Satellite Observation Requirements of Canopy chlorophyll content

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Acronyms and Abbreviations

CBD	Convention on Biological Diversity
CEOS	Committee on Earth Observation Satellites
COP	Conference Of the Parties
EBV	Essential Biodiversity Variable
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
GEO-BON	Group on Earth Observation – Biodiversity Observation Network
HISUI	Hyper-spectral Imager SUIte
HR	High Resolution
HyspIRI	Hyperspectral Infrared Imager
IPBES	Intergovernmental Platform on Biodiversity and Ecosystem Services
LAI	Leaf Area Index
LPV	Land Product Validation
MERIS	Medium Resolution Imaging Spectrometer
MTCI	MERIS Terrestrial Chlorophyll Index
NIR	Near-Infrared Region
RED	Red Edge Position
RS	Remote Sensing
RS-enabled EBV	Remote Sensing enabled Essential Biodiversity Variable
SBG	Surface Biology and Geology
SDG	Sustainable Development Goals
SOR	Satellite Observation Requirement
SRL	Science Readiness Level
TIR	Thermal Infrared
TM	Thematic Mapper
WGCV	Working Group on Calibration and Validation

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.

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 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).
Essential Biodiversity variable	A variable that is measurable at particular points in time and space and is essential to document biodiversity change.
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.
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.
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.
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.

1. Introduction

1.1. Purpose

This 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 document 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 required to monitor terrestrial ecosystem canopy chlorophyll content (CCC).

1.2. Scope

The scope of this chapter is to assemble the satellite observation requirements for RS-enabled EBVs-CCC 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 CCC. Overall, this document provides the observational requirements needed to monitor CCC 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 1). 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.

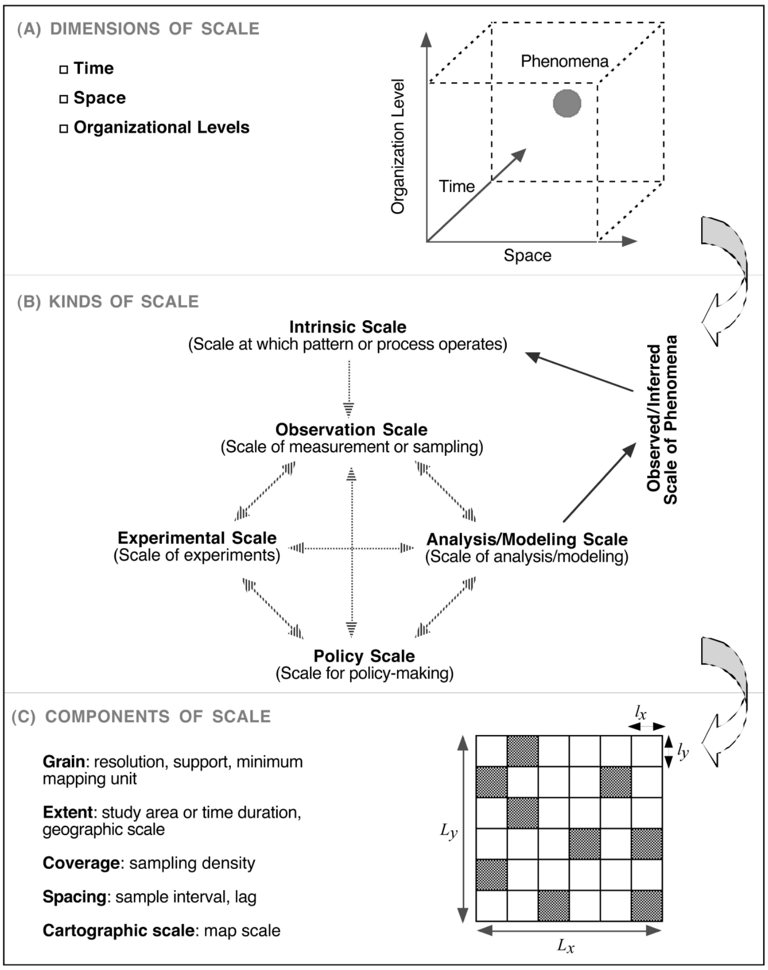

Figure 1: A hierarchy of scale concepts: (A) dimensions of scale, (B) kinds of scale, and (C) components of scale (from Wu et al., 2006).

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.

1.6.11. Specific measurement requirements summary

Summary of the satellite measurement specifications such as spatial, spectral and temporal resolutions together with delivery format, and other specific measurement requirements is presented in this section.

2. Canopy Chlorophyll Content Satellite Observation Requirement Definition and Analysis

2.1 Definition of canopy chlorophyll content

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 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.

2.3 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.

2.4 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 (Table 1), 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 1: 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.

2.5 Spatial extent and temporal frequency requirements

The spatial and temporal observation requirements needed to produce CCC products are indicated in Table 2 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 2: 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.

2.6 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.

2.7 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.

2.8 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.

2.9 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.

2.10 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.

2.11 Specific measurement requirements summary

The satellite measurement specifications and delivery format for the RS-enabled EBV are tabulated in Table 3. 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 3: Specific measurement requirements of the four RS-enabled EBVs.

Requirement	**CCC**
Spatial extent	All terrestrial ecosystems
Temporal extent	5 – 10 years
Spatial Resolution	10 - 20m
Spectral Resolution	Narrow band
Temporal Resolution	5-10 times/yr.
Thematic Accuracy	≥ 80 %
Geometrical Accuracy	0.5 pixel
Spectral domain	400-2500 nm
Existing RS data	S2, S3 and Landsat
Product format	GeoTiff, ESRI Grids, others on request
Reference system	UTM

Reference

Almond, S. F. 2009. *Validation and application of the MERIS Terrestrial Chlorophyll Index*. Bournemouth.

Asner, G. P. 1998. Biophysical and biochemical sources of variability in canopy reflectance. *Remote Sensing of Environment,* 64**,** 234-253.

Basu, M. & Xavier, S. 2016. *Fundamentals of Environmental Studies,* India, Cambridge University press.

Blackburn, G. A. 1998. Quantifying chlorophylls and caroteniods at leaf and canopy scales: An evaluation of some hyperspectral approaches. *Remote Sensing of Environment,* 66**,** 273-285.

Blackburn, G. A. 2007. Hyperspectral remote sensing of plant pigments. *Journal of Experimental Botany,* 58**,** 855-867.

Cavender-Bares, J. & Bazzaz, F. A. 2004. From leaves to ecosystems: using chlorophyll fluorescence to assess photosynthesis and plant function in ecological studies. *Chlorophyll a Fluorescence*. Springer.

Chapin, F. S., Matson, P. A. & Vitousek, P. M. 2002. *Principles of terrestrial ecosystem ecology*.

Chappelle, E. W., Kim, M. S. & McMurtrey, J. E. 1992. Ratio analysis of reflectance spectra (RARS): An algorithm for the remote estimation of the concentrations of chlorophyll A, chlorophyll B, and carotenoids in soybean leaves. *Remote Sensing of Environment,* 39**,** 239-247.

Chen, J., Chen, J., Liao, A., Cao, X., Chen, L., Chen, X., . . . Mills, J. 2015. Global land cover mapping at 30m resolution: A POK-based operational approach. *ISPRS Journal of Photogrammetry and Remote Sensing,* 103**,** 7-27.

COP-CBD 2010. The Strategic Plan for Biodiversity 2011-2020 and the Aichi Biodiversity Targets, COP-10 Decision X/2, 29 October 2010, UNEP/CBD/COP/DEC/X/2

Croft, H., Chen, J. M. & Zhang, Y. 2014. The applicability of empirical vegetation indices for determining leaf chlorophyll content over different leaf and canopy structures. *Ecological Complexity,* 17**,** 119-130.

Croft, H., Chen, J. M., Zhang, Y., Simic, A., Noland, T. L., Nesbitt, N. & Arabian, J. 2015. Evaluating leaf chlorophyll content prediction from multispectral remote sensing data within a physically-based modelling framework. *ISPRS Journal of Photogrammetry and Remote Sensing,* 102**,** 85-95.

Croft, H., Chen, J. M., Luo, X., Bartlett, P., Chen, B. & Staebler, R. M. 2017. Leaf chlorophyll content as a proxy for leaf photosynthetic capacity. *Global Change Biology***,** n/a-n/a.

Cui, S. & Zhou, K. 2017. A comparison of the predictive potential of various vegetation indices for leaf chlorophyll content. *Earth Science Informatics,* 10**,** 169-181.

Curran, P. J., Dash, J., Lankester, T. & Hubbard, S. 2007. Global composites of the MERIS terrestrial chlorophyll index. *International Journal of Remote Sensing,* 28**,** 3757-3758.

Dash, J., Curran, P. J. & Foody, G. M. 2009. Remote sensing of terrestrial chlorophyll content. *Global Climatology and Ecodynamics*. Springer.

Delegido, J., Verrelst, J., Alonso, L. & Moreno, J. 2011. Evaluation of Sentinel-2 Red-Edge Bands for Empirical Estimation of Green LAI and Chlorophyll Content. *Sensors,* 11**,** 7063.

Dey, A. K., Sharma, M. & Meshram, M. R. 2016. An Analysis of Leaf Chlorophyll Measurement Method Using Chlorophyll Meter and Image Processing Technique. *Procedia Computer Science,* 85**,** 286-292.

ESA 2015. Scientific Readiness Levels (SRL) Handbook.

Gitelson, A. A., Viña, A., Ciganda, V., Rundquist, D. C. & Arkebauer, T. J. 2005. Remote estimation of canopy chlorophyll content in crops. *Geophysical Research Letters,* 32, n/a-n/a.

Houborg, R. & Boegh, E. 2008. Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data. *Remote Sensing of Environment,* 112, 186-202.

IAEG-SDGs 2016. Report of the Inter-agency and Expert Group on Sustainable Development Goal Indicators (E/CN.3/2016/2/Rev.1). United Nations.

Inoue, Y., Sakaiya, E., Zhu, Y. & Takahashi, W. 2012. Diagnostic mapping of canopy nitrogen content in rice based on hyperspectral measurements. *Remote Sensing of Environment,* 126, 210-221.

Lewandowska, M. & Jarvis, P. G. 1977. CHANGES IN CHLOROPHYLL AND CAROTENOID CONTENT, SPECIFIC LEAF AREA AND DRY WEIGHT FRACTION IN SITKA SPRUCE, IN RESPONSE TO SHADING AND SEASON. *New Phytologist,* 79, 247-256.

Muñoz-Huerta, R. F., Guevara-Gonzalez, R. G., Contreras-Medina, L. M., Torres-Pacheco, I., Prado-Olivarez, J. & Ocampo-Velazquez, R. V. 2013. A review of methods for sensing the nitrogen status in plants: advantages, disadvantages and recent advances. *Sensors,* 13, 10823-10843.

Murchie, E. H. & Lawson, T. 2013. Chlorophyll fluorescence analysis: a guide to good practice and understanding some new applications. *Journal of Experimental Botany,* 64, 3983-3998.

Myster, R. W. 2001. What is Ecosystem Structure?

Nevalainen, O., Hakala, T., Suomalainen, J., Mäkipää, R., Peltoniemi, M., Krooks, A. & Kaasalainen, S. 2014. Fast and nondestructive method for leaf level chlorophyll estimation using hyperspectral LiDAR. *Agricultural and Forest Meteorology,* 198, 250-258.

O'Connor, B., Secades, C., Penner, J., Sonnenschein, R., Skidmore, A., Burgess, N. D. & Hutton, J. M. 2015. Earth observation as a tool for tracking progress towards the Aichi Biodiversity Targets. *Remote Sensing in Ecology and Conservation,* 1, 19-28.

Ollinger, S. V. & Smith, M. L. 2005. Net primary production and canopy nitrogen in a temperate forest landscape: An analysis using imaging spectroscopy, modeling and field data. *Ecosystems,* 8, 760-778.

Ollinger, S. V. 2011. Sources of variability in canopy reflectance and the convergent properties of plants. *New Phytologist,* 189, 375-394.

Plummer, S. E. 2000. Perspectives on combining ecological process models and remotely sensed data. *Ecological Modelling,* 129, 169-186.

Reich, P. B., Buschena, C., Tjoelker, M. G., Wrage, K., Knops, J., Tilman, D. & Machado, J. L. 2003. Variation in growth rate and ecophysiology among 34 grassland and savanna species under contrasting N supply: a test of functional group differences. *New Phytologist,* 157, 617-631.

Schneider, D. C. 2001. The Rise of the Concept of Scale in EcologyThe concept of scale is evolving from verbal expression to quantitative expression. *BioScience,* 51, 545-553.

Secretariat of CBD 2010. Global Biodiversity Outlook 3.

Sievering, H., Fernandez, I., Lee, J., Hom, J. & Rustad, L. 2000. Forest canopy uptake of atmospheric nitrogen deposition at eastern US conifer sites: Carbon storage implications? *Global Biogeochemical Cycles,* 14, 1153-1159.

Ustin, S. L., Gitelson, A. A., Jacquemoud, S., Schaepman, M., Asner, G. P., Gamon, J. A. & Zarco-Tejada, P. 2009. Retrieval of foliar information about plant pigment systems from high resolution spectroscopy. *Remote Sensing of Environment,* 113, S67-S77.

Wu, H. & Li, Z.-L. 2009. Scale Issues in Remote Sensing: A Review on Analysis, Processing and Modeling. *Sensors (Basel, Switzerland),* 9, 1768-1793.

Wu, J., Jones, K. B., Li, H. & Loucks, O. L. 2006. *Scaling and uncertainty analysis in ecology: Methods and applications.*

Wulder, M. A. & Coops, N. C. 2014. Make Earth observations open access: freely available satellite imagery will improve science and environmental-monitoring products. *Nature,* 513, 30-32.

Yang, X., Tang, J. W., Mustard, J. F., Wu, J., Zhao, K. G., Serbin, S. & Lee, J. E. 2016. Seasonal variability of multiple leaf traits captured by leaf spectroscopy at two temperate deciduous forests. *Remote Sensing of Environment,* 179, 1-12.

Zheng, G. & Moskal, L. M. 2009. Retrieving Leaf Area Index (LAI) Using Remote Sensing: Theories, Methods and Sensors. *Sensors (Basel, Switzerland),* 9, 2719-2745.