and Zhou, 2017). Chlorophyll is a controlling factor for plant growth and terrestrial ecosystem carbon, as well as being an important variable which interacts with climatic change (Sievering et al., 2000). It can be used as a proxy for leaf photosynthetic capacity to determine forest carbon exchange, which is a central priority for understanding ecosystem response to increased atmospheric CO_2 levels and improving carbon cycle modeling (Croft et al., 2017). Since chlorophyll is highly correlated with leaf nitrogen concentration, it can be used as an operational proxy for nitrogen content (Muñoz-Huerta et al., 2013).

CCC is an input variable of terrestrial biosphere models to quantify carbon and water fluxes (Luo et al., 2018), primary productivity (Houborg et al., 2013, Peng and Gitelson, 2011), and light use efficiency (Wu et al., 2012). Changes in CCC indicate the effects of disease, nutritional and environmental stresses (Korus, 2013, Zhao et al., 2011, Inoue et al., 2012). At the stand level, canopy chlorophyll content has been used to infer nitrogen stress, diseases and water deficit (Inoue et al., 2012). CCC is also an important input variable required by ecological process models (Plummer, 2000, Ollinger and Smith, 2005) and plant growth models (Delegido et al., 2011). It is related to functional diversity metrics including light use efficiency, wood growth, net and gross primary productivity that can be used for global carbon cycle modeling and agricultural applications (Plummer, 2000, Ollinger and Smith, 2005).

CCC is one of vegetation biochemical properties that are highly related to ecosystem functioning and is an important indicator of ecosystem health and vegetation physiological status. Chlorophyll plays a role in the assessment of the terrestrial carbon budget by supporting an accurate estimate of gross primary productivity. Information on the amount and distribution of CCC has been utilized to answer many ecological questions related to monitoring and evaluating terrestrial vegetation properties such as identifying types of vegetation, mapping vegetation cover and understanding the condition of vegetation (Dash et al., 2009).

CCC can also be used for forage quality assessment, ecosystem classification, and biomass estimation, as well as being a key input to estimate CBD indicators such as trends in carbon stocks and patterns in resilience within ecosystems of Aichi target 15, and net primary productivity of Achi target 3 (Secretariat of CBD, 2010). Information on the amount and distribution of CCC helps countries to assess and report biodiversity indicators related to ecosystem processes and functional aspects of biodiversity (e.g., ecosystem health and vegetation physiological status). The RS-enabled EBV supports efficient and timely evaluation of measures taken to implement the CBD and the effectiveness of these measures. Similarly, the spatially and temporally contiguous information on CCC can be used to support measuring indicators of the 15th goal of the SDGs indicators such as 15.2, 15.3, and 15.4, which are related to the sustainable use of terrestrial ecosystems. Therefore, spatially-explicit knowledge of vegetation's CCC is fundamental for the understanding of terrestrial ecosystems and for assessing plant health and biodiversity status. In general, CCC products have a tremendous role in capturing anthropogenic effects on the state of planet earth because of its application in quantifying vegetation productivity, vegetation stress and land cover mapping (Dash et al., 2009). It helps to understand the fundamental mechanisms of photosynthesis, the responses of plants to environmental change, genetic variation, and ecological diversity (Murchie and Lawson, 2013). Because of its importance to ecosystem function and its value as an indicator of ecosystem health, CCC is one of the most important variables to consistently monitor.

2.2.3. Spatiotemporal coverage

Chlorophyll content assessment is mostly used as an index to diagnose disease and retrieve the nutrient and nitrogen status in plants (Dey et al., 2016). Thus, the target geographical areas where CCC has to be derived include all vegetation in all terrestrial biomes such as grassland, tundra, tropical rainforests, temperate coniferous forests and Boreal forests (taiga). However, quantifying the chlorophyll content of water bodies is beyond the scope of this RS-enabled EBV product, and thus all water bodies including freshwater bodies such as rivers, lakes, and ponds have to be excluded. A global land cover product can be used to discriminate against the non-vegetated terrestrial surface and water bodies from the vegetated terrestrial earth.

Chlorophyll content changes in response to biotic and abiotic stresses such as pathogen infection, light stress and under water deficit conditions. However, there is a significant change in the amount of CCC due to seasonal variation and plant growth stage. Climate condition in different seasons leads to varying amounts of chlorophyll content during the growth periods. A study made in evergreen Sitka spruce to investigate the seasonal variation of leaf traits showed a steady increase in chlorophyll content throughout the summer from bud break in June until September, and a slight decrease during winter (Lewandowska and Jarvis, 1977). Therefore, it is of high importance to have a long-term record of CCC to disentangle the temporary changes that occur under normal growth conditions from a permanent alteration of CCC that indicates change patterns in the functioning of the ecosystem. A long-time series record of CCC product is required to examine and understand plants' response to climate and other environmental changes. The ideal optimal temporal domain would be 5-10 years record of the RS-enabled EBV at regular intervals.

2.2.4. Remotely sensed EBV products

The main product used to monitor CCC is a quantitative map that shows the spatial distribution of the average top of canopy chlorophyll content per unit vegetated area. The product is derived from high-resolution imageries in the reflective optical domain by applying robust and straightforward operational algorithms as a unique, cost-effective source for detailed knowledge of the spatial and temporal variations of this crucial canopy variable. A series of CCC products along with leaf area index could be utilized to detect seasonal variations. Since the canopy chlorophyll content is the product of leaf chlorophyll content and leaf area index (**Error! Reference source not found.**), the availability of

LAI products is of importance particularly when CCC mapping is up-scaled from leaf level to canopy to landscape levels or vice-versa.

Table 8: vegetation properties related to the RS-enabled EBV-CCC and their definition

RS-Enable property	Definition (unit)
Leaf chlorophyll content	Leaf chlorophyll content per one-side leaf area (ug/cm^2)
Leaf area index	The one-sided green leaf area per unit ground surface area (m^2/m^2)

Two of the RS-enabled EBVs discussed in this document have an essential role in the development process of global CCC products. Land surface phenology is vital in discriminating the growth stages when CCC products have to be generated. The other ecosystem structural EBV–ecosystem extent global product helps to mask out non-vegetated earth surface during the production of global CCC products.

2.2.5. Spatial extent and temporal frequency requirements

The spatial and temporal observation requirements needed to produce CCC products are indicated in Table 9 Monitoring and assessing terrestrial ecosystem function demands to detect subtle variation in canopy chlorophyll, which in turn requires high resolution (i.e., spatial and spectral) remote sensing data. There is also a high demand for detail information by ecological process models to quantify local variations. However, the accuracy of remote sensing-based CCC retrieval relies on distinguishing the difference in released signals due to a change in chlorophyll concentration. When the spatial resolution becomes coarser, the effects of vegetation structure, canopy cover, shadows, and background could be high and degraded the accurate retrieval of CCC. Based on freely available RS data, a spatial resolution of 20m would be an optimal spatial resolution value achievable currently and in the foreseeable future while maintaining frequent and global coverage for accurate prediction of CCC products.

The temporal frequency of the desired product is driven by the need to detect changes in the state of vegetation. CCC varies widely along the growing season, and monitoring strategy varies across growing season and ecosystem types. Hence, a wide dynamic temporal range is required. Besides, a much more frequent temporal sampling is needed to account for the presence of clouds and other factors that limit the number of useful observations.

Table 9: Spatial extent and temporal frequency requirements to produce canopy chlorophyll content (CCC) products for various ecosystem function monitoring and assessment use.

Target Geographic Location	Terrestrial biomes such as grassland, tundra, tropical rainforests, temperate coniferous forests and Boreal forests (taiga)
Temporal frequency	• Depending on the biome type, season and geographical location, in the beginning, green-up and senescence for deciduous forests • Two or three times a year for evergreen biomes • Multiple years (5-10 years) time series required for studying plants' response to climate and other environmental changes.
Spatial detail (resolution)	Generally, high-resolution data required to map chlorophyll across biomes. CCC products based on:

	• 100+ m resolution images can be used for primary productivity analysis, photosynthesis capacity plants response for environmental change, and ecological process models. • 30 -100 m resolution images can be used for assessing ecosystem health conditions, ecosystem classification, and biomass estimation. • High resolution (<30 m) imageries are required to assess nitrogen stress, diseases, and water deficit in vegetation.

2.2.6. Transferability of retrieval approaches

a) Transferability among biomes

Although a strong correlation exists between canopy reflectance and chlorophyll content that can be used to retrieve CCC from remote sensing data, their relationship changes in different biomes due to the variations of leaf, canopy and image acquisition variables. As such variations in internal leaf structure, leaf thickness, water content, LAI, foliage clumping, stand density and understory vegetation in different biomes alter the relationship between canopy reflectance and CCC. As a result transferring retrieval methods developed for one biome, universally across all biomes in broad spatial extents, containing different species or plant functional types, is challenging. Therefore, the proposed method for global CCC retrieval should account for those variations in different biomes. The feasible strategy could be biome based calibration of the proposed CCC mapping method instead of one generic algorithm across broad spatial extents, containing different biomes.

b) Transferability across scale

Many studies performed at leaf and canopy level (small scale) showed that CCC could be retrieved from hyperspectral remote sensing with high accuracy, but when the observation scale moves from leaf to canopy to landscape scale, the accuracy tends to weaken (Ustin et al., 2009). The spectral property caused by variation in CCC is then confounded by soil, non-photosynthetic vegetation (litter, bark, and branches), stem characteristics, canopy structure, and shadows. Algorithms that have been initially designed at a small scale are particularly likely to suffer from these additional heterogeneity factors when used at a larger scale (Ustin et al., 2009, Ollinger, 2011, Asner, 1998). It is, therefore, possible that reflectance factors from two forest canopies may differ, even if the reflectance spectra of the component leaves are the same (Croft et al., 2014, Blackburn, 1998). Heterogeneity of land surface texture is another source of error when locally developed algorithms up-scaled to regional and global scales. Sometimes due to the non-availability of good-quality imagery covering the land surface of the entire Earth from one sensor demands to combine data obtained from multiple sensors, which make global CCC mapping much more complicated.

Hence, the global mapping of CCC requires an operational mapping strategy to develop a reliable approach. A variety of mapping strategies and classification approaches were proposed for high spatial resolution global mapping of land cover products and biophysical variables such as LAI (Zheng and Moskal, 2009, Chen et al., 2015). Chen et al. (2015) implemented pixel-based classifiers, and object-based identification approaches in mapping global land cover at 30 m resolution from Landsat imagery and achieved an overall classification accuracy of over 80%. They proposed this integration of pixel- and object-based methods with knowledge (POK-based) as a feasible operational approach compared to fully automated methods, which provide higher efficiency but ineffective because of the low classification accuracy achievable (typically below 65%) at a global scale at 30 m resolution.

The global CCC products have to be developed using operationally feasible approaches like POK-based that can be applied to high spatial and temporal resolution Earth observation systems such as the Copernicus Sentinel satellite missions. The proposed up-scaling and retrieval approach should account for differences in scaling among different sensors to create long-term records of global CCC products.

2.2.7. Calibration and validation

Current validation approaches are mainly based on in-situ observations. Accurate field observations provide the basis for demonstrating the reliability and accuracy of the estimated RS-enabled EBV products from EO. This demands the development of methods, procedures, and standard protocols to ensure accurate in-situ measurements of CCC at scales comparable with the spatial sampling frequency of satellite observations.

The type and amount of in situ datasets required for calibration and validation of CCC depend on the algorithm used to quantify the RS-enabled EBV from satellite remote sensing data. Some algorithms demand to integrate *in situ* measurements with remote sensing data for both the calibration and validation of algorithms. This requires a lot of effort to collect *in situ* data, which are, by their nature expensive and time-consuming. The alternative is calibrating through simulated datasets and validation using *in situ* measurements or vice versa. Thus, the latter approach minimized the cost of *in situ* data collection and recommended for calibration and validation of the CCC products.

The required datasets for CCC calibration and validation from *in-situ* measurement and simulations using radiative transfer models (RTMs) are:

1. *In situ* measured CCC. CCC is not a variable that can be directly measured in the field. It is obtained by up-scaling leaf-level measurements to canopy level using the leaf area index of the canopy. Therefore, leaf chlorophyll content and leaf area index measurements in representative sample plots are needed to determine CCC.
2. RTM input parameters. The RTM simulated dataset has to be representative of the actual reflectance of the selected pilot sites and, thus, require a priori information on observation geometry and biophysical properties of the test sites. As such for forest biomes, *in situ* measurements of the range/average of RTM input variables such as vegetation height, canopy closure, crown shape, crown size, leaf angle distribution, clumping index, and LAI are needed to produce an independent dataset for validation/verification of the CCC product.

The strategy for calibration and validation is the widely accepted best practice guidelines produced by the Land Product Validation (LPV) sub-group of the CEOS Working Group on Calibration and Validation (WGCV) for estimating product accuracy and uncertainty. The Committee on Earth Observation Satellites (CEOS) has established Quality Assurance for Earth Observation (QA4EO) through discussion with calibration and validation experts from around the world. The protocols in the QA4EO should be adapted for CCC product while maintaining the three mandatory and complementary components of the strategy: 1) Accuracy assessment, the comparison of global products with reference *in situ* data; 2) Precision assessment, evaluation of the spatial and temporal consistency of the products; and 3) Inter-comparison, assessment of the relative consistencies between similar products.

2.2.8. Existing data sets and performance

Hundreds (if not thousands) of successful studies have been performed to develop methods and predict chlorophyll at leaf, canopy and landscape levels. Remote sensing has become the most popular means to retrieve chlorophyll content, by establishing empirical relationships between different vegetation indices and chlorophyll content or through physical models. Consequently, retrieval of CCC has been performed using a wide variety of remote sensing data ranging from the optical ground and airborne hyperspectral sensors to space-borne satellite systems. Field spectroradiometer measurements have been utilized to investigating the relationship between leaf optical property and laboratory-measured leaf chlorophyll content and other biochemical content of vegetation in order to develop algorithms for biochemical content estimation from optical RS data. Such leaf-level studies are the theoretical and operational basis for the discovery of chlorophyll content retrieval scaling up techniques at canopy and landscape-level using hyperspectral and/or multispectral sensors data.

RS data from airborne hyperspectral sensors have been widely utilized for accurate retrieval of CCC at the canopy scale for ecological and agricultural applications. Various platforms (e.g., airplanes and balloons) have been used to obtain field-scale imagery to estimate CCC. They are an alternative to intensive ground-level sampling and can be used to cover large areas and reflect spatial variability. Several indices based on airborne sensor readings have been developed to characterize plant canopy structure. Since the CCC retrieval requires a timely acquisition of high spatial and spectral resolution remote sensing data, airborne hyperspectral sensors are ideal platforms.

Besides hyperspectral passive remote sensing data, some studies indicate hyperspectral LiDAR instruments' potential to estimate vegetation biochemical parameters such as chlorophyll content. They could produce 3D point clouds with spectral information for every point and could efficiently combine the benefits of passive and active remote sensing sensors. The instrument provides a significant improvement over single wavelength LiDAR or passive optical systems for environmental remote sensing (Nevalainen et al., 2014).

For regional and global studies of CCC, the Landsat satellite series and the SPOT (Système Pour l'Observation de la Terre) are high-resolution data sources. Landsat, in particular, provides the longest-running continuous collection of fine-spatial resolution imagery—dating back to Landsat 1 in 1972 and continuing with the recent launch of Landsat 8 in February 2013 (Croft et al., 2015). This longtime series data offers a freely available data for historical and systematic analysis of CCC to monitor changes over a long time frame.

The EO-1 Hyperion-high resolution hyperspectral sensor (lifetime 2000-2017) was capable of resolving 220 spectral bands and can be used for quantifying fine-scale historical changes in CCC in different canopy structures. EO-1 Hyperion enables one to select and test several wavelengths at the red edge of the vegetation spectrum for accurate prediction of CCC. Another hyperspectral sensor that offers high spectral data with the medium spatial resolution is the Hyperspectral Imager SUIte (HISUI) composed of 185 spectral bands in the visible and near-infrared to the shortwave infrared region at 30-m spatial resolution (Matsunaga et al., 2015). The multispectral remote sensing data from RapidEye sensor, which is a constellation of five identical EO satellites records radiance in five broad bands corresponding to blue, green, red, red-edge and near-infrared (NIR) part of the electromagnetic spectrum at 5 m spatial resolution could be potentially used to estimate CCC (Planet, 2016).

There are high expectations for Sentinel-2 complemented with Landsat 8 data for current and future accurate global mapping of canopy chlorophyll content with the required high spatiotemporal resolution, long-term data sets, and free access. Valid change detections of global CCC benefit from the efforts that have been undergoing to make the Sentinel-2 and Landsat-8 data compatible to develop joint archives for the provision of consistent EO data (Wulder and Coops, 2014).

The upcoming hyperspectral missions such as the Environmental Mapping and Analysis Program (EnMAP) of Germany, Hyperspectral Infrared Imager (HyspIRI) and Surface Biology and Geology (SBG) of NASA and PRISMA of the Italian Space Agency will provide detail information for global mapping of CCC and other RS-enabled EBVs in the future. The Hyperspectral Environment and Resource Observer (HERO) will also facilitate the development of a greater range of practical applications (Blackburn, 2007).

Nevertheless, long-term and global EO time series of measurements relevant to biodiversity monitoring are generally lacking (O'Connor et al., 2015). The availability of high-resolution satellite data highly constrains current capabilities. As a result, the application of remote sensing data to retrieve chlorophyll has been limited to the local level. The only attempt made to retrieve CCC at a continental and global scale is using the MERIS Terrestrial Chlorophyll Index (MTCI) based on band 8, 9, and 10 of the MERIS data at 300 m spatial resolution (Curran et al., 2007). However, the MERIS spatial resolution (300m) may pose challenges to address the spatially-explicit comprehensive information needed for biodiversity monitoring. This is because chlorophyll content varies with vegetation type and partly it is challenging to have *in situ* records of chlorophyll content for validating coarse spatial resolution remotely sensed products.

Another challenge in global CCC mapping is the availability of reference data for uncertainty analysis. Like other variables, there is uncertainty in predicting CCC from remote sensing data that stem from the model used, model input parameters, the area over which CCC is predicted, positional errors, and temporal location. To successfully estimate chlorophyll content from remote sensing data, all variables that may contribute to pixel reflectance and the methods used need to be understood and accounted for (Almond, 2009). Uncertainty varies spatially and requires a large reference dataset for thorough quantification. Thus, reference dataset scarcity exacerbates the inconsistency of remote sensing analysis in predicting the RS-enabled EBV. Although remote sensing-based CCC prediction and uncertainty are inextricable, efforts must be made to understand uncertainty as an error or uncertainty propagation problem for the eventual reduction of the impact of uncertainty on the EBV product.

2.2.9. Feasibility, scientific and technology readiness levels

a) Limitations of remote sensing in measuring CCC

In situ measurement of CCC is destructive and time-consuming. By using remote sensing data from spectroradiometers, imagery from satellite sensors, and digital cameras, optical properties can be used to estimate CCC in plants with high repeatability, lower acquisition cost, and higher spatial extent. However, remote sensing data are constrained in some regards. In a dense canopy with high chlorophyll content, remote sensing-based estimation of CCC could suffer from a saturation problem. RS sensors become insensitive when CCC concentration reaches a certain level which leads to CCC being underestimated (e.g., Houborg and Boegh, 2008). In an open canopy environment, the applicability of remote sensing is hindered by the fact that canopy spectra are affected by background including bare soil, litters, mosses, lichens, etc. Besides, atmospheric conditions, shadows and canopy structures could easily alter the relationship between biochemical content (chlorophyll) of plants and canopy spectra.

Consequently, it is prevalent that the same vegetation type on the ground may have different spectral features in remotely sensed images or different vegetation types that may possess similar spectra, which makes accurate CCC estimation from RS data challenging. CCC estimation from remote sensing data also demands repeated measures with a high degree of accuracy and requires *in situ* calibration and validation datasets. Furthermore, RS data measures only top of canopy chlorophyll content, but chlorophyll content decreases as one goes from the illuminated upper canopy to shaded lower canopy (Yang et al., 2016).

b) Feasibility and readiness levels

There are a plethora of optical remote sensing techniques that prove the feasibility of hyperspectral remote sensing data for chlorophyll content estimation. Remote sensing researchers across the globe have developed various algorithms ranging from the most straightforward ratio vegetation index to the more complex three-dimensional radiative transfer model inversion to estimate chlorophyll from remote sensing data. Chlorophyll content estimation from remote sensing data at leaf, canopy, and landscape scales is among the well-established science. Among vegetation biochemical parameters that can be measured using remote sensing data, accurate estimation of CCC takes the lead, which confirms the fact that CCC retrieval from RS data is verified. According to the guideline for assessment of Scientific Readiness Level (SRL) by ESA (2015) a product falls at step seven of the nine steps in the SRL if the retrieval algorithms verified using real mission activity measurements. There is a clear theoretical understanding of the relationship between CCC and satellite measured data (reflectance), and the strong relationship is validated by applying algorithms on existing EO missions such as Sentinel-2 and Landsat. Therefore, CCC mapping can be categorized as a demonstrated science (SRL 7).

Although many studies showed the efficacy of remote sensing data and techniques for CCC measurement, its retrieval requires high-resolution RS data. This poses a severe challenge in managing the volume of data needed to get global coverage. Because of the voluminous of RS data, satellite remote-sensing systems compromise between spatial resolution and spectral and/or temporal resolution, which potentially limits the use of currently available remotely sensed data for the generation of CCC products over the globe as required.

Because of the trade-off between spatial and spectral resolutions, currently available satellite remote sensing systems offer a high spatial resolution associated with a low spectral resolution. Therefore, it is necessary to either find compromises between the different resolutions according to the individual application or to utilize alternative methods of data acquisition. Investigation of satellite observation requirement of CCC product needed for biodiversity monitoring demands high spatial, spectral and temporal resolutions. Emphasis cannot be relayed on one specific resolution (e.g., spatial resolution) and accept low attendant resolutions for others (e.g., spectral and temporal resolutions) at the same time, which raises question over the Technology Readiness Level TRL) of currently operating EO systems for accurate retrieval of global CCC. Recent advancements will help to overcome these limitations in the future. The upcoming satellites such as EnMAP, HyspIRI, SBG, and PRISMA are planned to provide high spatial, and spectral resolution data with relatively short revisit time that can make long-term global CCC mapping feasible.

2.2.10. Summary and outlook

Canopy chlorophyll content is a crucial biochemical RS-enabled EBV that plays a pivotal role in assessing and monitoring the functioning of terrestrial ecosystems. The quality measure of the EBV from satellite remote sensing data demands high-resolution imagery. The outlook for long-term continuity of accurate global mapping of the RS-enabled EBV will be a success if the emphasis is given on the following recommendations:

- To overcome the data volume limitation due to the fine resolution RS data, more focus has to be given to the red edge region of the electromagnetic spectrum.

There is ample evidence that significant improvements in accuracy can be gained by acquiring observations in several narrow spectral bands between 650-850 nm.

- Future space-based optical instruments are needed, with finer resolutions than current sensors and more frequent global coverage.
- While advances in remote sensing sensors bring increased resolution and sensitivity, there persists a need to explore the feasibility and implementation of robust and fast methods that enable to quantify CCC accurately from the future super-spatial and super-spectral satellite missions.
- To assure the quality of the EBV product, consistent and centralized calibration and validation data have to be acquired from past, current field campaigns and stored in platforms like OLIVE (On-Line Interactive Validation Exercise) platform, which is developed for validation of global products.

2.3. RS-enabled EBV ecosystem extent and fragmentation

2.3.1. Definition of Ecosystem extent and Fragmentation

Reducing the rate of habitat loss and fragmentation, and eventually halting it, is essential to protect biodiversity and to maintain the ecosystem services vital to human wellbeing (Aichi Targets 5 and 14 respectively). Fragmentation, next to ecosystem distribution, land cover, and vegetation height (VH), is related to the EBV 'Ecosystem structure' or habitat structure (Skidmore et al., 2015). Monitoring EBV Ecosystem structure can be supported by remote sensing (RS) through the collection of information on the spatial distribution of habitats, how fragmented they are, and the impact on the distribution of species in those habitats.

Within the expert workshop with a focus on the prioritization of RS-enabled EBVs (Zurich, February 2018), the EBV fragmentation was defined as: "The EBV fragmentation should measure structural ecosystem discontinuity in a defined time-space. This can include connectivity, core, and edge characterizations, calculated across a range of scales as long as the EBV is globally applicable, scale-free, and ecologically meaningful."

2.3.2. The role of the RS-Enabled EBV in assessing and monitoring biodiversity

There is broad recognition that fragmentation affects both biodiversity and ecosystem functioning (Haddad et al., 2015). The fundamental role of habitat in limiting species richness is emphasized by the fact that habitat loss is the main cause of declining biodiversity worldwide (DAVIS, 2006, Hanski, 2015, Assessment, 2005, Pimm et al., 2014, Haddad et al., 2015). Habitat loss usually is causing habitat fragmentation (Tscharntke et al., 2012), and according to Hanski (2015), the fragmentation poses an extra threat to biodiversity, in addition to and on top of the threat posed by the declining total amount of habitat. The effect of direct habitat loss is larger than changes in habitat configuration (Fahrig, 2003). However, Didham et al. (2012) show that indirect and interaction effects may be the dominant cause of the ecological changes, which are mostly solely assigned to the loss of habitat.

Natural habitats in most parts of the world continue to decline in extent and integrity, although there has been significant progress to reduce this trend in some regions and habitats. This decline at landscape scale of habitat loss and increased isolation is widely known to be important to forecast the dynamics of species populations and communities (Macarthur and Wilson, 1967, Diamond, 1982, Caspers, 1984, Schoener and Spiller, 1987). A synthesis of fragmentation experiments spanning multiple biomes and scales, five continents, and 35 years demonstrates that habitat fragmentation reduces biodiversity by 13 to 75% and impairs key ecosystem functions (Haddad et al., 2015). Even more, the effects of habitat fragmentation on populations, communities, and ecosystems can take up to decades before being significantly evident, indicating that current shrinking habitats will continue to lose species and see declines in ecosystem functions (Krauss et al., 2010, Hanski, 2011, Wilson et al., 2016).

Wilson et al. (2016) summarized the latest key findings related to the loss and fragmentation of habitat. As habitat fragmentation ultimately is a derivative from habitat loss, "three broadly defined mechanisms mediate the ecological consequences of fragmentation:

1. Effects related to the loss of habitat area.
2. Effects related to changes in the spatial configuration of the landscape, such as isolation.
3. Effects related to indirect or interaction effects of habitat loss and changes in spatial configuration, and to the interaction of fragments with the non-habitat areas surrounding it."

There is no scientific evidence that, at global and landscape levels, human-induced fragmented natural- and semi-natural ecosystems, will show higher biodiversity values, compared to comparable non-fragmented systems (Haddad et al., 2015, Liu et al., 2018, Wilson et al., 2016). To a specific extent fragmentation of original natural habitats is creating opportunities through the creation of new habitat types[2] for species related to more fragmented ecosystems. E.g., species bound to forest edges will, up to a certain amount of fragmentation, see an increase of their habitat "forest edge." However, correspondingly, the habitat related to species needing a vast amount of forest interior will decline. Unfortunately, much of the literature testing for the influence and dependency between the effects of edge and area has been confounded, which makes a single deduction very difficult (Fletcher et al., 2007).

Biodiversity can be measured on the basis of the population viability of species related to the quality and extent of habitats (Opdam et al., 2003, Verboom and Pouwels, 2004). The fragmentation of habitats plays a paramount role in the viability of species since

[2] "habitat type" can be defined as a unit of land or water, consisting of an aggregation of biotic and abiotic characteristics having equivalent structure, function, and responses to disturbances

populations in small patches are more likely to go extinct than those in large patches (Caspers, 1984, Diamond, 1982, Hanski, 1994b, Schoener and Spiller, 1987). Many empirical studies have demonstrated that isolated habitat patches are less likely to become colonized than well-connected patches (Hanski, 1994a). At the landscape level, the fraction of available habitat that is occupied by a species in a certain time-space is an important indicator of its viability. This "metapopulation" concept is based on the dynamics of animal species with a shifting occupation over habitat patches in fragmented landscapes (Hanski, 2011, Opdam et al., 2003). It applies most naturally to highly fragmented habitats, such as networks of small meadows, but the processes of local extinction and colonization occur in any kind of habitat. When the habitat is continuously distributed, movements of individuals are unrestricted, and many species can be expected to occur practically everywhere. Since habitat loss and fragmentation impair free movements, it has adverse consequences for the distribution and abundance of species, and so for the prediction of their occupation of the remaining habitat fragments (Hanski, 2011). As a resultant Hanski (2015) explains that to be ecologically meaningful, the fragmentation analysis of landscapes should focus on the effects of habitat configuration, isolation, and dispersal capacity on the persistence of organisms across habitats types

EBV fragmentation can be used by stakeholders such as governments, NGOs, research centers, ecosystem service providers, that are concerned by the decline of biodiversity in fragmented landscapes and are for example involved in the impact assessment of new transport infrastructure on the sustainability of populations and or are involved in finding mitigating solutions for fragmentation such as conservation landscapes or building ecological corridors (Hanski, 2011, Opdam et al., 2003). Improved landscape coherence is increasingly considered a viable management strategy to maintain biodiversity, ecosystem functions, and services (Ziter et al., 2013). For instance, (Ziter et al., 2013) found that carbon stocks can be increased by considering species-specific management, improving habitat coherence, and taking care of functional diversity in forest ecosystems. Additionally, the significant contributions of small forest fragments to regional diversity and service provision emphasize the important role that these fragments can play in conservation efforts (Ziter et al., 2013).

2.3.3. Spatiotemporal coverage

Both the spatial and temporal resolution to be selected is dependent on the target level (geographical extent), and the habitat under consideration and can vary from a kilometer to meter resolution, and from yearly to every decade. In theory, an ecosystem (and its related fragmentation component) can be as small as a few amphibians living in some small scattered ponds, or as large as the Amazon tropical rainforest stretching across thousands of kilometers.

To be globally measurable, global-scale monitoring of habitat fragmentation will and must, therefore, be related to global land cover monitoring activities. The status of current global land cover products vary in resolution between 20 meters and 300 meters and is being updated at a maximum frequency of once a year. From a species perspective this update frequency at a spatial resolution of 10-30m is applicable for a) a large range of species covering major species groups, b) observable (major) changes in ecosystem patterns at global scale and c) related to minimum temporal shifts in population fragmentation patterns (Opdam et al., 2003).

2.3.4. Remotely sensed EBV products

The main basic EBV product used as a source to calculate fragmentation of ecosystems is habitat suitability. Recent years have seen a massive increase in the availability of regional- and global scale spatial data sets to support the quantification and extent of habitats; these include detailed global data of elevation at 30-m resolution, land-cover data, and forest cover at 30-m resolution (Brooks et al., 2019, Ocampo-Penuela et al., 2016).

Based on these data, Habitat Suitability Indices (HSI) are a representation of the suitability of habitat for a given species or group of species representing an ecosystem, based on an assessment of habitat attributes; HSI's generally derive a single composite index by combining multiple variables (such as land cover, soil type, and elevation) ((Schamberger et al., 1982, Thuiller and Münkemüller, 2010). Rondinini et al. (2011) show a clear application of the combined use of coarse resolution global land cover data (10x10km) and information on species elevation preferences, to globally assess how land cover change alters the global extent of suitable habitat of species and their risk of extinction. Another global application is the mapping of the extent of suitable habitat as showed by Brooks et al. (2019) for the IUCN Red List of Threatened Species. This Red List assesses the extinction risk of approximately 100000 species, including documentation of a range map, habitat, and elevation data for each species. These range, habitat and elevation data were matched by Brooks et al. (2019) with terrestrial land cover and elevation datasets to map the species' HSI.

Currently, there are many methods to quantify the fragmentation of habitat (Hanski, 2011, Opdam et al., 2003). Habitat coherence, being the antonym of habitat fragmentation, is often measured using simple structural metrics, e.g., Euclidean distances between habitat patches. Functional metrics calculated with more advanced (meta-)population models account for behavioral aspects of species or ecosystems (Hanski, 1994b). While simple structural metrics can be used to investigate local or small-scale effects on species diversity, landscape-scale fragmentation analyses should consider species behavioral aspects by using more complex functional ecological scaled metrics (Vos et al., 2001). Such species' behavioral aspects can be summarized in a so-called 'eco profile' or 'flagship species': a set of species demanding similar dimensions of ecosystem coherence in order to persist at a regional scale. "Similar" is meant herein a relative sense and refers to the similarity in choice of a) required ecosystem type(s), b) area requirements, and c) dispersal capacity of the species, encompassed by a single ecoprofile, relative to the difference between species classified in other ecoprofiles (See figure 6)

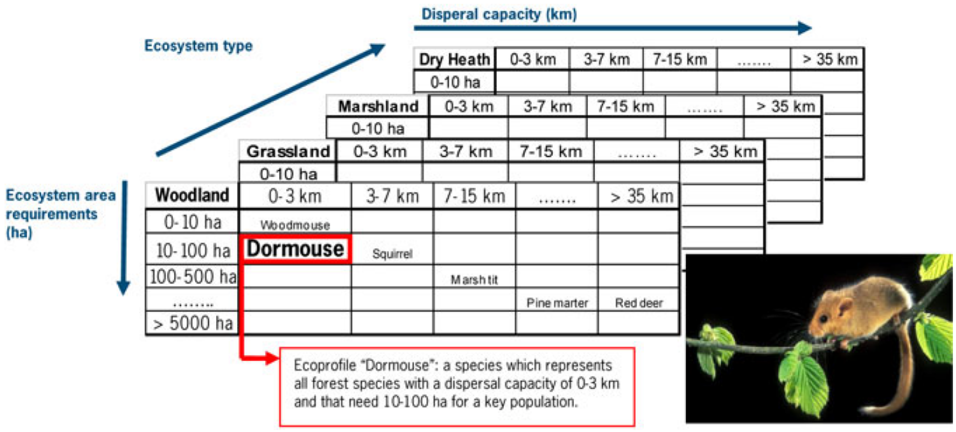

Figure 6: Design of three-dimensional eco profile matrices, one per identified ecosystem type, based on the carrying capacity of regional ecosystems (vertical axis), and the inter-patch distance that can be crossed during dispersal. Species are assigned to cells in the matrix by their habitat preference, individual habitat area requirements, and dispersal capacity. Each cell in the matrices represents one ecological profile (Opdam et al 2008).

In general, maps showing cohesion of habitat areas can be used to derive clusters of connected patches, to construct ecological networks, and thus evaluate fragmentation of the landscape. Patterns of cohesion values can be used for planning corridors between local patches or to improve weaker spots in networks. Depending on the application and species different thresholds for habitat coherence levels can be set to create such clusters forming networks of non-fragmented habitat. In this way, the effects of habitat configuration, isolation, dispersal capacity on the persistence of organisms across habitats types can be evaluated (Hanski, 2015, Opdam et al., 2003).

The main products of the RS-enabled EBV habitat fragmentation are quantitative maps that show the spatial distribution of the level of fragmentation of a specific ecosystem. Since fauna species can require a combination of land cover types in their habitat (See HSI definition above and in table 10), it should be possible to combine individual habitat-class based spatial cohesion maps to one based on a specific composed habitat. Quantitative maps of individual habitat types should be combined as a stack of spatial-temporal datasets based on remotely derived habitat types using multiple dispersal distances (if the metric is sensitive for those distances). In principle, this approach can be applied to many types of connectivity, core and edge metrics (McGarigal et al., 2012), as long as such combinations are considered ecological meaningful. Some metrics, e.g., contagion (McGarigal et al., 2012) need a specific final combination of habitat types before they can be calculated (McGarigal et al., 2012, Soille and Vogt, 2009). For such metrics, a stacked approach is not feasible.

A stacked calculation method on an RS-derived (multi-)habitat-type product gives maximum flexibility. Not only is the spatial cohesion calculated per habitat or land cover type, but also a tailor-made combination of the individual results for multiple specific flagship species, species groups or ecosystems can be assessed. This stack of spatial cohesion metrics (Figure 7) can be created using different land cover/habitat products.

Table 10 summarizes typical properties that are used and useful for habitat fragmentation studies.

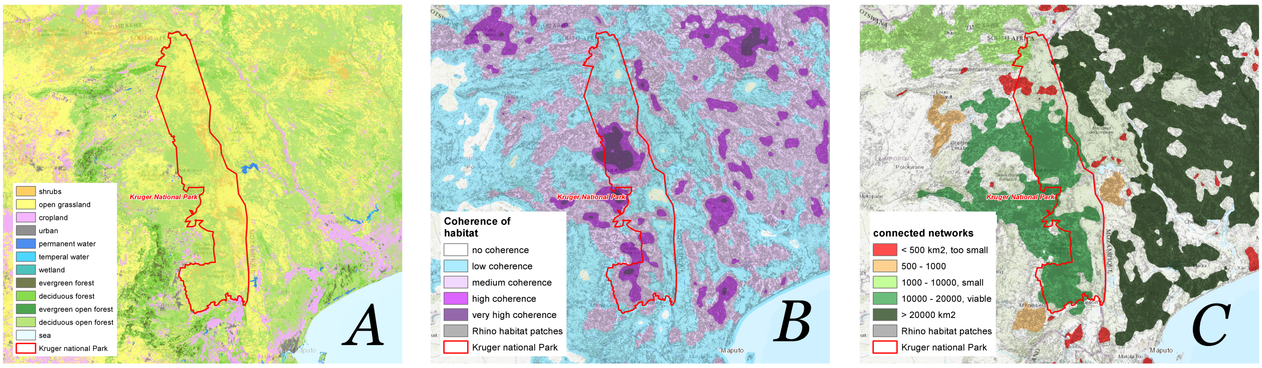

Figure 7: Example of a typical habitat fragmentation analysis (following the method as applied in Bruinderink et al. (2003): tropical / sub-tropical shrubland habitat area extent (A) in Kruger National Park, South Africa. Based on a selection of habitat classes (shrub and open forest) a spatial cohesion output map (B) can be calculated, for a specific fragmentation distance (10000m). Connected clusters based on species-specific thresholds can then be derived (C).

Table 10: Typical definition of fragmentation properties

Fragmentation property	**Definition**
Input A: Classified land-cover	*Classified land-cover relevant to the ecosystem to be analyzed. Fauna species can require a combination of land cover types in their habitat varying in potential use [Class A, Class B, etc., / Year]*
Input B: Abiotic specification (optional)	*Factors needed to describe the ecosystem to be analyzed. E.g. Water extent/duration of flooding [Class X, Class Y, etc., / Year]*
Input A×B: Habitat Suitability (HSI)	*A single composite index by deriving potential suitability directly from one variable (e.g. 'Input A'), or combining multiple variables (e.g., a combination of 'Input A' × 'Input B.' The result is the potential distribution of suitable habitat for a flagship species, species group or ecosystem. [Unit HSI 0-1].*
Output A: Fragmentation • *Output A1: simple structural metrics* • *Output A2: Functional spatial cohesion metrics*	*Spatial-temporal distribution of the level of fragmentation of a specific ecosystem* • *Connectivity, core and edge metrics aggregating the level of structural fragmentation of a specific ecosystem [Unit is metric dependent]* • *Quantitative maps of Habitat Coherence accounting for behavioral aspects of species or ecosystems. [Unit is related to, e.g. fraction of successful dispersers, and average patch carrying capacity]*
Output B: Habitat Clusters Network Strength	*Networks of non-fragmented habitat showing potential to maintain a sustainable population. Only possible in combination with A2 "Functional spatial cohesion metrics" [Unit e.g. population size]*

2.3.5. Spatial extent and temporal frequency requirements

Depending on the aims of the user and the level of detail of the available input data, both regional species-specific fragmentation analysis, as well as continental and global-wide generalized assessments of fragmentation are possible (Bruinderink et al., 2003, Opdam et al., 2003). To support this, the preferred method to calculate fragmentation should be generically applicable to cover a wide range of applications, ecosystems and -profiles. A rule of thumb is that the scale of the landscape as perceived/used by the species is decisive for the scale of the needed input data (Opdam et al., 2003). Generally, to be useful at regional/landscape level a spatial resolution of 10-30m is applicable for a broad range of applications and Eco profiles (Opdam et al., 2003, Hanski, 2011, Hanski, 1994a). The analysis uses species-specific lists of suitable habitats available within the scientific community (and the amount of habitat required for one reproductive unit), dispersal characteristics (which means the maximum distance between habitat sites for targeted fauna species), as well as the permeability of the landscape matrix between habitat sites (sensitivity to barriers).

Since the EBV Fragmentation is strongly related to species- and biodiversity monitoring purposes, a yearly (or longer) temporal resolution or time interval of the data is generally sufficient. In specific cases, a shorter (e.g., seasonal) interval can be necessary to capture specific fragmentation effects related to changes in seasonal dependencies within the ecosystem. As stated in the introduction, the effects of habitat fragmentation on populations, communities, and ecosystems can take a long period (Hanski, 2011, Wilson et al., 2016, Krauss et al., 2010). Therefore a shorter time frame than one year seems not relevant for applying the EBV a global scale.

2.3.6. *Transferability of retrieval approaches*

a) Transferability across biomes

Human-induced fragmentation is present in all globally defined biomes (Haddad et al., 2015). However, the scale at which fragmentation is observable can vary significantly per biome, ecosystem or habitat type, within and between geographical regions. E.g., forest cover loss can be observed at the global level with reliable measurements using intervals of yearly or fewer datasets, showing national observable deforestation patterns in the tropics, but also high intensive forest management in European Boreal forests, causing local temporal shifts in fragmentation patterns (Hansen et al., 2013). Opposite to such rapid shifts in land cover patterns is, e.g., the climate-induced composition change of vegetation patterns within an ecosystem. The arctic tundra is a much more gradual process that is observable at a more local level over a timeframe of multiple years causing a more gradual shift in (fragmentation of) suitable habitats for species over time.

The scope is to produce products with global coverage with transferable retrieval approaches. The most challenging part when upscaling or transferring the EBV fragmentation to other biomes is to relate the suitable species or ecotypes to the observed or expected fragmentation process in an ecosystem and having the correct input data related to the selected (umbrella) species (Opdam et al., 2003, 2008, Haddad et al., 2015). Since the measured fragmentation should be related to the scale of the landscape as used by species, the scale of the needed input data and the used parameters in the analysis should therefore also always be connected to each other (Opdam et al., 2003, Hanski, 2011).

b) Transferability across scales

To date, GeoBON's process of identifying and prioritizing EBVs has largely been based on expert knowledge about globally relevant biodiversity measurements (Navarro et al., 2017), making the global application the starting point to develop also the EBV Fragmentation. However, GeoBON is aiming at a consistent set of globally applicable EBV-metrics with

(RS-) data to be quickly mobilized and standardized across scales, transferring these EBV's into local and national organizations and their own monitoring schemes (Navarro et al. 2017). Model accuracy is likely to increase with decreasing raster cell size, so the choices of what data to include in HSI modeling is likely to increase at a regional-local scale where fine resolution (RS-)data is available (Manzoor et al., 2018). As explained by Manzoor (2018), when modeling the potential habitat extent of *Rhododendron ponticum* in Wales, the choice of resolution and the number of variables in an HSI analysis is not just species-dependent. They tested model performance and transferability to a different geographical area by varying the raster cell size (50m, 300m, and 1km). Based on species relevant multiple RS-derived variables (land cover, distance to water, elevation slope, aspect and a series of climate variables), they found that use of the coarser bioclimatic variables could negatively affect the predictive potential of the HSI model since the used biophysical variables are likely to be more important determinants of suitable habitat extent at fine spatial scales. However, successful model transferability to other regions was found to be optimal at medium raster cell size, indicating that the coarser climatic variables may have a greater effect in determining the potential suitability for a species over a larger spatial scale (Manzoor, 2018).

The responses of the fragmentation algorithms on changing raster cell size vary significantly among different landscape metrics and across different landscapes (Uuemaa et al., 2005). Metrics like 'contagion' and 'mean euclidean nearest neighbor distance' (McGarigal et al., 2012) are directly dependent on raster resolution; therefore, they should be used and interpreted carefully in case of changing the resolution of the input data (Uuemaa et al., 2005). Also, most known core and edge indicators based on RS-data are highly sensitive for variations in resolution of the used product (McGarigal et al., 2012, Riitters et al., 1995, Uuemaa et al., 2005), which makes it also more difficult to transfer, calibrate or validate these metrics across a range of scales biomes and RS-products.

Some metrics, especially in the group of (focal) area-based metrics, are much less sensitive for differences in raster resolution as long as the minimum fragmentation area and distances are kept larger than the raster cell-size, and input habitat is comparably defined across different spatial resolutions (are derived in a comparable manner, from similar sources) (Brown et al., 2004). This ensures that the total habitat area share is kept as equal as possible, less effecting the metric results. E.g., the Hanski fragmentation algorithm (Hanski, 1994b) calculates for each raster cell the amount of habitat-area in its surroundings. Habitat further away is accounted for less than habitat close by, using Hanski's negative exponential function for cohesion related to a given (species dispersal) distance. As such this metric is accounting for fragmentation, both related to changes loss of habitat area and the spatial configuration of the landscape, the isolation of habitat. As long the dispersal distance of the species of interest is larger than the used resolution of the raster product this metric enables us to calculate and compare fragmentation in both local as continental /global context (Pouwels et al., 2002). Eupen et al. (2001) conclude for the Mean Proximity Index (a similar focal-area-based metric (McGarigal et al., 2012), that a factor 10 between cell resolution and fragmentation distance is sufficient to eliminate the raster resolution effect completely. For example, based on a remote sensed based input product with a 10x10m resolution, one should focus on an output EBV product with a minimal fragmentation distance of around 100m or a minimum fragmented area of 0.1 hectares.

2.3.7. Calibration and validation

The total amount of habitat and the degree of fragmentation are typically closely correlated; which makes it hard to tease apart their effects with observational data (Fahrig, 2003, Hanski, 2015, Wilson et al., 2016), however, several approaches have been tested in the past to come with robust parameters to (correlatively) link structural ecosystem discontinuity to biodiversity values. Most of these approaches are based on empirical studies validating the size, configuration defining the isolation of habitat patches for specific species (Hanski, 1994a). For example, Pouwels (2016) validated a fragmentation metric for bird and mammal species showing a high correlation between the fragmentation metric and the species persistence in the landscape over space and time. From a data point of view, creating HSI models with predictor variables at very small raster cell size leads to very specific species-habitat relationships, and thus needs to be verified with accurate presence records (Manzoor et al. 2018).

Approaches like described in Pouwels (2016), Manzoor et al. (2018), and Opdam et al., (2003) clearly showed that to define robust fragmentation parameters, clearly defined and derived habitats types are needed to monitor fragmentation. Concluding, the focus of a validation process should be on an assessment of (an) EBV-fragmentation metric(s) based on comparing independent local species distribution maps or GPS tracking / -movement data in defined pilot areas. This ancillary information can be used to calibrate and validate the EBV-fragmentation results and judge the transferability across regions.

Secondly, an analysis using different RS land cover products can be carried out to check the reliability of the metric(s) used. Such an assessment can be done using and comparing at least three different scaled land use products. This step can be used to calibrate the metric over different scales and RS-products and show its uncertainties using different classifications.

2.3.8. Existing data sets and performance

In global applications, habitats and their spatial configuration are normally a refinement of RS derived land cover products See, e.g. section 2.3.4 for examples from Rondinini et al. (2011) and Brooks et al. (2019). Global land cover classifications derived from high and medium resolution satellite imagery are already available, such as ESA's GLOBCOVER product and Global Land Cover at 30m spatial resolution (www.globallandcover.com). Habitat can be selected from land cover products, directly, or by combining them with other products through geo-processing. To serve a variety of potential species ranges, the fragmentation EBV can be calculated for each habitat-class from a chosen product. Individual output maps can then be combined to represent the habitat and species of choice. At the regional level, habitat or land cover data can be derived from products like

Landsat 8, Sentinel-2, depending on the level of detail in the habitat classification (e.g. forest, shrubs, grasslands). However, at continental or global level such detailed land cover products are often not available (except for some major land cover types, e.g. Hansen et al. (2013) for global forest and the Copernicus high-resolution layers (https://land.copernicus.eu/pan-european/high-resolution-layers)), and still, depend in most cases on coarser-resolution products such as MODIS and PROBA-V at 100-300 meter resolution.

An analysis testing existing datasets should be based on a variety of input data (local habitat data, EU-wide ecosystem types maps, classified Sentinel/Landsat data. A typical analysis focusing on using different RS land cover products could look like this:

- Local land cover data as provided by pilot areas with a spatial resolution varying from less than 20m to +/- 30m. Such pilot areas should preferably also have ancillary information about species distribution to calibrate and validate and calibrate the EBV-fragmentation metrics.
- 20m classified Sentinel-2 land cover data for a wider region, with a limited number of classes (e.g., the “Land Cover Classification System” (LCCS) as developed by FAO (FAO.org))
- 100m classified land cover data (e.g., PROBA-V with LCCS legend) for a complete continent.

2.3.9. *Feasibility, scientific and technological Readiness Levels*

There are many scientifically described methods to quantify the fragmentation of landscapes (Wilson et al., 2016; Opdam et al., 2003). Most of this work is dating back to the basic work on landscape metrics development from the 1980s onwards. Many of these studies describing methods using generic landscape-level metrics derived from GIS-based tools (e.g., Fragstats (Neel et al., 2004, Riitters et al., 1995)). Other more specific fragmentation focused toolboxes exist, like the LARCH-SCAN (Landscape Analysis and Rules for Configuration of Habitat) toolbox which calculate a relative measure for spatial cohesion based on dispersal characteristics of species (Bruinderink et al., 2003), or the GUIDOS-toolbox creating fragmentation metrics based on morphological shapes of land cover (Soille and Vogt, 2009). Stand-alone versions of the most interesting metrics are up-and-running or not difficult to be implemented.

The feasibility to calculate such metrics is mainly depending on the availability of classified input ecosystem data. Regarding the available RS data, a wide range of such data is globally and regionally available. Habitat types can be selected from remoted sense based land cover products, directly or by combining them through pre-processing (Mücher, 2009, Mücher et al., 2015).

2.3.10. *Summary and outlook*

Depending on the aims of the user and the level of detail of the available input data, both regional species-specific network analysis as well as European wide generalized assessments of fragmentation are possible to derive from satellite-derived products. The scale of the landscape, as used by the species, is decisive for the scale of the needed input data.

Habitat types can be selected from remoted sense based land cover products directly or by combining them through pre-processing, although the EBV fragmentation can be relatively straightforwardly implemented across different scales using basic land cover data. However, habitat maps directly derived from global products are often a rough indication of how species perceive and use the landscape. It is therefore often difficult to relate species-specific habitat classifications to global land cover products, indicating that existing land cover products should be thematically refined to derive the suitable habitat types (e.g., instead of broadleaf forests we need to know were old broadleaved forest are located or where they are dominated by specific tree species that characterize the specific forest habitat type).

Depending on the metric to be chosen, a variety of potential species ranges can be served. Habitat fragmentation can be measured for each habitat-class from a chosen product. Individual output cohesion maps can then be combined to represent the habitat and species of choice.

2.4. RS-enabled EBV Vegetation structure

2.4.1. Definition of vegetation structure

The complexity of terrestrial ecosystems can be assessed in the following domains (McElhinny et al., 2005):

- **Structure** refers to the spatial arrangement of the various components of the ecosystem, such as the **heights** of different canopy levels and the spacing of trees.
- **Function** refers to how various ecological processes, such as the production of organic matter, are accomplished and the rates at which they occur.
- **Composition** refers to the identity and variety of ecosystem components, as characterized by species richness and abundance.

These three ecosystem domains (structure, function, and composition) are closely inter-related. In terms of the availability of satellite-derived vegetation structure observations, vegetation height, is considered the most feasible variable to be retrieved as part of "Vegetation Structure" (Hall et al., 2011, Goetz et al., 2010, Bergen et al., 2009, Goetz et al., 2007, Lefsky et al., 2002). Accordingly, in this document, the term "Vegetation Structure" is used as a container term for a set of variables related to the horizontal and vertical abundance of canopy material. The RS-enabled EBV Vegetation Structure (VS) therefore, contains the observable "height," which is understood to be one aspect of ecosystem structure. However, for the height value to be informative with respect to structure, its distribution, both vertically and horizontally, needs to be measured. In the following sections, we focus on describing 1) measures of vegetation height, as both the vertical variation thereof (e.g., the foliage or the canopy profile, and 2) the horizontal distribution (e.g., surface roughness, vegetation density or fragmentation). These measures have successfully been linked to biodiversity and are in particular relevant for forest biomes with a minimum of tree cover and partly applicable for grasslands. Consequently, the RS-enabled EBV vegetation structure could also be used to inform other RS-enabled EBVs such as fragmentation.

2.4.2. The role of vegetation structure in assessing and monitoring biodiversity

Vegetation structure is closely tied to ecosystem processes and species diversity (Ruiz-Jaen and Aide, 2005, Naeem et al., 1994). Accordingly, vegetation structure properties may yield information on habitat heterogeneity, the productivity of an ecosystem and its potential successional pathways (Wang et al., 2004, Silver et al., 2004, Jones et al., 2004). Moreover, vegetation structure and derived vegetation structure properties, are closely linked to ecosystem structure, function, and composition, which in turn are strongly interrelated and interdependent. It follows, therefore, that vegetation structure properties that describe habitat heterogeneity can provide insights into ecosystem structure, functioning and composition (Benton et al., 2003, Hinsley et al., 2008). In effect, the horizontal and vertical arrangement of plant communities, and in particular of forests, has a significant impact on ecosystem processes, such as competition, carbon balance, as well as nutrient and water cycling (Benton et al., 2003). Importantly, vegetation structure, notably its complexity, three-dimensional (3D) structure and heterogeneity are tightly linked with biological diversity (Bergen et al. 2009), be it for plants (MacArthur and Horn, 1969) or animals (Zellweger et al., 2014, Froidevaux et al., 2016).

The arrangement of plants in an ecosystem and their structural complexity is closely correlated with species diversity (i.e., species richness and species evenness). In particular, the distribution of canopy material is a major determinant of potential niches and hence of species richness. In effect, the “habitat heterogeneity hypothesis” is a central premise in ecology; essentially, it considers that the added structurally complex habitats support a larger number of niches, higher niche diversity, more ways of exploiting these niches, increased environmental resources availability, and hence, greater species diversity. Accordingly, in the majority of habitats, plant community composition controls ecosystem structure and therefore has a major influence on the interactions and distributions of species (Macarthur and Wilson, 1967, Tews et al., 2004, Bazzaz, 1975, McCoy and Bell, 1991).

Importantly, the vegetation structural information can be linked to key ecosystem processes (i.e. decomposition, production, nutrient cycling, and fluxes of nutrients and energy) and properties, including niche characteristics described by three morphological traits of plant communities. Niche characteristics may include such properties as vegetation height, vegetation density (canopy cover), and canopy profile or vertical arrangement. Thus, properties describing habitat heterogeneity are directly related to biodiversity metrics, such as species diversity and richness.

Many ecosystem disturbances, such as insect pests, may alter forest and vegetation structure (Solberg et al., 2006), for instance, by increasing defoliation or fuel buildup (Bright et al., 2017). These disturbances may have a direct or temporally lagged impact on the biological diversity of a forest ecosystem as a whole, although they might not always be detrimental to species richness or niche availability (Kortmann et al., 2018). Multi-temporal quantification of ecosystem structure offers the potential for the detection of short-term changes in forest canopy structure, such as those results from logging or storm damage. In effect, such disturbances generally result in marked changes in vegetation structure and species composition; however, for such applications, measures such as vegetation activity (i.e., NDVI) may be appropriate (Souza and Barreto, 2000, Bullock et al., 2018). Therefore, measures of vegetation structure, and in particular vegetation height and horizontal distribution, exhibit large potential for assessing and monitoring many aspects directly related to key ecosystem processes and changes, which are in turn strongly linked to measures of biological diversity.

2.4.3. Remotely sensed EBV vegetation structure products

Vegetation structure, provided ideally in a raster, is one of the main target products, along with canopy cover (vegetation density), as these products allow spatial and temporal analyses, which are valuable for undertaking biodiversity assessment and monitoring.
However, already a single value of for instance, vegetation height as a property for vegetation structure without spatial context may provide valuable information on vegetation and ecosystem structure, e.g., when used in conjunction with the biome type, land cover or land-use.

An additional product shown to be relevant for biodiversity assessment is the vertical canopy profile, which provides of profile of canopy abundance with height. However, as the profile is a vector comprised of multiple values, it is often reduced to the derived single-value metric foliage-height diversity (FHD), reflecting the diversity of height values within the canopy profile (MacArthur and MacArthur 1961; S. J. Goetz et al. 2010). From the vertical canopy profile, other products can be derived, such as the number of canopy layers or the average and maximum canopy height (Morsdorf et al., 2010). The main VS products are listed in Table 11.

Table 11: Properties of Vegetation Structure (VS) and its short definition.

VH Property	Definition
Vegetation Height	Height of the tree canopy above the ground [m]
Canopy profile	The abundance of canopy material along with a vertical profile or its vertical arrangement.
Vegetation Density / Canopy Cover	Density is described as a measure of vegetation elements in a given area and can be provided as a percentage [%] (i.e., fractional cover) or as plant area index (PAI) [-].

2.4.4. Spatiotemporal coverage

Vegetation structure is relevant for all biomes containing vegetation of minimum height and extent, including forests, other wooded lands like savannahs, and grassland biomes with bushy vegetation. Regarding the temporal aspect, one has to differentiate between (sudden) disturbances (natural or unnatural) and growth. The former needs high temporal frequencies (e.g., weekly to monthly) for continuous monitoring and/or a distinct observation after the disturbance (e.g., a storm) for comparison with a base-line observation from before the disturbance. Capturing the latter (growth) would likely only require one to two plot visits per year (K. Dolan et al. 2009). In general, a too-long revisit time (e.g. several years) would make trend estimation challenging as too few temporal sampling points would support such a trend.

2.4.5. The spatial extent and temporal frequency requirements

Capturing the latitudinal gradients in vegetation structure, ranging from tropical over temperate to boreal forests and associated grasslands, is highly relevant to the vegetation structure RS-enabled EBV, and therefore approximately global coverage spanning all relevant biomes is fundamental in the context of global-scale biodiversity monitoring (Patterson and Healey 2015; Healey et al. 2012; Pereira et al. 2013, Vihervaara et al. 2017). In addition, local vegetation structure data, for instance, can inform on regional changes due to processes like insect infestations and forest degradation by human-induced land-use change.

Vegetation structure is a rather slowly changing parameter (e.g., no diurnal cycle), but disturbances can cause fast changes. The lowest cycle for continuous monitoring is seasonal in order to catch the effect on the structure between leaf-on and leaf-off conditions for forest areas with seasonal profiles. For instance, temperate forests exhibit marked and synchronous leaf seasonality, while in contrast, tropical forest biomes exhibit a weak and often asynchronous leaf seasonality. Given the seasonal differences between biomes, a temporal resolution resolving seasonal cycles would be most advantageous (Hall et al. 2011); this could be considered as best-case temporal resolution. Observation intervals longer than ten years would likely not provide meaningful information in most biomes. Nevertheless, if local disturbances need to be detected, higher observation times are required depending on the process, with clearings being visible after a couple of days and insect pests and other natural mortality showing up over months and years.

The spatial resolution required is highly dependent on the fragmentation and structure of the vegetation. In particular, areas with sparse, single tree coverage need a higher spatial resolution if individual trees and shrub areas should be characterised. In contrast, areas with homogenous vegetation cover such as arctic tundra require a lower spatial resolution for biodiversity and habitat mapping.

2.4.6. Transferability of retrieval approaches

a) Transferability among biomes

Vegetation structure properties are physical characteristics of vegetation, which can be measured and include, for example, height in meters; therefore, there are generally no limitations regarding transferability among biomes. However, for biomes with very sparse and/or low canopies such as grass and shrublands, the transferability and retrieval of canopy height estimates may be limited by the spatial resolution (Lefsky et al. 2002). In contrast, in very dense forests (i.e., tropical humid), there might be the potential to miss the ground return in a remote sensing signal and therefore, either a bias could be introduced, or the derivation of vegetation height could become impossible (Lefsky et al. 2002; Hall et al. 2011).

b) Transferability across scales

Vegetation structure is scale-invariant, however, depending on the spatial scale at which a property is estimated, different semantics may be used, for example, when referring to stand height or individual tree height (Nilsson 1996). For the latter, the range of observed values might differ between scales as well, e.g., for smaller scales, the ranges of observed canopy cover might be between 0 and 100 percent (e.g., gap vs. no-gap), but for larger scales, closed-canopies will be less prevalent.

2.4.7. Calibration and validation

Airborne light detection and ranging (LiDAR) observations with high spatial resolution footprints are often used to retrieve vegetation structure properties; in turn, these can serve to validate retrievals of current and future space-borne missions (Khalefa et al., 2013). Moreover, airborne LiDAR can be used for validation at the product level (i.e. canopy cover, vegetation profile), and can also be used to simulate and thus validate a space-borne LiDAR level-0 product (i.e., the waveform) directly. Such a dual-tier validation approach was chosen for the NASA mission Global Ecosystem Dynamics Investigation (GEDI) (Hancock et al., 2019).

Cross-comparison of different LiDAR data products is, however, challenging where they have substantial spatial and temporal variation, and where they are sensitive to different sensor and survey configurations. While, for instance, vegetation height products are more robust with respect to canopy changes, other LiDAR-based, structure-related observables, such as canopy cover, are more affected by changes in instrumentation (Korhonen and Morsdorf, 2014). Validating vegetation structure products using direct field observation networks is not a suitable strategy in such cases, due to the mismatch of spatial and temporal scales. However, a viable validation strategy could be either (i) thematic validation of derived structure variables using observational networks, or (ii) product forward validation by radiative transfer modeling. In the case of the first point, a global validation (plausibility test) using the derived product(s) in the context of a use-case demonstration study, for example, as input to an ecosystem model, may be performed. In the case of the second point, the best practice may be to use radiative transfer models to simulate Earth Observation (EO) data and its derived products and then use the derived virtual domain as a reference. Such an approach has been applied in the ESA 3DVegLab project, as demonstrated in Schneider et al. (2014).

2.4.8. Existing data sets and performance

Up to now, no satellite mission exists to assess vegetation height from space. The available space-borne LiDARs were not initially aimed at providing vegetation height estimates; for instance, the Ice, Cloud, and land Elevation Satellite (ICESat) with the Geoscience Laser Altimeter System (GLAS) instrument on-board, launched on the 12 January 2003, was operational for seven years, however, had an orbit optimized for polar coverage in order to measure ice sheet elevations and changes in elevation through time, which resulted in large across-track gaps in the tropics (Zwally et al., 2002). The present GEDI mission, in contrast, aims to help to quantify the aboveground carbon balance of the land surface, explore the role of the land surface in mitigating atmospheric CO_2, and map canopy height, canopy vertical structure and surface elevation, in order to investigate how ecosystem structure links to habitat quality and hence biodiversity (Duncanson et al., 2014). GEDI has a footprint of about 25 m diameter and better coverage in the tropics, but with a latitudinal limitation at above ~60˚, the coverage of boreal areas is restricted. The instrument has been in operation onboard the International Space Station (ISS) since March 2019 and is restricted to the ISS's flight path, however, will be providing data for two years (Qi et al., 2019).

Deforestation and forest degradation, which lead to drastic changes in forest height, can be detected by high spatial and temporal resolution multi-spectral missions such as Sentinel-2, even though it will be difficult to obtain a direct height difference using passive optical data only. Such datasets can nevertheless make a significant contribution towards informing forest structure estimates from space-borne LiDAR missions, which comprise spatial point coverage and low temporal resolution (Hansen et al., 2016). Characterization of the canopy profile can be obtained by LiDAR instruments and to a certain degree by multi-frequency Synthetic Aperture Radar (SAR) approaches - preferably in a tomographic configuration. Mean and maximum canopy height can also be derived from stereo images of passive optical and Interferometric Synthetic Aperture Radar (InSAR) data; since these methods only provide surface elevations, they must be used in conjunction with terrain models. For LiDAR, in contrast, the recorded waveform often facilitates the detection of the ground, so that the height of the profile corresponds to the height above the ground. Occlusion causes the LiDAR waveform to deviate from the actual canopy profile, and this is especially the case in denser forests (Morsdorf et al., 2010). However, how this impacts the meaningfulness of the canopy profile for biodiversity assessments needs still to be evaluated (Bergen et al. 2009).

Airborne LiDAR, with its many forestry applications, has been a key contemporary research focus, with many countries owning wall-to-wall datasets that provide valuable forest structure information. However, access to these data is not streamlined, although some countries recently started to make them freely available (UK, Finland, Spain). Thus, airborne LiDAR currently often contributes only a partially complete information source for policymakers and stakeholders at any level above national. In the context of a global RS-enabled EBV assessment, the role of these datasets is primarily in up-scaling, calibration and validation (Cal/Val), as well as for building better science cases to support future space-borne mission designs. As all space-borne LiDAR missions so far have been point-based sampling designs, spatial extrapolation of the derived information is mandatory to derive wall-to-wall maps (Hansen et al. 2016). Such up-scaling should best use data that is directly linked for instance, to surface height, e.g., Polarimetric Interferometry (PolInSAR), InSAR or stereo imagery (Qi et al. 2019). Alternatives may include, the use of empirical models that link vegetation height with multi-spectral reflectance derived by high-resolution missions such as Landsat 7/8 and Sentinel-2 (Hansen et al. (2016).

2.4.9. Feasibility, scientific and technology readiness levels

The LiDAR technology is mature and already an integral component in the EO toolboxes of regional to national authorities. For instance, many countries in Europe use airborne LiDAR to inform and regularly update their national forest inventories. The technological readiness level of space-borne LiDAR is currently more limited, especially with respect to a power supply and laser longevity, while the sampling design is generally not considered a limitation (Healey et al. 2012). The GEDI mission, however, will demonstrate the technology to derive high-quality estimates of canopy structure and facilitate data fusion approaches enhancing the potential for future radar missions. The GEDI Lidar is generating high-resolution estimates of canopy vertical structure and will contribute to understanding how ecosystem structure affects habitat quality and biodiversity (Stavros et al., 2017). Finally, current and future space-borne designs are likely to be limited in the reliable detection of canopies with very low height (i.e. < 1 m) in biomes with very sparse tree cover (e.g., desert shrub) (Lefsky et al. 2002).

2.4.10. Summary and Outlook

The structural complexity of vegetation canopies has been extensively linked to biodiversity and ecosystem processes in a large body of historical and contemporary studies. As such, the retrieval of various vegetation structure products has proved pivotal for quantifying key ecosystem variables as vegetation height, canopy cover and vegetation density; concurrently, these have provided detailed insight into structure, function and composition of terrestrial ecosystems. In particular, they have enhanced our understanding of the global patterns, processes and controls on vegetation and ecosystem structure, and their impacts on biodiversity (Goetz et al., 2010, Bergen et al., 2009, Goetz et al., 2007, Lefsky et al., 2002, Macarthur and Wilson, 1967, MacArthur and MacArthur, 1961). The present challenges of retrieving vegetation structure properties synoptically are related to the low spatial and temporal density of observations currently available. However, the new LiDAR missions such as GEDI are expected to bridge this gap together with past space-borne and a range of air-borne datasets; in effect, they will provide global observations of ecosystem structure at a high spatial and temporal density, from which key vegetation structure properties can be derived at a global scale (Stavros et al., 2017, Abdalati et al., 2010). It is therefore anticipated that such global vegetation structure datasets will, when combined with ancillary vegetation structure properties such as those retrieved from optical and SAR sensors, contribute substantially toward the generation of an annual, synoptic and continuous RS-enabled EBV Vegetation Structure product in the near future.

2.5. Specific measurement requirements summary

The satellite measurement specifications and delivery format for the four RS-enabled EBV are tabulated in Table 12; note that Vegetation Structure measurements requirements are provided for ICESAt-2. This table summarizes key requirements parameters under the following headings: spatial and temporal extent, spatial, spectral and temporal resolution, thematic and geometrical accuracy, spectral domain, existing RS data sources, product delivery mode, format and reference system.

Table 12: Specific measurement requirements of the four RS-enabled EBVs.

Requirement	**LSP**	**CCC**	**EEF**	**VS**
Spatial extent	All terrestrial ecosystems	All terrestrial ecosystems	All terrestrial ecosystems	All terrestrial ecosystems
Temporal extent	5 – 10 years	5 – 10 years	5 – 10 years	2 years
Spatial Resolution	10 – 30 m	10 - 20m	10 – 30 m	25 m
Spectral Resolution	Broad band	Narrow band	Broad band	1064 nm LiDAR
Temporal Resolution	1 -2 times/week	5-10 times/yr.	yearly	2 years
Thematic Accuracy	≥ 80 %	≥ 80 %	≥ 80 %	N/A
Geometrical Accuracy	1 pixel	0.5 pixel	1 pixel	5 m
Spectral domain	400 – 2500 nm	400-2500 nm	400-2500 nm	LiDAR
Existing RS data	S2, S3, Landsat & MODIS	S2, S3 and Landsat	S2 and Landsat	ICESat-1, ICESat-2, GEDI, air-borne, SAR
Delivery mode				Level 3A-B
Product format	GeoTiff, ESRI Grids, others on request	GeoTiff, ESRI Grids, others on request	GeoTiff, ESRI Grids, others on request	GeoTiff, ESRI Grids, others on request
Reference system	UTM	UTM	UTM	UTM

Reference

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Annex 1: List of candidate RS-enabled variables of terrestrial ecosystem structure and function, their prioritization rank, and their potential support for Aichi targets and SDGs

EBV class	Original EBV candidates (GEOBON)	RS-biodiversity variable	RS-biodiversity variable products	Relevance	Feasibility	RS status		Total score	Rank within EBV class	Rank across all EBV classes	Aichi targets	SDG targets
						Accuracy	Maturity					
Ecosystem structure (an ecological structure that can be monitored at a global level)	Habitat structure	*Ecosystem Bio-physical structure*	Land cover (Vegetation type)	1	1	1.5	1	4.5	3	5	5,7,9,14,15	15.2, 15.3, 15.5
			Fraction of vegetation cover	1	1	2	2	6	7	11	5,7,9,14,15	15.2, 15.3, 15.5
			Above-ground biomass	1	1.5	1	2	5.5	6	9	5,7,9,10,12,14,15	15.2, 15.3, 15.5
			Leaf area index	1	1	1.5	1	4.5	3	5	5,7,9,10,12,14,15	15.2, 15.3, 15.5
			Urban habitat	2	1	2	1	6	7	11	5,7,9,14,15	15.2, 15.3, 15.5
			Ice cover habitat	2	1	1	1	5	5	8	5,7,9,14,15	15.2, 15.3, 15.5
			Deadwood habitat	1	3	3	3	10	14	32	5,7,9,14,15	15.2, 15.3, 15.5
	Ecosystem composition by functional type		Vegetation height	1	1	2	2	6	7	11	5,7,9,14,15	15.1, 15.2, 15.3, 15.4,15.5
			Plant area index profile (canopy cover)	1	1	2	2	6	7	11	5,7,9,14,15	15.1, 15.2, 15.3, 15.4,15.5
			Habitat structure	1	1	2	2	6	7	11	5,7,9,14,15	15.1, 15.2, 15.3, 15.4,15.5

EBV class	Original EBV candidates (GEOBON)	RS-biodiversity variable	RS-biodiversity variable products	Relevance	Feasibility	RS status: Accuracy	RS status: Maturity	Total score	Rank within EBV class	Rank across all EBV classes	Aichi targets	SDG targets
			Biological effects fire disturbance (direction, duration, abruptness, magnitude, extent, frequency)	1	1	1	1	4	1	1		
			Biological effects of Irregular inundation	1	1	1	1	4	1	1	5,7,9,10,12,14,15	15.1, 15.2, 15.3, 15.4,15.5
	Ecosystem extent and fragmentation	Spatial configuration	Ecosystem fragmentation	1	1	2	2	6	7	11	5,7,9,14,15	15.1, 15.2, 15.3, 15.4,15.5
			Ecosytem structural variance	1	1	2	2	6	7	11	5,7,9,14,15	15.1, 15.2, 15.3, 15.4,15.5
Ecosystem function (an ecological function monitored over time at a global level)	–	Ecosystem phenology	Land surface peak (max of season)	1	2	2	2	7	8	21	5,7,9,12,14,15	15.4
			Land surface green-up (start of season)	1	2	2	2	7	8	21	5,7,9,12,14,15	15.4
			Land surface senescence (end of season)	1	2	2	2	7	8	21	5,7,9,12,14,15	15.4
	Net primary productivity	Physiology	Gross primary productivity	2	1	2	1	6	5	11	5,7,9,10,12,14,15	15.2
			Net primary productivity	1	2	2	1	6	5	11	5,7,9,10,12,14,15	15.2
			Leaf area index	1	1	1.5	1	4.5	3	5	5,7,9,10,12,14,15	15.2
			Plant specific leaf area	1	2	2	2	7	8	21	5,7,9,10,12,14,15	15.2

EBV class	Original EBV candidates (GEOBON)	RS-biodiversity variable	RS-biodiversity variable products	Relevance	Feasibility	RS status		Total score	Rank within EBV class	Rank across all EBV classes	Aichi targets	SDG targets
						Accuracy	Maturity					
			foliar N/P/K content	1	1.5	1	2	5.5	4	9	5,7,9,10,12,14,15	15.2
			Evapotranspiration	1	2	3	3	9	15	28	5,7,10,12,14,15	15.2
			Fraction of absorbed photosynthetically active radiation	2	1	2	1	6	5	11	5,7,10,12,14,15	15.2
	Secondary productivity		*Ecosystem soil moisture*	1	3	2	2	8	14	27	5,7,10,12,14,15	15.2
			Carbon cycle (sequestration)	1	2	3	3	9	15	28	5,7,10,12,14,15	15.2
			Carbon cycle (below ground biomass and carbon)	1	2	3	3	9	15	28	5,7,10,12,14,15	15.2
			Carbon cycle (above-ground biomass)	2	1	2	2	7	8	21	7,9,12,14	15.4
	Nutrient retention		*Chlorophyll content and flux*	1	2	2	2	7	8	21	7,9,12,14	15.4
	Disturbance regime	*Ecosystem Disturbance*	Biological effects fire disturbance (direction, duration, abruptness, magnitude, extent, frequency)	1	1	1	1	4	1	1	7,9,10,12,14,15	15.2, 15.3
			Biological effects of Irregular inundation	1	1	1	1	4	1	1	5,7,9,10,12,14,15	15.2, 15.3
			Biological effects of Pest and disease outbreak	1	2.5	2.5	3	9	15	28	7,9,10,12,14,15	15.2, 15.3

Annex 2: Participants of the three expert workshops with a focus on the prioritization of RS-enabled EBVs

Participants of the prioritization and selection of remote sensing based essential biodiversity variables expert workshop on 07-08 September 2017 at ITC, Enschede Netherlands.

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