BIODIVERSITY – A NEW SPACE MISSION TO MONITOR EARTH ECOSYSTEM AT FINE SCALE

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Résumé

L'imagerie hyperspectrale a démontré son intérêt pour la caractérisation des propriétés biochimiques, biophysiques et structurelles de la végétation, des sols naturels et agricoles ainsi que des surfaces artificialisées. A la suite de la mission Hyperion, de nouvelles missions spatiales ont vu le jour (PRISMA, EnMAP), ou sont en phase d'étude (SBG, CHIME). Ces spectro-imageurs ont une résolution spatiale au sol de l'ordre de 30 m, un large champ de vue et peuvent couvrir de vastes zones du globe terrestre afin de caractériser les écosystèmes terrestres et océaniques avec un temps de revisite variant de 4 à 16 jours. Néanmoins, leur résolution spatiale est limitée ce qui induit un nombre important de pixels mixtes réduisant leur potentiel de discrimination pour des zones hétérogènes. La mission BIODIVERSITY a pour objectif de compléter ces missions par des acquisitions de meilleure résolution spatiale (typiquement 8-10 m) avec une revisite de l'ordre de 5 jours sur des sites de référence ciblés possédant des caractéristiques identifiées et bien localisées. Elle permettra ainsi de répondre à deux problématiques scientifiques qui vont dimensionner l'instrument. La première problématique porte sur la distribution spatiale et temporelle des traits de la végétation dans les assemblages d'espèces ; ces traits sont associés à la résilience des écosystèmes terrestres, aux influences anthropiques et à la biodiversité des écosystèmes en termes de composition et d'assemblages en espèces. La seconde problématique porte sur l'amélioration de nos connaissances des zones côtières et des eaux continentales en termes de biodiversité, de qualité des eaux et de bathymétrie, pour ensuite évaluer l'impact de l'activité anthropique sur leurs écosystèmes. Enfin, ces deux applications qui déterminent les spécifications de l'instrument seront complétées par l'étude, à fine résolution spatiale, de l'impact des pratiques de gestion des sols dans un processus environnemental tels que le stockage du carbone dans les sols, l'infiltration et la rétention d'eau en surface ou l'érosion des sols. Elles ouvrent également de nouvelles voies pour évaluer comment les matériaux urbains influencent notre environnement proche et pour caractériser les pollutions urbaine et industrielle. Les défis scientifiques ainsi que les exigences-utilisateurs pour une telle mission sont présentés pour chaque application.

Mots-clés : imagerie hyperspectrale, mission spatiale, végétation, biodiversité, écosystèmes côtiers, zone critique, qualité des sols, milieu urbain

Abstract

Imaging spectroscopy has demonstrated an interest in characterizing the biochemical, biophysical and structural properties of vegetation, natural and agricultural soils, as well as artificial surfaces. Following the Hyperion mission, new space missions have emerged (PRISMA, EnMap), or are under study (CHIME, SBG). Most of these space missions have a ground sampling distance (GSD) of 30 m, a wide swath and thus they can cover large regions of the Earth simultaneously to characterize different terrestrial and oceanic ecosystems with a revisit period varying from 4 to 16 days. However, their spatial resolution is limited which induces a large number of mixed pixels reducing their potential to discriminate heterogeneous areas. The BIODIVERSITY mission aims to complement these space missions with a better GSD (typically 8-10 m), a 5-day revisit on targeted reference sites with identified and well-located characteristics. It will thus provide answer to two scientific issues that will design the instrument. The first issue concerns the spatial and temporal distribution of vegetation traits in species assemblages; these traits are associated with the resilience of terrestrial ecosystems, anthropogenic influences, and the biodiversity of ecosystems in terms of species composition and assemblages. The second issue relates to improving our knowledge of coastal areas and inland waters in terms of biodiversity, water quality and bathymetry, to assess the impact of human activity on their ecosystems. Finally, these two applications, which determine the specifications of the instrument, will be supplemented by the study, at fine spatial resolution, of the impact of soil management practices in an environmental process such as soil carbon sequestration, infiltration and retention, runoff or soil erosion. They also open new avenues for evaluating how urban materials influence our close environment and for characterizing urban and industrial pollution. The scientific challenges as well as the user requirements for such a mission are presented for each application.

***Keywords**: imaging spectroscopy, hyperspectral, space mission, vegetation, biodiversity, coastal ecosystems, critical zone, soil quality, urban area*

1. Introduction

The world is experiencing a biodiversity crisis due to unprecedented high rates of loss and transformation of natural habitats, invasion by exotic species, and global climate change (Cardinale et al., 2012; Dornelas et al., 2014; McGill et al., 2015). Radical changes in biodiversity are observed over a broad range of terrestrial and aquatic ecosystems from tropical to boreal regions (Battistella et al., 2015; Magurran et al., 2015; Newbold et al., 2015; Cardinale et al., 2018). Biodiversity is also a natural capital, delivering a multitude of benefits to humanity, from food to cultural heritage known as ecosystem services (Figure 1) (Costanza et al., 1998; Baveye, 2017), and biodiversity loss directly affects our livelihoods and well-being.

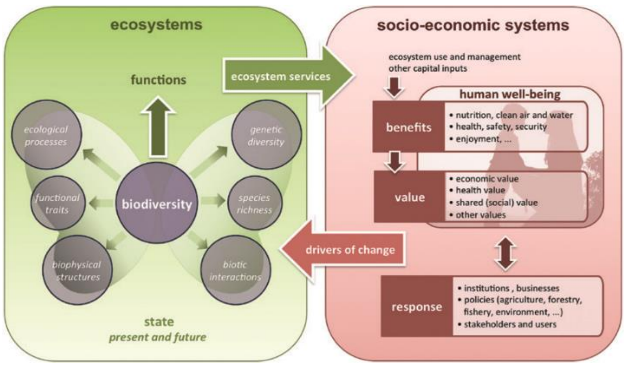

Figure 1: Conceptual framework drawn up by the MAES initiative (Maes et al., 2013). It links socio-economic systems with ecosystems via the flow of ecosystem services and through the drivers of change that affect ecosystems either because of using the services or as indirect impacts due to human activities.

Recent reports about the global state of nature and ecosystem services on land (IPBES, 2019; IPCC, 2019) conclude that neither climate mitigation and adaptation, nor biodiversity conservation strategies, will be successful unless these two challenges are jointly addressed. They further stress that neglecting the inter-linkages between ecosystem status and the generation of multiple ecosystem services, including those that underpin climate mitigation and adaptation, will fail to achieve the Sustainable Development Goals (SDGs) agreed under the UN Agenda 2030. The latest IPBES report (IPBES, 2019) highlights no progress in the achievement of global biodiversity conservation targets (the Aichi targets in the CBD biodiversity strategy 2010-2020, https://www.cbd.int/sp/targets/,). In particular, the targets the achievement of which needs to address trade-offs between conservation of (semi-)natural ecosystems and resource management (e.g., habitat loss halved, degradation and fragmentation reduced), are far from being reached. This means that current actions for biodiversity protection have failed to address the fundamental causes of biodiversity loss and ecosystem degradation (IPBES, 2019).

In order to meet the ambitions of biodiversity conservation and to act swiftly against its erosion, it is necessary to identify the relevant information to collect and to quantify biodiversity, and to set up a monitoring system based on regular collection of data on various ecosystems (Luque et al., 2018). These data acquired over time and space will allow deriving indicators characteristic of the state of the planet biodiversity in order to assess the effectiveness of the implemented conservation policies (Gardner et al., 2010; Hansen et al., 2013; Rocchini et al., 2016).

The Essential Biodiversity Variables (EBVs) framework sustained by the Group on Earth Observation – Biodiversity Observation Network (GEO BON) contributes to this pressing need to monitor the multiple dimensions of biodiversity. These EBVs include genetic composition, species populations, species traits, community composition, ecosystem function and structure attributes (Pereira et al., 2013; Skidmore et al., 2015; Jetz et al., 2016; Pettorelli et al., 2014, 2016, and 2018). GEO BON ensures the development of this framework towards an efficient monitoring system, combining appropriate tools and relevant indicators of ecosystem processes (Secades et al., 2013). As it is repeatable, consistent, borderless, and scale independent, remote sensing is crucial for long-term wide-area coverage. Thus, it appears as an appropriate tool to monitor EBVs. The EBVs framework is built upon the synergy between in situ experiments; fine-scale mapping of ecosystem attributes using remote sensing; and regional and global assessments of biodiversity changes using a combination of global observations and modelling tools (Figure 2).

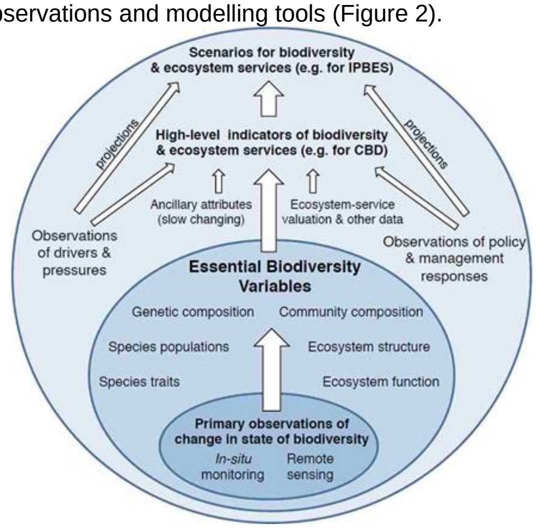

Figure 2: The Essential Biodiversity Variables framework (https://geobon.org/ebvs/what-are-ebvs/ after Pereira et al., 2013).

Biodiversity is a multidimensional, complex concept that refers to multiscale and multitemporal structures and processes occurring at different levels of functional organization, that is, from the genetic to the ecosystemic level (Figure 3).

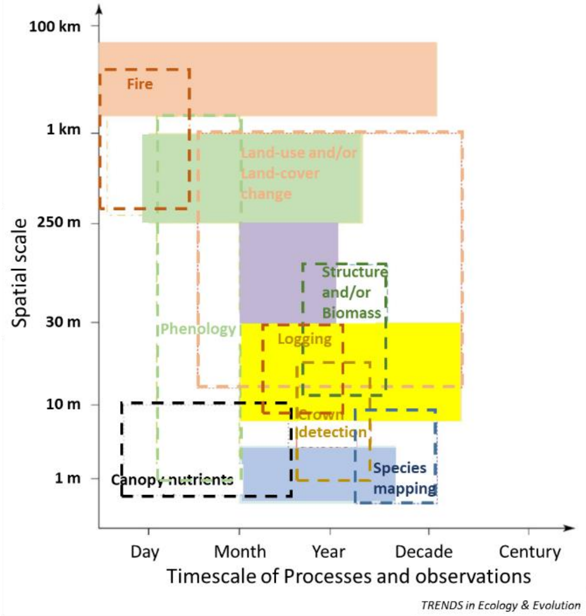

Figure 3: Scales and sensors. Recent advances in remote sensing of tropical forests have improved our understanding of a range of ecological processes that operate at varying spatial and temporal scales. Colored boxes show the spatial and temporal ranges of coverage from different satellite and airborne sensors (red, GOES; green, MODIS; pink, LiDAR, Radar; yellow, Landsat, EO-1; blue, IKONOS, Quickbird, Airborne). Suitable overlap between the scales of ecological processes, human actions and remote-sensing technology is denoted by dashed and dotted boxes (Chambers et al., 2007).

One of the most widely used methodology to track changes in species composition and turnover is based on taxonomic approaches and community ecology theories, yet there are satellite-based alternatives to this common approach. Jetz et al. (2016) highlighted the data gap in regional species trait measurements, leading to critical knowledge gaps on species and traits, especially in tropical regions (Figure 4).

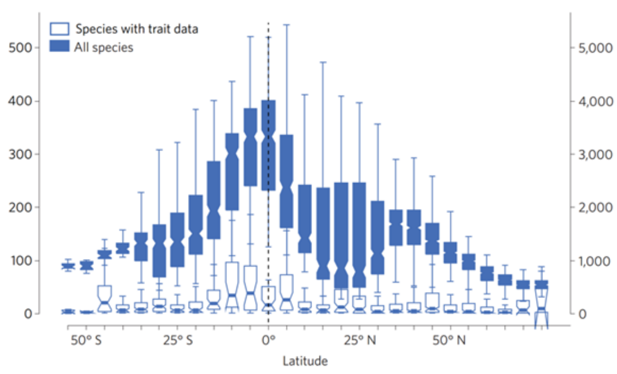

Figure 4: The gap in species and corresponding trait measurements. The graph shows the latitudinal variation in the number of vascular plant species for which at least one trait has been measured regionally (open boxes; left axis) in relation to all species expected for this region (filled boxes; right axis). Regions are here defined as 110 × 110 km² grid cells (n = 11,626); data on their expected richness is from Kreft & Jetz (2007), and region trait data comes from the TRY database, (Kattge et al., 2011). Regions are analyzed at the grid cell level and their variations are summarized in 5° width latitudinal bands. On average, only 2% of species have such regional measurements, and the data gap is the largest in the tropics. These limits understanding of both biodiversity and ecosystem functions and services (Jetz et al., 2016).

In this vein, previous and current Earth Explorer missions are focused on the understanding of the Earth System at a global scale, leaving behind environmental processes at local scales. However, key biodiversity processes occuring at spatial scale from local to regional (Loreau et al., 2001; Wang & Loreau, 2016) cannot be fully represented in global models, and our understanding of these processes requires strong improvements (Le Treut et al., 2007; Wang & Loreau, 2016). While global models describing local processes are refined, they still incorporate biosphere as simplified blocks or as a set of Plant Functional Types (PFTs), ignoring the relationships between biodiversity and other Earth System components. These models could benefit from a better description of multiple parameters such as the geographic distribution of biodiversity (α, β, γ diversity; Whittaker, 1972), or traits and functions of species and species assemblages, such as the photosynthetic phenology of vegetation, among others. Hence, few studies have addressed the measurement of species compositional turnover from satellite imagery. Rocchini et al. (2018) highlight the emphasis put on methodological developments for the estimation of α-diversity when using remote sensing, at the expense of methods focusing on β-diversity, and provided an overview of different methods applicable to map compositional turnover from airborne and spaceborne sensors. More recently, Laliberté et al. (2020) developed a method for partitioning plant spectral diversity, into additive α and β components of diversity, based on imaging spectroscopy. Partitioning spectral diversity improves the understanding of underlying biological traits driving spectral diversity at different spatial scales.

Advantages of imaging spectroscopy

Ustin & Middleton (2021) reviewed current and near-term advances in Earth observation for ecological applications, covering the optical domain from 0.4 to 12 µm. They pointed out the benefits of hyperspectral missions. Indeed, imaging spectroscopy is now a well-established technique (Schaepman et al., 2009) to map and monitor the composition and functional biodiversity of a large variety of ecosystems, including croplands, grasslands, forests, seagrasses and coral reefs (Feilhauer et al., 2011; Hochberg, 2011; Moisan et al., 2013; Féret & Asner, 2014a, 2014b; Asner et al., 2015b; Cavender-Bares et al., 2020). Jetz et al. (2016) suggested that spaceborne sensors providing global coverage could fill the gaps in the plant traits. The main advantage of imaging spectrometers over broadband sensors is their ability to quantitatively estimate the biophysical and biochemical properties of various surface types including soil, water and vegetation, based on their interactions with sunlight. Narrow spectral bands are particularly relevant to disentangle the relative contribution of the many factors that contribute to the dimensions of biodiversity in complex ecosystems. In case of vegetation, it is assumed that the set of morphological, physiological and phenological traits of plant species that respond to light correspond to unique optical traits that can be measured by imaging spectroscopy and provide a quantification of the function of plant species, assemblages and ecosystems (Ustin & Gamon, 2010; Violle et al., 2014). Characterizing and monitoring these traits requires high spectral resolution for traits discrimination, high temporal revisit to capture changes and phenological traits, and high spatial resolution to link *in situ* observations from species or species assemblages to spaceborne measurements with low uncertainty. To our knowledge, there is no currently operational or planned mission that can fulfill such requirements.

The BIODIVERSITY mission seeks to characterize environmental changes on the spatial and temporal evolution of species assemblages, including their traits and composition at all scales from local to regional. More particular, it aims at answering two major scientific questions (SQ) using hyperspectral imagery:

SQ1 - Does the spatial and temporal distribution of traits within species assemblages affect their resilience capacities? Is the resilience of terrestrial ecosystems to anthropogenic impact linked with their biodiversity in terms of species composition and assemblages?

SQ2 - What are the biodiversity, water quality and bathymetry of selected shallow water test areas? How much do anthropogenic activities affect both coastal and inland waters biodiversity?

Additionally, BIODIVERSITY will address two other SQ:

SQ3 - What is the impact of management practices on environmental processes such as soil carbon storage, soil infiltration, surface retention, runoff and soil erosion?

SQ4 - How do urban materials and industrial pollution impact on vulnerable surrounding?

Imaging spectroscopy is to date the most appropriate remote sensing technology for fine description of complex and heterogeneous surfaces, giving access to a wide range of biophysical and biochemical properties (Lausch et al., 2016, 2018). In this perspective, BIODIVERSITY aims at 1) exploring and implementing novel technologies and methods at different spatial scales; 2) establishing formal links with the Copernicus and GEO Global Ecosystem initiative; 3) exploring and suggesting innovative opportunities New Space companies.

The objective of this study aims at presenting the scientific user requirements based on a new hyperspectral mission, BIODIVERSITY, originally submitted at CNES SPS (Séminaire de Prospective Scientifique) 2019 at Caen (France). It will especially focus on the spectral resolution and range, the ground sampling distance, the landscape size, and the revisit required answering SQ1 to SQ 4. SQ1 and SQ2 are the drivers for the mission design as they focused on biodiversity analysis. SQ3 and SQ4 are two added applications, which could benefits of such a mission, they are presented but less detailed.

2. SQ1 –Does the spatial and temporal distribution of traits within species assemblages affect their resilience capacity? Is the resilience of terrestrial ecosystems to anthropogenic impact linked with their biodiversity in terms of species composition and assemblages?

Biodiversity loss has been well documented in the past decades. Attempts to halt or reduce it did not succeed despite the awareness of the international community (Tittensor et al., 2014; Hallmann et al., 2017; Sánchez-Bayo & Wyckhuys, 2019; Ceballos et al., 2020). In the case of terrestrial ecosystems, multiple drivers are associated with biodiversity loss, all linked to human activity: habitat loss, land use and cropping practice changes, pollution, changes in biogeochemical cycles, climate alterations, and spread of diseases and invasive species (Morris, 2010; Ceballos et al., 2015). These drivers show complex interactions and feedbacks with biodiversity, changes in ecosystem functions, climate change, and habitat degradations (Chapin et al., 2000). This results in the incapacity of natural ecosystems and anthropogenic areas to maintain their ecological functions, and to provide goods and services for society, with strong negative impacts on human well-being (Díaz et al., 2006).

Challenges for biodiversity monitoring

The EBVs framework is built upon the synergy between *in situ* monitoring, fine-scale mapping of ecosystem attributes using remote sensing, and regional and global assessments of biodiversity changes using a combination of global observations and modeling. The link between *in situ* measurements and remote sensing data remains challenging (Vanden Borre et al., 2011), as the spatial variability of key indicators such as traits, phenology and composition at each hierarchical level (individuals, assemblages, ecosystems, and biomes) needs to be accurately estimated to monitor changes in ecosystem functions occurring at different time scales (Lausch et al., 2016). From an ecological perspective, the species assemblage scale is particularly relevant but our understanding of the relation between biodiversity and ecosystem functions within species assemblages is limited (Wang & Loreau, 2016). Rare species may disproportionately contribute to the functional structure of species assemblages (Mouillot et al., 2013; Oliver et al., 2015; Leitao et al., 2016), suggesting that the tools dedicated to biodiversity monitoring should provide information at spatial scales close to the scale of the individual species.

BIODIVERSITY priority terrestrial ecosystems

The global map showing the species number of vascular plants (Mutke & Barthlott, 2008) highlights the strong influence of climate on plant biodiversity (Figure 5). These main world's biomes, listed below, differ from each other by their biodiversity, climatic conditions, and the origin of perturbation.

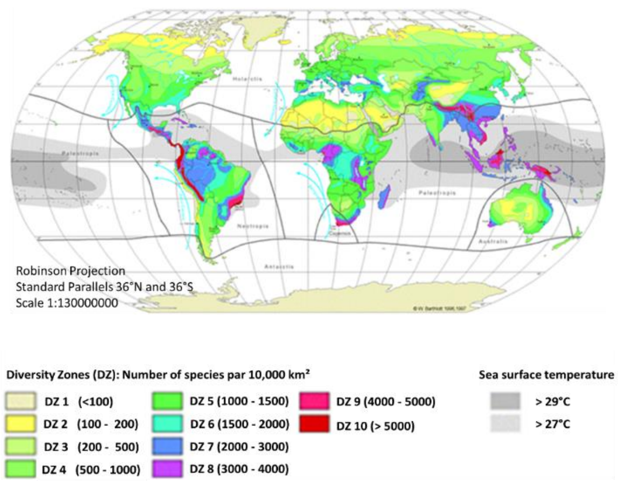

Figure 5: Global biodiversity of vascular plants (Mutke & Barthlott, 2008).

Tropical rainforests display the highest diversity in both plant and animal species (50%) over a small land fraction (6%). They are particularly vulnerable to climate change and we have limited knowledge of the environmental controls on their biodiversity (species compositions and spatial assemblages) (Myers et al., 2000). Increasing rates of deforestation and forest degradation are mainly due to human activities, with long-term consequences for global biogeochemical cycles. Quantifying biodiversity loss in tropical rainforests is challenging because they are difficult to access and hence accurately monitor. Therefore, the development of operational methods, strategies and ecosystem services is critical.

Temperate and alpine forests have been uniformly and extensively lost and altered by human activities for thousands of years. Despite their moderate biodiversity compared to tropical forests, they also face biodiversity loss and intense changes in their ecosystem functions. However, response to climate change of biodiversity and ecosystem functions in such forests may trigger very different ecological mechanisms than their tropical counterparts.

As for tundra, it is particularly vulnerable to climate change due to permafrost thawing, the increasing exploitation of oil and other natural resources, species extinctions, and changes in species migration routes in response to increasing temperatures (Schuur et al., 2008; Schaefer et al., 2014). Ecological response to permafrost thawing is critical in relation to carbon sequestration. Tundra ecosystems are also fundamental to climate regulation through the positive feedbacks between climate and albedo changes associated with reduced snow cover and increased shrub and forest cover. Tundra-dependent species such as migratory birds may face extinction when the melting of the permafrost will release methane in the atmosphere.

Croplands are found along a broad latitudinal gradient, but they dominate in temperate regions. In the 20th century, mechanized agriculture and selected cultivars led to major changes in farming practices. Moreover, the massive usage of pesticides resulted in a dramatic loss of biodiversity (Tscharntke et al., 2005; Pisa et al., 2017). The issue of soil conservation and fertility management, raised by soil loss due to unsustainable agricultural practices (e.g., the Dust Bowl episode), is still critical. Fertile croplands provide a number of ecosystem services, particularly carbon storage, which was recently emphasized through the 4p1000 initiative (http://4p1000.org/) (Minasny et al., 2017; Chabbi et al., 2017), but they are threatened by urban spread.

Grasslands, savannas and shrublands are also found from the tropical to the boreal regions. They are characterized by no or few trees. Savannas are particularly important ecosystems for a variety of animals including birds, large mammals, and insects, and they provide numerous ecosystem services to people. These ecosystems are threatened by changes in land use and conversion to agriculture, as well as climate change, which influences temperature, precipitation, fire regime, biodiversity and the stability of these systems (Sala et al., 2000).

Observation needs (Table 1)

Earth Observation provides valuable information to monitor biodiversity changes, mainly through the presence, the status and the dynamics of vegetation. Current satellites such as Landsat and MODIS are particularly appropriate at regional and global spatial scales (Tuanmu & Jetz, 2015). The Sentinel-1 and Sentinel-2 satellites of the Copernicus program now offer radar and multispectral images of the Earth at high spatial resolution. They should strongly contribute to the improvement of regional monitoring in the next decade (Bae et al., 2019; Ma et al., 2019). However, it is important to move beyond trend and change detection, towards better understanding, more comprehensive modeling of complex systems, and more robust prediction of how global changes may affect ecosystem functions. A better monitoring of fine scale processes, which requires appropriate observation tools, is urgent. This is particularly true when attempting to monitor heterogeneous natural ecosystems with limited *in situ* information (Soudani & Francois, 2014). Accessing and integrating this fine scale and spatially exhaustive information is a critical step towards regional upscaling and global monitoring (Schimel et al., 2013; Violle et al., 2014; Costion et al., 2015). For example, Earth System models lack fundamental inputs like continuous metrics of functional diversity to parameterize biogeochemical cycle models. Emerging concepts such as functional biogeography depend on the accurate estimation of various plant biophysical properties in a continuous surface. In addition, ecological models may also benefit from such continuous input variables as they help to provide a greater understanding of, for example, functional adaptation of vegetation to climate change, invasive species, and pathogens (Underwood et al., 2007; Violle et al., 2014; Pappas et al., 2016; Royimani et al., 2019).

Imaging spectroscopy is the only technology so far that fulfills these aims for fine scale mapping of a wide variety of species (Figure 6) and biophysical and biochemical vegetation properties. Such properties help to improve the description and monitoring of several dimensions of biodiversity, including taxonomic and functional diversity, plant traits, and structure, for a wide range of ecosystems (Schimel et al., 2013; Schaepman et al., 2015; Jetz et al., 2016). BIODIVERSITY will monitor leaf chemical traits (Jacquemoud & Ustin, 2019), species richness and abundance, as well as the spatial distribution of species communities (Table 1) to define indicators of the state and functions of these assemblages. The latter will inform us about physiological, structural, and biochemical properties, which are indicators of plant responses to ecological processes and environmental conditions or disturbances (Ustin & Gamon, 2010; Homolova et al., 2013; Hill et al. 2019).

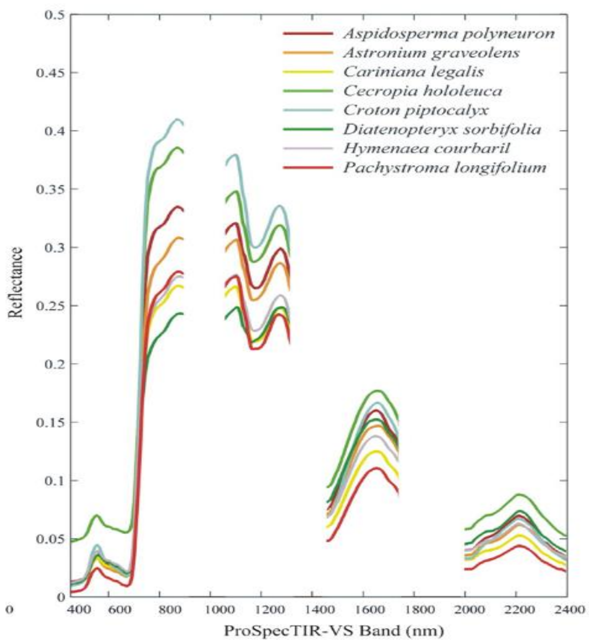

Figure 6: Mean reflectance spectra of plant species collected in tropical seasonal semi-deciduous forests (Ferreira et al., 2016). The missing values correspond to strong atmosphere absorption bands.

One might consider that this mission can produce additional bio-geophysical products in the near future: monitoring of phenology, including pollination (Chen et al., 2019; Bera & Gaulton, 2021; Dixon et al., 2021) and spatial distribution of species communities.

Table 1: Biogeophysical vegetation traits as a function of the BIODIVERSITY mission characteristics (spectral, spatial and temporal) linked to the three dimensions of the biodiversity (taxonomy, structure and function).

BIODIVERSITY	Spectral	Spatial	Temporal
Taxonomic biodiversity	Identification of species, composition and richness	Mapping individuals, population and community	Change in species composition and distribution (persistence, local extinctions)
Structural biodiversity	Identification of physiognomic and morphological traits	Heterogeneity in structural traits, connectivity, fragmentation	Change in structural patterns
Functional biodiversity	Identification of biochemical and biophysical traits	Interspecific and intraspecific variability of functional traits Heterogeneity in structural traits, connectivity, fragmentation	Phenology, interannual variability of ecosystem productivity, biotic and abiotic stress

BIODIVERSITY as an ideal platform for ecological monitoring

High spatial resolution (< 10 m) Visible to Short Wavelength InfraRed (VisSWIR) imaging spectroscopy is particularly adapted to monitor optically distinguishable functional types defined as “plant optical types” (Ustin & Gamon, 2010). Erudel et al. (2019) recently showed that the optimal GSD to discriminate temperate forest species from hyperspectral imagery around 12-15 m. Feilhauer et al. (2011) mapped floristic gradients in open heterogeneous temperate landscapes with HyMap (Cocks et al., 1998) data (4 m GSD). Species richness, community composition and leaf chemical traits were mapped in the Amazon forest and in the Bushveld of South-African with the CAO AToMS (2 m GSD, http://cao.carnegiescience.edu) and related to landscape biogeochemistry and microtopography (Gamon et al., 2019; Baldeck et al., 2014; Féret & Asner, 2014a, 2014b; Asner et al., 2015a; Chadwick & Asner, 2016). Imaging spectroscopy demonstrated its efficiency for mapping key vegetation characteristics, from tropical to boreal ecosystems. Many studies also showed the potential of imaging spectroscopy for the detection of invasive species (Ustin et al., 2002; Asner et al., 2008; Hestir et al., 2008) or subtle changes in leaf chemistry (pigment, water) induced by vegetation stress due to climate, pollution or other environmental factors (Somers & Asner, 2012; Gholizadeh & Kopačková, 2019). These products can be useful to monitor threatened ecosystem services such as pollination (Szigeti et al., 2016).

Completing Miglani’s works on Hyperion satellite data (Miglani et al., 2008), Thenkabail et al. (2013) determined the optimal number of bands to retrieve crop and vegetation biophysical parameters and showed the benefits of using the entire spectral range from 0.4 to 2.3 µm. These studies support hyperspectral data characterization and applications from missions such as the Hyperspectral Infrared Imager (HyspIRI, 2018) and the

Advanced Responsive Tactically Effective Military Imaging Spectrometer (ARTEMIS-TacSat3, https://directory.eoportal.org/web/eoportal/satellite-missions/t/tacsat-3). They suggested that the main parameters characterizing crops like pigments, LeafArea Index (LAI), dry matter, water content and soil properties could be estimated with a 10 nm spectral resolution. Two parameters seem to be more difficult to estimate as they require a higher spectral resolution of 1 nm and a high SNR to measure the solar induced fluorescence of vegetation and a high SNR at 405 nm for nitrogen estimation.

So far, imaging spectroscopy is the only technology that fulfills these needs for fine scale mapping of a variety of biophysical and chemical properties of vegetation. Such vegetation properties also directly contribute to improved description and monitoring of several dimensions of biodiversity, including taxonomic diversity, traits and function, for a large range of ecosystems (Schimel et al., 2013; Schaepman et al., 2015; Jetz et al., 2016). Thenkabail et al. (2013) showed the benefits of hyperspectral imagery compared with broadband imagery 1) to improve the discrimination/separation between vegetation and crop types and their species; 2) to explain greater variability in modeling vegetation and crop biophysical, yield, and biochemical characteristics; 3) to increase accuracies (reducing errors and uncertainties) in vegetation/land cover classification; and 4) to allow the study of specific biophysical and biochemical properties from specific targeted portion of the spectrum. Despite a wide spectrum coverage and a high number of spectral bands, many useful wavebands are not covered by Sentinel-2 MSI and most of them are dedicated to vegetation studies only. There is a gap between Band 9 (945 nm) dedicated to water vapor assessment and Band 10 (1375 nm) dedicated to cirrus assessment. This gap covers wavelengths of interest for the estimation of water stress, LAI, biomass, and plant height among other vegetation variables (Thenkabail et al., 2014; Miglani et al., 2008). The other gap between Bands 11 (1614 nm) and 12 (2202 nm) covers some applications such as cellulose, lignin, starch or biomass estimation. Even if Sentinel-2 is well suited for biomass estimation (Müller et al., 2013; Sibanda et al., 2015, 2016), one could expect better results with a full coverage of these spectral ranges.

A revisit time higher than one week gives access to applications such as crop and vegetation monitoring. Considering cloud cover, a revisit time of 5 days with a constant viewing zenith angle is recommended. There are only a few operational airborne systems dedicated to ecological monitoring. They include APEX (Marcinkowska et al., 2014; Schaepman et al., 2015), CAO AToMS (Asner et al., 2012; Féret & Asner, 2014b), and NEON (Kampe, 2010). Financial and logistic limitations prevent frequent acquisitions needed to monitor terrestrial ecosystems, hindering the contribution of these programs to the future Biodiversity Observation Networks (BON, https://geobon.org/). In this context, a satellite mission would be more appropriate to such global needs as it would bring benefits to a broad scientific community.

The monitoring strategy for the BON is built upon biodiversity metrics, which are being discussed, and the combination of sensors monitoring these metrics at different time and spatial scales has yet to be defined. Scale and knowledge gaps between global environmental and physical information monitored at very fine scales on the one hand, and very coarse information about species traits and composition on the other hand, are clearly identified (Schimel et al., 2013; Jetz et al., 2012, 2016).

The vegetation covering the latitude range between ±80° requires access over this range.

To take variability gradient into account, an area around a few hundreds of km² is recommended.

In short, the BIODIVERSITY mission intends to bridge the gap between field studies on vegetation properties and regional monitoring and modelling of ecosystem processes, in order to gain a better understanding of vegetation functioning. They are often collected at resolutions finer than other geographically structured environmental datasets such as topography or land cover (Jetz et al., 2012). Filling in such a gap will provide continuous products on the distribution of traits and biophysical properties, which will be inputs of unprecedented accuracy to ecological models (e.g., species distributions, ecosystem processes, etc.) and physical models (e.g., radiative transfer, biogeochemical cycling) that will bring about benefits to a transdisciplinary scientific community information. It will enable to assess the impact of human activities on biodiversity composition and functionality, which is highly relevant to decision makers. To sum up the main user requests are summarized in Table 2.

Table 2 : User requirements for vegetation characterization.

User requirement types	
Ground sampling distance (m)	< 15
Area size (km²)	100-200
Spectral range (µm)	0.4 – 2.5
Spectral resolution (nm)	8-15
Revisit (days)	5
Accessibility	Worldwide

3. SQ2 – What are the biodiversity, water quality and bathymetry of selected shallow water test areas? How much do anthropogenic activities affect coastal and inland waters biodiversity?

Inland water and coastal ecosystems play an essential role in human life. Areas less than 100 km from the coastline provide benefits equivalent to over 60% of global gross national product (MEA, 2005). They include economic value, food, energy and space for cultural and recreation activity. However, with more than 50% of the world population living within a 60 km coastal belt, the impact of increased population has important implication for the maintenance of coastal water ecological quality.

Challenges for marine biodiversity monitoring

Coastal and inland waters ecosystems are subject to high spatial and temporal variability in their bio-optical (e.g., absorption and scattering processes), morphological and biogeochemical (e.g., phytoplankton biomass, mineral-like hydrosols) properties. Marine ecosystems are defined as physically and biologically structured habitats where organisms and communities develop. Characterizing their structures as well as the shifts due to human activities and changing climate is a key subject for many scientific researches. However, it is difficult to address such relevant questions at a global scale since biodiversity assessment is often temporarily and spatially limited to small areas (typically < 100 km²), and because of the strong spatial heterogeneity of coastal ecosystems. Indeed, although field measurements are very detailed and informative, they are expensive, difficult to conduct, and often limited to accessible areas. Thus, for the most part, the aquatic habitats in the coastal areas remain among the most under-sampled on Earth. To be relevant for scientific, conservation, and socioeconomic goals, these observations need to be acquired synoptically and frequently. Satellite remote sensing that provides consistent observations and sensitive measurement can characterize changes in inland water and coastal ecosystems and meet these objectives. For instance, quantification of absorption by accessory or marker pigments beyond chlorophyll-*a* is often necessary to identify phytoplankton or macrophytes by taxonomic group or species. To better understand the functioning of these complex dynamic ecosystems, it is therefore essential to observe them both at high spatial (typically < 10 m) and spectral resolutions with an appropriate radiometric resolution and a revisit period better than those of current sun-synchronous satellites. In addition, such observations are required inputs for mesoscale physical models predicting the evolution of these ecosystems, which is needed for coastal and inland water socio-economic management as well as European Directives implementation by means of biological indicators.

BIODIVERSITY priority targeted coastal ecosystems

While it is likely that climate change affects all ecosystems, it is important to prioritize which ones have the highest biodiversity so that they may be concerned first and will be the most heavily damaged. Such critical zones can thus be used as study sites of key ecosystems. The maximum coverage necessary for a coastal and inland water observatory is less than global, but it should cover most of the Earth’s landmasses and waters near their margins (Figure 7). An approximate site number lower than 100 is recommended to be able to consider different types of waters (clear, moderated turbid, turbid, eutrophization…). The minimum coverage corresponds to a set of representative sites, which depend on the scientific issues and conservation requirements.

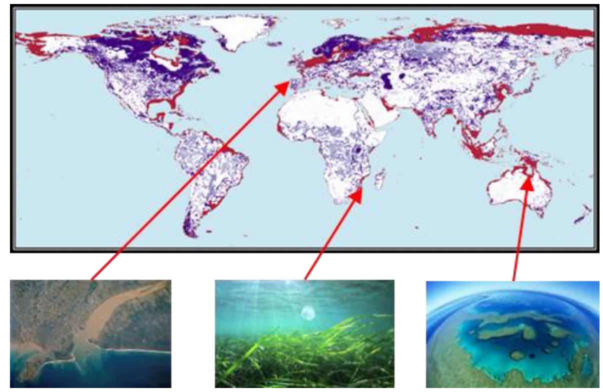

Figure 7: Global distribution of coastal and inland aquatic ecosystems. The red color indicates regions where water depth is lower than 50 m and where land elevation is lower than 50 m. Light to dark violet color gives the concentration of inland wetlands, lakes, rivers and other aquatic systems. Increased darkness means greater percentage of area coverage for inland aquatic ecosystems (UNEP-WCMC, 2005a, 2005b).

Shallow coral reefs form some of the most diverse ecosystems on Earth. They cover less than 0.1% of the area of the World's oceans but they support at least 25% of all marine species. Coral reefs deliver ecosystem services to tourism, fisheries and shoreline protection managements. The annual global economic value of coral reefs is estimated between US$ 29.8-375 billion. However, they are fragile ecosystems and some of the most vulnerable to climate change. In addition to the threat posed by ocean acidification due to increased dissolved carbon dioxide in seawater, coral reefs also suffer from high mortality due to coral bleaching in response to increased seawater temperature (Carpenter & Brock, 2008). Finally, they have both high ecological and economic values, as they serve as habitat for many other species, and they play a major role in food production and other materials, with an estimated value of US$ 6,075 per hectare per year (Costanza et al., 1997). Moreover, coral reefs are more sensitive than most other coastal environments to anthropogenic threats (Paskoff, 2003).

Seagrass meadows, a biodiversity hotspot, play an important ecological and environmental role by providing food and shelter for many marine animals. Seagrasses also provide services to people by cleaning water, protecting coastlines by weakening wave energy and stabilizing sediments. The most important threats to seagrasses are damage from boat anchors, dredging, and pollution. They are also vulnerable to the effects of chemical pollution and exposure to toxic substances. Costanza et al. (1997) estimated the economic value of a hectare of marine angiosperms beds at US$ 19,004 per year. This habitat is however subject to natural and anthropogenic pressure, with an annual decline of 2 to 5% of their area globally (Duarte et al., 2008). Monitoring the spatio-temporal dynamics of seagrass meadows is thus essential to implement appropriate management and protection measures.

Estuaries are semi-enclosed bodies of water formed when freshwater from rivers and coastal streams flow into and mix with seawater from the oceans. They can generate year-round primary production from macrophytes (seaweeds, seagrasses, and marsh grasses), benthic microphytes (mud algae), and phytoplankton. Many commercially and recreationally important species depend on this ecosystem. However, estuaries are one of the coastal areas most at risk due to human activities. Both urbanization in and around estuaries and increasing population growth affect these areas.

Inland waters are also a topical issue for the management of freshwater resources. “Increased discharges of untreated sewage, combined with agricultural runoff and inadequately treated wastewater from industry have resulted in the degradation of water quality around the world” (UNEP-WCWC, 2005a, 2005b). The EU Water Framework Directive and the Bathing Water Directive should safeguard our EU inland waters. Inland waters are optically complex as the concentrations of optically active substances in the water column (suspended particulate matter, CDOM (Colored Dissolved Organic Matter), phytoplankton pigments) can vary significantly between lakes and independently from each other. The absorption features of these optically active constituents vary in depth, width and location and may even overlap leading to confounding effects when isolating any one biophysical parameter (Ampe et al., 2015; Hestir et al., 2015).

Imaging spectrometers are required to provide repeated and global coverage of coastal areas. There are key gaps in knowledge in the extent, fragmentation, degradation and condition of temperate coastal marine habitats, kelp forests, intertidal and sub-tidal ecosystems, vulnerable habitats, and benthic habitats. Information that is more accurate is necessary to meet this gap, with high spatial resolution sensors. More importantly, hyperspectral data are required to distinguish accessory pigments and pigment assemblages that are specific to aquatic species. A limited number of wavelengths or large wavebands are not adapted as the absorption features of these pigments are generally narrow (Table 3).

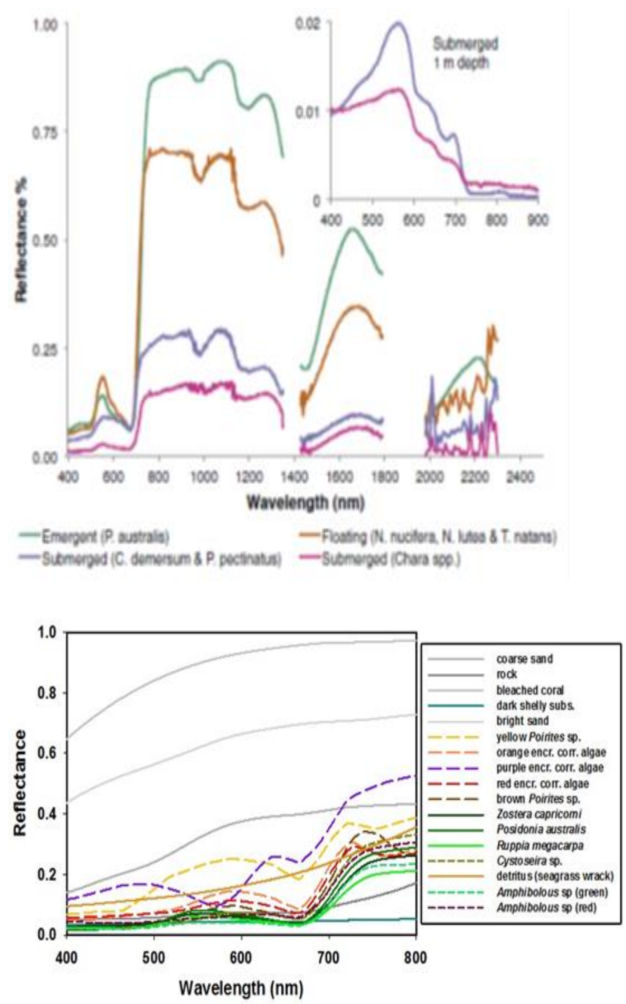

Figure 8: Top plot: Examples of surface reflectance of 17 selected representative substratum types (Australian Shallow Waters Spectral Library, Hestir et al., 2015). Bottom plot: Representative reflectance spectra of emergent, floating and submerged aquatic vegetation measured above water. The inset graph shows the above water surface reflectance of submerged vegetation under 1 m of water (CHL = 0.8 mg.m^{-3}, TSM = 0.7 gm^{-3}, and CDOM(440nm) = 0.2 m^{-1}) (Giardino et al., 2019)

Observations needs (Table 3)

Most of the methods to retrieve the sea bottom biodiversity estimate bathymetry and water column composition simultaneously.

Regarding benthic features, targeted metrics aim at recording both the presence/absence of species and habitats and quantitative estimates of biological variables such as the cover fraction of different seabed types as well as the biomass of the main marine vegetation (macrophytes, seagrasses). For benthic estimated metrics, ground truth data are needed to validate algorithms and to assess the accuracy of retrieved biophysical variables from hyperspectral images. Complementary laboratory analysis could also be required to validate quantitative estimates such as the microphytobenthos biomass, for instance. Measured metrics are key information about the diversity, composition, and functional traits of coastal benthic ecosystems (Table 3).

Bathymetry depends on the seabed topography but may also vary with sediment transfer. Maritime traffic requires accurate bathymetric maps acquired at high temporal resolution. However, high-resolution bathymetry can be affected by vegetation located on the seabed. The underwater plant height can be monitored using high spatial resolution images. Bathymetry can be measured by the attenuation of the sea bottom reflectance by the water column. Bathymetry influences all wavelengths, but some are more sensitive to water attenuation than others, especially in the blue and the green. Many narrow bands are needed to reduce the noise influencing each band on depth estimation.

The reflectance spectrum of water affected by the optical properties of the upper meters provides information about water quality and composition. The algorithms used to extract these parameters need to be validated using *in situ* reflectance measurements and the specific inherent optical properties (absorption and scattering coefficients) of the hydrosols are required. The link between the reflectance and the absorption/scattering coefficients is carried out using radiative transfer models and/or empirical relationships. The concentration and composition of the hydrosols is then determined through bio-optical algorithms already published (Lee et al., 1998, 2002, Giardino et al., 2014, Hedley et al., 2017, Vahtmäe et al., 2020) or to be developed in the frame of the BIODIVERSITY mission. They will be able to retrieve the absorption coefficient of phytoplankton, the scattering and backscattering coefficients of particulate matter, the concentration of phytoplankton and mineral-like suspended matter, and an indicator of their composition through the bulk refractive index (derived from the backscattering ratio of the particles).

These costal and inlands waters landscape are present all over the world and thus required an accessibility in the ± 80° latitudes range.

Table 3 details the geophysical variables of interest for the inland/water topic: species identification and spatial distribution of species assemblage.

BIODIVERSITY as the ideal platform for these observations

Efficient Earth observations require a new generation of satellite sensors with adequate specification related to 1) the spatial resolution, 2) the spectral resolution, 3) the radiometric quality in terms of signal to noise ratio (SNR) and absolute calibration stability, and 4) temporal resolution.

For coastal and inland waters, current sensors do not provide appropriate information for water applications. MODIS spatial and spectral resolutions are too coarse with a 1 km spatial resolution and nine large wavebands respectively. The sea column parameters (chlorophyll, CDOM) can be accurately mapped but neither the seabed nor the bathymetry. Although the Visible Infrared Imaging Radiometer Suite (VIIRS) has the same spectral configuration as MODIS, its spatial resolution is slightly improved (750 m) but still limited for bathymetry and seabed mapping in coastal areas. The Ocean and Land Colour Instrument (OLCI) onboard Sentinel-3 has a better spatial resolution (300 m) and a better spectral resolution (21 bands) but is inadequate to map benthic habitat in coastal areas (Minghelli-Roman & Dupouy, 2013, 2014). The main advantages of MODIS, VIIRS and OLCI are their revisit times (one to three days) and their high signal-to-noise ratios, adapted to low reflectance targets. Concerning the multispectral Instrument (MSI) onboard Sentinel-2, its spatial resolution is improved compared to MODIS, VIIRS and OLCI (10 to 60 m depending on the spectral bands) but the spectral richness remains too limited to catch spectral features of seawater reflectance. However, this sensor class lacks the spectral definition in the visible and near-infrared light (i.e., spectral resolution of about 10 nm between 380 and 900 nm, and about 10 to 20 nm between 900 and 2500 nm) needed to estimate the biodiversity of the main coastal habitats. The future NASA SBG (Decadal survey, 2018) mission concept, the JAXA HISUI instrument, and the DLR Environmental Mapping and Analysis Program (EnMAP, Guanter et al., 2005) will also have at least 30 m spatial resolution (Turpie et al., 2015). SBG is designed to sample nominally every 16 days, and EnMAP and HISUI are designed to acquire targets of interest intermittently. Thus, they lack temporal details needed to observe changes over days. Devred et al. (2013) reviewed water resource applications that can benefit from HyspIRI mission. They noted that algal bloom dynamics and ecosystem responses analysis were more difficult to perform, partly due to the low revisit time (19 days). Kudela et al. (2015) have reached the same conclusions. Sentinel-2 was also used to detect cyanobacterial blooms (Toming et al., 2016; Vanhellemont & Ruddick, 2016), to map water bodies (Du et al., 2016) and to estimate chlorophyll *a* content (Beck et al., 2016). However, a 30 m GSD is not sufficient to map cyanobacterial bloom spatial variability. Hedley et al. (2016) noted that Sentinel-2 was also able to discriminate reef benthic composition thanks to its fine spectral resolution, its 10 m GSD and its band at 443 nm, but not able to discriminate coral mortality of algal cover unlike HISHUI (Kakuta et al., 2013).

Segl et al. (2012) and Thenkabail et al. (2013) recommended the 413-758 nm spectral range to study water quality retrieval. The band at 440 band is identified as useful to estimate dissolved organic matter (Giardino et al., 2007). Nevertheless, an accurate atmospheric correction is required for retrieving sea floor composition or the deepness requiring information in the SWIR (Jiang & Wang, 2014; Frouin & Pelletier, 2015; Pahlevan et al., 2017). Atmospheric correction methods in coastal zones must be updated to address the radiative effect of aerosols (Pahlevan et al., 2017) at high spatial resolution, to incorporate a procedure to evaluate and correct the sunglint (Steinmetz et al., 2011; Devred et al., 2013; Botha et al., 2016, Vanhellemont, 2020) and the radiance from the adjacency effect (Duan et al., 2015).

Table 3: Coastal zones and inlands waters characteristics expected to be mapped with the BIODIVERSITY mission**.**

BIODIVERSITY	Spectral	Spatial	Temporal
Species and seabed types identification	Taxonomic diversity and composition (macrophyte and sediment types)	Structure: spatial heterogeneity of sea floor composition and vegetation coverage	Monitoring of taxonomic diversity, composition and function (habitats), dynamic trends
Species, assemblages and functional types	Species diversity and composition in shallow water	Composition, structure (sea floor topography, canopy height of underwater plants and macrophytes), habitat fragmentation	Monitoring of taxonomic diversity, composition, structure, function (sediment transport, growth of underwater vegetation),mapping change detection

As for inland waters, Hestir et al. (2015) showed that with a 300 m GSD similar to Sentinel-3 OLCI, MERIS could sense more than 50% of inland waters areas in Europe but only a few percents in Australia, where less than 50% was resolved with a 30 m GSD due to differences in topography and water body geometry. Verpoorter et al. (2014) showed that a GSD < 15 m was necessary to characterize most of the 117,423,552 lakes on Earth with, size higher than 0.002 km². With a 33 m GSD similar to EnMap, the number of lakes decreases down to 27,523,552. Turpie et al. (2015) illustrate the importance of a GSD < 10 m to resolve fine features, such as harmful algal blooms, or aquatic habitats formed from foundational species (e.g., submerged aquatic vegetation or emergent wetland vegetation). A 30 m GSD leads to significant degradation and, beyond 60 m, the loss is substantial.

Coastal habitats exhibit a high spatial variability. The physical, biological, geological, and biogeochemical properties of coastal waters greatly change with distance from the coast (Bissett et al., 2004). Observing and monitoring these features and their variability require a GSD between 30 and 100 m (Moses et al., 2016) in the first 5 km from the coastline. Wetland habitat variability occurs at smaller spatial scales. Turpie et al. (2015) studied the impact of the spatial resolution on mapping of coastal tidal wetland habitats and reported that 30 m or less was ideal to map wetlands. In fact, coarser spatial resolution sensors smear and confound spectral and spatial patterns necessary to identify biota and quantify habitat variability. Such a resolution seems to be a threshold to map submerged biologically structured habitats like coral reefs and seagrass beds (Andréfouët et al., 2005; Wabnitz et al., 2010; Hedley et al., 2016). Indeed, some applications like the monitoring of coral bleaching events or invasive species require a much higher resolution (Andréfouët et al., 2002; Dekker et al., 2017). Turpie et al. (2015) mentioned that a 30 m GSD was inadequate to study small patchy areas such as coastal wetlands. A spatial resolution of about 10 m would be optimal.

The spatial extension of these areas is limited to the coastline (< 5 km) with an extension along the coastline around 10 km. In spite of its poor radiometric quality, Hyperion has demonstrated its potential to derive bathymetry, identify bottom types, and discriminate wetland species in various coastal areas (Brando & Dekker, 2003; Pengra et al., 2007). A 10 nm spectral resolution is enough to estimate these variables but a lower resolution (6-8 nm) is recommended to separate diagnostic accessory pigments of phytoplankton as well as fluorescence signals in the reflectance spectrum (Dekker et al., 2017) or to discriminate benthic cover types at higher depths (Botha et al., 2013). A 10 nm spectral resolution is recommended over the 410-800 nm range and SWIR bands are necessary to improve the atmospheric correction to retrieve the bottom-of-atmosphere reflectance.

Airborne hyperspectral images (CASI, Phills, HyMap, MIVIS, etc.) also proved to characterize sea bottom types (Lee et al., 1999, 2001; Minghelli-Roman et al., 2002; Mobley et al., 2002). In clear water, several studies demonstrated the feasibility of mapping the coastal seabed: sand substrates, benthic communities such as microphytobenthos (Kazemipour et al., 2012), seagrass (Jaubert et al., 2003; Bargain, 2012) or coral reefs (Mumby et al., 1998; Mishra et al., 2007).

The most difficult aspect of coastal and inland waters is the ambiguity of the reflectance spectrum (Defoin-Platel & Chami, 2007), i.e., the variations arising from changes in water depth, bottom type, and scattering and absorption in the water column may be indistinguishable. A number of models or assumptions have addressed this issue (Polcyn & Sattinger, 1969; Jerlov, 1976; Paredes & Spero, 1983; McKee et al., 2007) but methods to derive bathymetry, bottom type or water constituents in shallow waters from multispectral data generally fail when the bottom reflectance is too much variable (Jupp, 1988; Gege, 2014).

Contrary to aerial images, satellite images give access to a global spatial coverage. However, the spatial resolution of these sensors does not permit detailed mapping of pollution plumes or small lakes. Similarly, the intertidal zone is a very sensitive area where changes occur at a small scale. The BIODIVERSITY mission will deliver images at a resolution that supports local scale applications determining water quality in coastal and inland waters through parameters like phytoplankton, suspended particulate matter, and sediment grain size. It will also provide the capability for multi-temporal monitoring of events such as algal blooms or green algae invasion. High spectral and spatial resolutions are also required to better estimate concentrations of hydrosols over oceans/lakes, such as mineral-like particles or biogenic particles (phytoplankton). Knowledge of hyperspectral remote sensing reflectance can also provide information about phytoplankton functional types (PFTs) that dominate the surface waters: diatoms, dinoflagellates (Gege, 1998; Alvain et al., 2008), cyanobacteria (Kudela et al., 2015). Techniques used to identify PFTs mostly rely on the spectral signature of phytoplankton pigments, which justifies the need for a spaceborne hyperspectral sensor.

The BIODIVERSITY mission will allow studying the biodiversity of aquatic ecosystems by identifying corals or benthic plankton species that are essential to monitor the anthropogenic impacts on coastal environments.

It must be emphasized that imaging spectroscopy was mainly developed with airborne sensors. This limits the construction of multi-temporal datasets and generally reduces coverage to relatively restricted areas and to scientific studies. As mentioned by Lucas et al. (2004), Hyperion provided the first opportunity to explore the potential of multi-temporal hyperspectral data for Earth observation, but this sensor was experimental with a limited swath width and a low SNR. Dekker et al. (2001) review on imaging spectroscopy of water demonstrates its efficiency in managing complex coastal and lake systems at various scales on a sustainable development basis. High-spectral and high-spatial resolution measurements of inland and coastal waters are of great interest for determining the geophysical variables of primary importance for monitoring these ecosystems.

The BIODIVERSITY mission will have many environmental applications for the community: 1) remote sensing of harmful algal blooms, which have an impact on tourism and aquaculture; 2) detection of phytoplankton filaments induced by ocean circulation and turbulence, which have an influence on fisheries activities; 3) quantification of suspended matter (mineral or biogenic) at land-ocean interfaces induced by river discharges, which will allow estimation of nutrient fluxes exported by rivers into coastal/inland waters; 4) measurement of dissolved organic matter for studying carbon fluxes and light attenuation affecting primary productivity; 5) estimation of bathymetry, which is of interest for coastal geomorphology evolution, military applications, and underwater vision; 6) identification of bottom-type for ocean/lakes (sand, corals, benthic habitats), which help to study the biodiversity of these ecosystems; and 7) detection of the optical properties of hydrosols, which provide information about water quality and aid the detection of pollution. To sum up the main user requirements are provided in Table 4.

Table 4: User requirements for Coastal and inland waters.

User requirement types	
Ground sampling distance (m)	< 10
Area size (km²)	100
Spectral range (µm)	0.4 – 2.5
Spectral resolution (nm)	10 - 15
Revisit (days)	5
Accessibility	Worldwide

4. Complementary Mission Objectives

4.1 SQ3 - What is the impact of management practices on environmental processes such as soil carbon storage, soil infiltration, surface retention, runoff and soil erosion?

Bare surfaces are characterized by drylands, arable ecosystems (also named agroecosystems) and urban soil ecosystems. They deliver essential services such as provision of food, fiber and fuel, carbon storage, water purification and soil contaminant reduction, climate regulation, nutrient cycling, biological habitat and gene pool (Robinson et al., 2009; Baveye, 2017; Bünemann et al., 2018). However, demographic pressure and climate change can disrupt these services and affect bare continental surfaces because of desertification processes, environmental hazards, mining and industrial waste pollution, and diminishing soil quality (e.g., related to erosion, salinization and contamination) (Rodrigo-Comino et al., 2020). Soils are amongst the most diverse habitats on Earth, hosting billions of bacteria, fungi and invertebrates (Paul, 2015; Cameron et al., 2018). According to the Land Degradation Assessment in the Drylands project (LADA), land degradation undergoes such an irreversible change that soils may no longer come back to their original uses (Biancalani et al., 2013). Desertification occurring in arid, semi-arid, and dry sub-humid areas, results from factors such as climatic variations and human activities (Article 1 of the United Nations Convention to Combat Desertification, UNCCD, Paris, 1994). As soil integrates a variety of important processes involving vegetation growth, overland flow of water, infiltration, land use and management, land degradation is closely related to soil degradation (Stocking & Murnaghan, 2001). Soil degradation is a change in soil quality resulting in a decreased capacity of the ecosystem to provide goods and services for its beneficiaries. It is also defined by IPCC as “a negative trend in land condition, caused by direct or indirect human-induced processes including anthropogenic climate change, expressed as long-term reduction or loss of at least one of the following: biological productivity, ecological integrity, or value to humans” (Hermans et al., 2019). Degraded soils do not provide services according to original potential in a given ecosystem. Soil loss, erosion, compaction, salinization, and pollution are some of the main processes leading to soil degradation, which occur over space and time. Soil degradation is likely to be mitigated or even countered by C stocking practices, which enhance soil carbon storage (Chenu et al., 2019) and hence restore soil structure and quality (Bünemann et al., 2018) as well as fertility (Tan et al., 2005). Soil erosion is a land degradation process that often occurs in cultivated environments due to natural processes (e.g., climate events) and that is accelerated by human activities (Le Bissonnais et al., 2007). Soil erosion may reduce crop production potential, lower surface water quality, and damage tile drainage systems (Toy et al., 2002). Extensive tillage over extended time periods may cause soil compaction due to tillage operations and heavy machinery (Lagacherie et al., 2006) and may involve loss of soil nutrients and organic matter which are soil stabilizing factors (Ramos & Martinez-Casasnovas, 2006; Novara et al., 2011). Therefore, these cultivated soils are more sensitive to water and wind erosion over time. Soil salinization is a process occurring in arid and semi-arid regions where low precipitation cannot maintain a regular percolation of rainwater through the soil (Szabolcs, 1989). Soil salinity is usually due to rising water tables, either induced by land clearing alone, referred to as dry land salinity, or by irrigation-induced salinity. It is one of the major factors affecting biomass production as saline soils are highly erosive given a poor structure and they are less fertile with reduced microbial activity and salt toxicity. Industrial waste pollution affects soils all over the world, especially in urban ecosystems and industrial areas (Science Communication Unit, University of the West of England, Bristol, 2013). It may originate from various sources such as refineries, cement, steel, fertilizers, and pesticides factories, coal and mineral industries, engineering and chemical industries, mining and transportation activities (e.g., Castagliola et al., 2008; Ettler et al., 2009; Ahmaruzzaman, 2010; Piatak & Seal, 2010; Gräfe et al., 2011; Paldyna et al., 2013). Depending on the process involved, solid waste can take different forms such as fly ash deposits, slags, red mud, heaps, mine tailings, etc. Soil and groundwater contamination may occur from massive quantities of industrial residues produced because of their temporary storage or neglectful disposal in various soil sites. Therefore, the management and possibly the remediation of these sites require characterizing and mapping the minerals associated with pollutions.

Soil degradation processes are all variable in time and space and depend on the initial soil composition, climate (including rain events and temperature), and crop sequence and management practices for agroecosystems. In agroecosystems, site specific crop management (SSCM), also known as precision agriculture (PA), refers to technologies and concepts applied to agricultural management system that promotes variable management practices according to small scale (typically within field) crop and soil variations (Jian et al., 2020). Precision agriculture is based on innovative technologies and principles to identify and manage spatial and temporal variability in crop production. It may combine various benefits: increased resource use efficiency by producing more and better with less damages (so may ensure food security), reaching targeted product quality, improved sustainability of production, support product traceability and minimized environmental impact.

Observations needs, linked to this objective

There is a real need to provide soil characteristics to 1) support soil degradation processes model and crop production model parameterization, 2) monitor soil degradation processes and improve their understanding, 3) monitor carbon storage and 4) support SSCM/PA and industrial site remediation decisions. The characteristics to be retrieved are topsoil primary properties (soil organic carbon, mineralogy, texture, iron oxide and calcium carbonate) and soil surface conditions (dry vegetation residues, soil moisture).

BIODIVERSITY as the perfect platform for these observations

Imaging spectroscopy proved to be a promising tool to map and monitor topsoil properties (e.g., Selige et al., 2006; Ben-Dor et al., 2009; Stevens et al., 2010; Gomez et al., 2012; Lagacherie et al., 2012; Schmid et al., 2016; Vaudour et al., 2016; Hong et al., 2020), minerals (e.g., Clark et al., 1993; Resmini et al., 1997; Chabrillat et al., 2002), soil surface conditions including crop residues (Daughtry et al., 2005), soil moisture (Finn et al., 2011; Bablet et al., 2018), and aggregate stability (Shi et al., 2020). In the solar domain (400–2500 nm), soil reflectance spectra display spectral signatures that enable quantitative analysis of several soil features (Stenberg et al., 2010; Demattê et al., 2016). It is well established that the quality of hyperspectral data is crucial for quantitative assessment of soil properties (Ben-Dor et al., 2009). However, such data are not easily accessible. Airborne data are expensive and difficult to obtain at repeated periods, with limited flight prints. Operating hyperspectral satellites are at the end of their life span, their spatial resolution is coarse (30 m and 17 m for Hyperion and Chris/Proba, respectively), and they have noisy or no SWIR information. Multispectral sensors like ASTER, Landsat-8 or Sentinel-2 have large swaths and several spectral bands, but with coarse spectral resolution. However, with a frequent revisit rate, and through its VSWIR range, Sentinel-2 exhibited promising capabilities at regional scales for key topsoil properties, such as soil organic carbon, in temperate agroecosystems with annual crops (Castaldi et al., 2019a, 2019b; Vaudour et al., 2019a, 2019b). Yet due to insufficient spectral resolution and spectral richness in the SWIR range, it has some limitations concerning clay content (Vaudour et al., 2019a) and clay mineral prediction in particular. Altogether, current sensors are not able to fulfill all the requirements related to the above described processes and characteristics.

A number of topsoil compounds necessary to evaluate the soil quality have specific features located in the SWIR: calcite, dolomite, quartzite, and clays minerals, such as kaolinite (Hunt, 1977; Kruse et al., 2002; Mielke et al., 2014; Boesche, 2015; Boesche et al., 2016), metallic ions or soil moisture. Most terrestrial materials are characterized by spectral absorption features typically 20 to 40 nm in width (Hunt, 1977). According to Goetz (1987), a 10 nm sampling interval is sufficient for describing salient features in the reflectance spectra of rocks, minerals, organic matter plants, and suspended matter in water bodies across the 0.4-2.5 µm spectral region. Swayze et al. (2003) selected the optimum sampling interval to discriminate seven rocks taking the sensor noise into account. They recommended a 14 nm (respectively 10 nm) sampling interval in the VisNIR (respectively SWIR) range.

To reduce the percentage of mixed pixels in an image, a spatial resolution better than 10 m is recommended. A global accessibility is required to access the large variety of bare soils along the year at different latitudes. For land use, a revisit of 15 days might be sufficient but for other events such as cultural operations or a pollution, 5 days or less are necessary. To sum up the main user requirements are provided in Table 5.

Table 5: User requirements for soil quality.

User requirement types	
Ground sampling distance (m)	< 10
Area size (km²)	100
Spectral range (µm)	0.4 – 2.5
Spectral resolution (nm)	10
Revisit (days)	≤ 5
Accessibility	Worldwide

4.2 SQ4 - How do urban materials and industrial pollution impact on vulnerable surrounding?

Rapid urbanization and accelerated urban sprawl have a significant impact on urban climate (Bechtel et al., 2015) and on conditions of urban biophysical processes and physical environment, thus they influence the quality of human life. Timely and accurate information on the status and trends of urban ecosystems and biophysical parameters is critical to develop strategies for sustainable development and for improving urban residential environment and living quality (Yang et al., 2003; Song, 2005). Therefore, developing techniques and enhancing ability for monitoring urban land use and land cover (LULC) changes are important for city modeling and planning.

Challenges for urbanized areas

Urban area detailed mapping is mandatory to model the interactions within the city extent or with the surrounding areas. Besides the simple monitoring of urban environment expansion, imaging spectrometers enable to collect valuable information on materials and landscape in order to detect changes in materials (wear or damage), density, surface permeability ratio, and physical characteristics of urban elements. They enable to assess their impact on local climate/hazardous events. They also ease the monitoring of urban vegetation that is crucial to temper urban heat island (Degerickx et al., 2017; Aval et al., 2018) and mitigates atmospheric pollution. These data offer the possibility to track urban area changes within the overall human environment and to feed 2D or 3D interaction models. Urban environments actually have their own features:

- A large spatial heterogeneity, the scale of which depends on the city type, geographical, economic, social and environmental factors;
- An extensive number of different materials, extremely variable with respect to their spectral characteristics;
- Important artefacts for remote sensing from air and space as shadowing and superposition effects, due to inherent 3D structure of the urban landscape.

That is why land cover mapping in urban areas, and consequently land use mapping, relies on VHR sensors (< 5 m) that provide details required by most of urban planners. Imaging spectroscopy is thus very useful to characterize urban and peri-urban elements, improving the identification and therefore the mapping of soils, material or vegetation types, as well as atmospheric water vapour content and aerosols. Moreover, buildings are prominent objects needed for a variety of applications like 3D city visualisation, microclimate forecast or real estate databases for which imagery is one of the most consistent information in modelling at various scales. Indeed, roof material identification leads to an accurate extraction of building models (Avbelj, 2016) or innovative application like solar panels (Karoui et al., 2018). Digital elevation models provide information about the vertical dimension of urban areas. Independently of the spatial resolution, higher spectral resolution and continuous acquisition increase the number of classes to identify and map (Le Bris et al., 2017). Helden et al. (2011) listed the applications that benefit from a spatial resolution ranging between 2 and 20 m: local mapping of build-up area, imperviousness, material and biotope mapping, change detection at building/material level and identification of hazardous materials (Le Bris et al., 2016; HYEP, 2018). Nevertheless, a large spectral range at different wavelengths allows better separation between artificial and natural materials (mainly in the VisNIR from 450 to 950 nm) and better identification of the surface contents (e.g., mineral contents in the SWIR) (McDowell & Kruse, 2015).

Therefore, urban vegetation monitoring, ranging from highly cultivated lawns to street trees and from horticultural plantings to remnant patches of original or regenerated native vegetation, is feasible using imaging spectroscopy at fine spatial resolution (Mc Kinney, 2002). This is also true for urban soil, including exposed soil and/or dry vegetation (Hung & Ridd, 2002). They have a distinct function from vegetation and impervious surface in an urban ecosystem, e.g., increasing aerosol concentration above urban area. Similarly, monitoring anthropogenic impervious surfaces, such as rooftops, roads, and parking lots, is a key indicator of intensity of urbanization and urban sprawl (Xian & Crane, 2006), as well as a major contributor to the environmental impacts of urbanization associated with increased surface runoff, erosion and impaired stream biodiversity (Lee & Lathrop, 2005).

However, very high spatial resolution hyperspectral data can be only obtained from airborne platforms so far. Although they help to improve the understanding of urban environments, airborne campaigns are limited in time and rather expensive, leading to compromises, such as combinations of VHR multispectral images with moderate resolution hyperspectral data sets (Moeller et al., 2009; Yokoya et al., 2012; Grohnfeldt et al., 2013). As a consequence, the BIODIVERSITY mission, with its combined very fine spectral characterization of urban surfaces and fine spatial resolution, can tremendously contribute to these tasks and be considered as a quantum leap with respect to urban area monitoring.

Observations needs

More specifically, the fine spectral characterization of urban surfaces by BIODIVERSITY, coupled with a spatial resolution of comparable size to most objects in a human settlement, will lead to more accurate maps of natural and artificial materials and structures. Information about the age/status of roofs and roads (Herold et al., 2004), urban vegetation health (Wania & Weber, 2007), and the degree of surface imperviousness (Van der Linden & Hostert, 2009) provided by the BIODIVERSITY mission will become available as standard products. They will be routinely used as inputs to urban environmental models, urban risk and building/population vulnerability analyses, as well as for the computation of more reliable urban quality of life indexes.

The solid scientific basis of these products is based on algorithms that have been tested by the scientific community over a decade. The scientific soundness of these products will be coupled with their availability locally (i.e., for the urban area of choice) but with a global coverage (i.e., for any geographical area) with an unprecedented spatial resolution. In turn, this will allow an up-to-date and geographically uniform characterization of many parameters required to address challenges like the interactions between natural and human components of the Earth system, as well as conflicts between urbanization and ecosystem services. Additionally, gas (Marion et al., 2004; Popp et al., 2012; Dennison et al., 2013; Thorpe et al., 2013, 2014, 2016) and aerosols (Deschamps et al., 2013) concentrations in the lower layers of the atmosphere will be an invaluable input to air quality and urban pollution models. One can couple them with meteorological models, the effectiveness of which is connected to the availability of accurate maps of urban climate zones (Bechtel et al., 2015). BIODIVERSITY will make such data available as a standard product in urban areas.

BIODIVERSITY as the perfect platform for these observations

Several authors pointed out the interest of using the full spectral range between 0.4 – 2.5 µm to identify manufactured materials (Swayze et al., 2003). Moreover, Roussel et al. (2018) have demonstrated the benefits of using the SWIR in comparison with a multispectral sensor at the same spatial resolution to improve the land cover classification performances. The requirement on the spectral resolution is similar to that recommended in the previous section. The size of a city is typically 20 km x 20 km and can reach 100 km x 100 km for the largest. The temporal evolution of the city structure remains slow but the monitoring of its vegetation requires frequent revisits: a 5 days revisit time is required to follow it during the greenness period or a heat wave event. Table 6 summarizes the main user requirements.

Table 6: User requirements for urban area studies.

User requirement types	
Ground sampling distance (m)	< 5
Area size (km²)	100-200
Spectral range (µm)	0.4 – 2.5
Spectral resolution (nm)	10
Revisit (days)	Monthly
Accessibility	Worldwide

5. Conclusion

The BIODIVERSITY mission aims at 1) improving our knowledge on heterogeneous habitats characterized by a high biodiversity like terrestrial ecosystems and coastal and inlands water, and their resilience to anthropogenic activities; 2) providing an unprecedented information for analysing soil surface characteristics in relationship with soil fertility and crop management, soil restoration and remediation, managing urban land cover and industrial pollution; 3) providing key knowledge that improves understanding of coastal and inland water ecosystem functioning as well as their status assessment. Its limited swath balanced by its high spatial and temporal revisit allows focusing on small hotspots serving as reference for several habitats present around the Earth. A summary of the main user requirements driven by SQ1 and SQ2 is provided in Table 7.
They are also compared to more recent missions (Ustin & Middleton, 2021). As shown, no existing or planned mission can fulfil the requested GSD around 10 m, all of them are around 30 m. However, EnMap and Chime coverage are global with a high revisit. They can sense large area even though BIODIVERSITY can answer to its user mission group. Finally, these two mission classes could be considered as complementary. Indeed, the 30 m GSD mission family can cover large area with a small heterogeneity and BIODIVERSITY can sense some specific hot spot where the 30 m intrapixel biodiversity variability is not sufficient (Mariotto et al., 2013).

The area size is in the 100-200 km². Thus BIODIVERSITY swath could be limited across track to 10-20 km depending on the concerned regions of interest, with an along track length of at least 10-20 km. This corresponds to a large hotspot area covered by on ground station, allowing bridging the gap between the two levels of measurements. As it could be noted, the recommended spatial resolution < 10 m fulfils SQ1, SQ2 and SQ3 GSD requirements but not SQ4. To overcome this limitation, a panchromatic band with a 2 m GSD, co-registered to the hyperspectral instrument could be added. Existing works on the fusion of two images by pan-sharpening (Constans et al., 2020) or unmixing methods (Rebeyrol et al., 2020) will allow to answer to SQ4 challenge.

The future works will be focused on the demonstration of the benefits of such a mission based on an airborne acquisitions database simulated at top of atmosphere. In particular, these top-of-atmosphere synthetic images will help to define the tradeoff between our scientific requirements and the technological expected performances of the sensor. Indeed, first studies (CNES SPS (Séminaire de Prospective Scientifique, 2019 at Caen, France) of the sensor design related to BIODIVERSITY show the expected radiometric performances are better than Hyperion ones, allowing to fulfill most of the mission requirements. Thus, 2021-2022 years will precise the sensor performances to confirm our mission objectives and expected products

Table 7: User requirements for the BIODIVERSITY (Biodiv.) mission compared to recent developed ones or in preparation. (*: depointing capabilities)

User requirement	PRISMA	EnMap	Chime	SBG	Biodiv.
Ground sampling distance (m) at nadir (HIS / Pan)	30 / 5	30 / No	20-30 / No	30-45 / No	< 10 / 2
Swath (km)	30	30	290	n/a	10-20
Spectral range (µm)	0.4 – 2.5				
Spectral resolution (nm)	< 12	VNIR:6.5 SWIR:10	10	n/a	10
Revisit rate (day)	7	Up to 4*	10-12.5	n/a	5
Accessibility	Worldwide				
Launched date	2019	2021	2025	2026	2025
Global coverage	Yes	Yes	Yes	Yes	No

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